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Building a Simple Analytics Setup to Improve Sales and Manage Inventory Better in Omnichannel Retail

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ABSTRACT

Shopping today is very easy for customers. People can find what they need quickly. Some people browse on their phones when they are on their way to work or school. They compare options on their laptops when they are at home. They complete purchases in stores without thinking about where they are shopping whether it is online or in person. Shopping is easy these days. Businesses have made shopping very smooth by connecting stores and websites and mobile apps. This makes it easy for customers to shop at stores or shop on websites or shop, or on apps wherever they want. Shopping is convenient for customers. It is not without its challenges for businesses. Retailers often face problems because their sales data, inventory records and customer information are all in systems. These systems do not always talk to each other which makes it hard to get a picture of what is really happening in business. When information is not connected it is hard to see what is really going on. This study is about solving that problem of information. It offers a way to bring sales and inventory data together so retailers can see everything clearly. The goal of this study is to use data to understand what customers want so retailers can predict what will sell and make inventory decisions. The framework for doing this has four stages. First it puts data from all channels, including stores, websites and mobile apps into one system. Second it uses forecasting models to guess what customers will want using data and machine learning to make predictions. Third it uses optimization models to make decisions about stock and orders balancing cost and customer satisfaction. Finally, it shows insights on a dashboard that track performance indicators making results easy to understand.

To test this framework a case study was done using six months of sales data from three channels: stores website app The dataset had 500 products and nearly 100,000 transactions, which is a lot of data. The findings were very good. The inventory turnover at the store got a lot better, it improved by 23 percent, which's a really big improvement for the inventory turnover. There were a lot of stock-outs, the number of stock-outs decreased by 31 percent so now customers can usually find what they want when they come to the store. The forecasting accuracy got better by 18 percent so retailers can now make guesses about what products will sell and what will not sell, which helps the retailers with forecasting accuracy. The cost of fulfilling orders fell by 15 percent, which means the retailers will save money on the fulfillment costs and that is a deal for the retailers and their fulfillment costs. Cross-channel analysis showed customer behavior patterns, which's interesting. Customers who browsed online had a 76 percent chance of buying in-stores, which shows that online browsing leads to in-store sales. Mobile app users brought in 28 percent value, which's a significant amount. This study shows that linking sales and inventory information is very important in an omnichannel retail environment. By breaking down data silos and using analytics retailers can improve financially. Delivery good customer experience.

Omnichannel retail is about making shopping easy for customers and this study helps retailers do that. The study uses sales analytics, inventory optimization, data integration, demand forecasting, retail performance, machine learning and convolutional neural networks to achieve its goals. These are all tools for retailers who want to succeed in an omnichannel retail world. Omnichannel retail, sales analytics, inventory optimization, data integration, demand forecasting, retail performance, machine learning and convolutional neural networks are all key to shopping, for customers.

1. Introduction

People buy things differently now. We do not have to go to a store to buy something anymore. Most businesses have stores they have websites and they have applications so customers can shop at any time and in any place they want. For example a person might look at products on their phone while they are traveling then they might compare options on a laptop when they are, at home. Finally they might visit a store to complete the purchase of the products. This is how people shop for things now using stores and websites and mobile applications like businesses have. From the customers side this process feels smooth and convenient. The customer can shop at the store they can shop on the website. They can even shop on the mobile application.

Behind this convenience there is a reality that businesses have to deal with. The systems that manage store inventory, online orders and customer information often do not work together. Sometimes an item listed as available on the website might already be sold out in the store. When you buy something online it may not immediately show up in the stock counts. These small mistakes can slowly cause problems like lost sales, frustrated customers and declining trust in the business. The store inventory and online orders are not connected it is hard to keep track of what's available. When systems are not connected retailers often have to make decisions without having all the information. The idea of omnichannel retail came about because of this transformation in commerce. Omnichannel retail means combining sales channels into a system that provides a customer experience. This means that the customer can shop at the store or they can shop on the website or they can even shop on the application and the business will have a picture of what is available.

Retailers are trying to connect sales and inventory data across both platforms because of the growth of data analytics and technological advancement. This is a deal for retailers. Research shows that when retailers integrate sales and inventory data it can really help with efficiency and customer satisfaction. It also supports the growth of the business. Retailers and data analytics are important in this process. Data analytics help retailers make sense of all the data they have. However fragmented data remains an obstacle causing forecasting, inefficient stock allocation and operational delays. The business needs to have a picture of what's available so they can make good decisions about omnichannel retail. Earlier inventory systems were designed for channel retail environments.

Many traditional models do not consider -channel demand interactions and shared inventory pools. Omnichannel analytics has recently gained attention in both areas. Modern approaches increasingly rely on machine learning and optimization techniques to create inventory views and predict demand patterns across channels. This means that the business can use data to make decisions about what to stock and when to stock it in omnichannel retail. This shift challenges the assumption that inventory in each channel should be managed independently. When analytics are integrated, they provide advantages by enabling allocation and faster response to demand shifts. Researchers have investigated methods to integrate sales and inventory information. Many studies combine modeling with optimization frameworks to improve stock decisions in omnichannel retail. The business needs to be able to respond to changes in demand so they can keep customers with omnichannel retail. Some methods use networks or advanced learning models to detect -channel behavior patterns while others rely on engineered features to capture relationships between browsing and purchasing trends. A large portion of existing research focuses on single-channel data overlooking channel interdependence or lacks generalizability beyond datasets. The field of omnichannel inventory optimization remains relatively young. The business keeps changing. The company needs to use information to make decisions so they can stay ahead in retail where people shop in many ways.

Machine learning and deep learning have worked well in areas like seeing things on computers and understanding what people say. In analytics these technologies are used often to identify patterns hidden within complex datasets. Their strength lies in handling relationships and scale transactional information which're essential for managing omnichannel retail systems. Business needs to use information to make choices so they can stay ahead of others in retail that happens in many places. As stores start to use numbers and details to run things looking at all the information together, it is changing how companies figure out what is working well and make choices. Business needs to use information to make choices so they can stay ahead of others in retail that happens in many places. Retail that happens in places is very important to stay ahead of others. Businesses need to use information to make choices, about retail that happens in many places.

1.1 Motivation

The research is important. Needs to be done now. The Cost of Inventory Inefficiency is the money that businesses lose when they do not manage their stock well. This happens when businesses have much stock, which ties up their money or not enough stock, which delays orders and upsets customers. These problems increase costs because of wasted storage space, higher borrowing costs. Lost sales. Businesses also have trouble with inventory records that're not accurate which affects their planning and decision-making. It is important to fix inventory inefficiency to reduce expenses and improve how businesses work. When products are not available retailers lose sales and risk losing customers forever. Excess stock locks up money increases storage costs. Often leads to losses when products are sold at lower prices. Reports say that these inefficiencies cost retailers over one trillion dollars every year. In a situation where businesses sell products in places, including warehouses, stores and fulfillment centers stock levels must be balanced across all these places, which makes the problem even harder. Combining sales and inventory data is a way to reduce these losses. What customers want has changed the way businesses provide services and products.People who buy things from companies want to feel special. They like it when companies do things the way they like. Companies should be truthful with people who buy things from them and keep them informed about what's happening. Companies need to change the way they do things to make people who buy things from them happy or else people will not come back to companies. It is really important for companies to know what people who buy things from them want. This helps companies stay ahead of companies. People who buy things from companies want to have experiences and they want companies to be open with them. If companies do this people who buy things from them will be happy with companies. People will keep coming to companies because they like the way companies treat them. Figuring out what people who buy things from companies want is the key to making them happy. Companies need to know what people who buy things from them want and give it to them. This is how companies make people who buy things from them happy and keep them coming to companies. People who buy things from companies are very important, to companies and companies need to take care of them. Today customers expect transparency and speed. They want to know if a product is in stock they want to be able to get their products delivered in a way that's convenient for them and they want to be able to return products easily no matter where they bought them. These are things that customers expect now. Retailers that do not meet these expectations will lose customers to competitors that have systems. The Data Disconnect Retailers get a lot of data every day from sales, website visits and loyalty programs.. This information is often not connected and is stored in separate systems. Sometimes online sales data does not match the data from in-store sales. Inventory levels may be updated at times across different platforms. Retailers often get confused because their data is fragmented of getting clarity from all the data they have. Combining data is necessary to turn data into useful information. Personal Perspectives During my internship as a data analyst, in the sector I saw these problems firsthand. Teams used spreadsheets, manual processes to reconcile data and delayed reports. Simple questions took hours to answer because we had to cross-check everything. It became clear that the problem was not that we did not have data but that we did not have a good way to combine all the data. This experience led to the creation of a framework that solves operational problems in a practical way.

1.2 Contribution

This research contributes meaningfully to both academic research and real-world retail practice. From an academic perspective, it extends traditional inventory theory by incorporating cross-channel demand interactions and shared inventory pools. The proposed framework reflects the realities of omnichannel operations, unlike single-channel models. It also provides empirical evidence supporting the benefits of integrated analytics. In the case study conducted, inventory turnover improved by 23 percent and stock-outs decreased by 31 percent, showing clear operational gains. The structured four-layer framework covering data architecture, predictive analytics, prescriptive optimization, and visualization provide a foundation for future research in omnichannel systems. For retail practitioners, this study presents an implementable methodology rather than a purely theoretical concept. It outlines clear steps for integrating data, selecting forecasting models, optimizing stock allocation, and building performance dashboards. The quantified results provide a strong business case for investment in integrated analytics. New performance indicators like cross-channel contribution and inventory availability accuracy help organizations measure factors that impact profitability and customer satisfaction. For data analysts and students, this work shows how analytical techniques translate into real business value. It shows the complete journey—from raw transactional data to predictive modeling, optimization, and strategic decision-making. This project is really helpful for learning about data integration and statistical analysis and machine learning and visualization and communication. The research says that when we combine sales data and inventory data from places it is a big help. It is not a technical thing that is good to have. For people who own stores and want to sell things sales and inventory data is very important to have. This project is about sales data and inventory data and how we can put them together to make a business better. By putting sales data and inventory data people who own stores can make good decisions and sell things better, than others

2. Related work

People have been studying how to make retail stores work better with all their sales channels for the ten years. When stores started selling things in than one place like in a store and online the old ways of keeping track of inventory were not good enough. Now that stores are trying to connect all their sales and inventory systems researchers want to figure out how to manage all the pieces of information how people buy things in different places and how to get products to customers from different locations. This part of the study looks at the work that has been done on putting the right amount of inventory in the right places guessing how much of something will be bought, combining all the different pieces of information understanding how people buy things and finding new ways to make inventory work better.

2.1 Putting Inventory in the Right Place in Stores that Sell Everywhere

One question for stores that sell everywhere is how to decide how much inventory to put in each place like online or in a physical store. Hassanzadeh and Martínez-de-Albéniz used a framework to try to answer this question. They wanted to find the way to control inventory so that stores can make the most money. The goal is to make sure that inventory is used in the way possible across all the different sales channels, including online and offline channels. By studying omnichannel retail and inventory optimization researchers, like Hassanzadeh and Martínez-de-Albéniz are helping stores to better manage their inventory and make sales. Their findings suggest that inventory allocation should follow a time-based strategy depending on the selling horizon. Their model suggests adjusting channel activity according to revenue potential and the remaining season time, instead of always maintaining high availability in all channels. This work challenges the traditional idea that maximizing availability everywhere always leads to better performance. Instead, it shows that strategic channel prioritization can sometimes protect overall profitability. Zhang and Liu [7] extended this discussion by introducing an omnichannel news vendor model that jointly optimizes inventory levels and online order acceptance thresholds. Their work explores the connection between two operational decisions, how much to stock and how many online orders to accept—that were often treated separately in earlier research. Their results show that factors such as cancellation costs and demand variability influence stocking decisions and safety stock levels. These studies show that managing inventory across all channels needs decision-making. This is of having separate strategies for each channel.

2.2 Demand. Cross-Channel Analytics

Forecasting demand in an omnichannel environment is more complex because demand in one channel often influences demand in another. Kok and Fisher addressed this challenge through a multichannel attraction model that integrates assortment planning with inventory decisions. Their work shows that ignoring demand variability and channel interactions can lead to inefficient product assortment decisions. Chang and Kao came up with a way to forecast things that is based on data. It also considers what happens on different channels. Wang and Zhang looked at how machine learning models do compared to the methods people use to forecast what will happen over time with data that shows patterns over time. They wanted to see which one works better the machine learning models or the traditional time-series forecasting techniques, so they compared the two to find out. Their findings consistently show that machine learning methods improve prediction accuracy in omnichannel settings. Customer behavior studies enrich this field. For example, the concept of webrooming, where customers research online before purchasing in-store, has important inventory implications. Chatterjee and Das [6] developed an analytical model that incorporates these cross-channel behaviors into fulfillment and assortment planning decisions. Their results show how understanding consumer journeys can directly improve revenue optimization and inventory alignment.

2.3 Data Integration Architectures

Effective omnichannel analytics needs a data system. Liu, Ali and Jabbar looked at omnichannel supply chain research. Found main areas related to warehouse management, logistics integration and information system interoperability. They found that real-time inventory visibility, automated stock tracking and standard data structures are crucial. Gupta and Nath proposed a data architecture for omnichannel analytics. This framework has an integration layer to bring together data from systems, a storage layer rules to keep data quality and security high and an analytics layer for predictive models. These studies show that advanced analytics needs a data foundation to work well. Omnichannel analytics relies on data and omnichannel data must be well-managed. Omnichannel supply chain research highlights the importance of data infrastructure, for omnichannel analytics.

2.4 Process Mining and Consumer Behavior Analysis

Understanding customer movement across channels has attracted attention. Tridalestari , Musta fid, and Jie used process mining techniques to analyze consumer journeys across marketplaces, web stores, and social media platforms. By comparing several process discovery algorithms, they found that the Fuzzy Miner algorithm most effectively captured real customer behavior patterns. Their analysis found that many customers use media a lot before buying things on marketplaces. This tells us that it's really important to combine data from channels. That way we can guess demand. Plan inventory better.

2.5 Optimization. Machine Learning

Application Optimization remains central to omnichannel inventory management. Kumar and Singh [18] created a mixed-integer programming model to find the best stock allocation across channels. Their model considers uncertainty, service levels, fulfillment costs, and capacity constraints. More recently, dynamic optimization approaches have gained traction. Zhang, Li, and Liu [15] applied reinforcement learning to fulfillment decisions, leading to better cost efficiency. Goedhart and colleagues modeled omnichannel fulfillment as a Markov decision process, which helped make inventory and replenishment decisions based on future demand projections.[3] found a way to use intelligence to improve marketing and the way they do things. They used something called reinforcement learning. Graph neural networks to see how their marketing and operations were going and to make them better. When they tried this out they found it really worked. They made a lot of money from sales. Got a better return on what they spent. This is part of a change in how stores make decisions. Now they are using data and artificial intelligence to make decisions of just doing the same things they always did.

2.6 Deep Learning, for Demand Forecasting

Deep learning models are increasingly applied to omnichannel demand forecasting. Research in [19] presents hybrid recurrent neural network models that capture temporal patterns in retail data. Experimental results show improved performance compared to conventional recurrent architecture. The Demand Stack approach introduced in [20] combines multiple deep learning models into an ensemble predictor, addressing volatility in omnichannel demand. Reported results show strong forecast accuracy and lower error rates compared to individual models. Another study uses convolutional neural networks with transfer learning to forecast demand across channels. By extracting features from historical sales data and transferring learned patterns across categories, the CNN-based model achieved higher predictive accuracy than alternative methods. The literature shows steady progress in forecasting, optimization, and data architecture in omnichannel retail. Many studies still focus on isolated components rather than fully integrated frameworks. This gap shows the need for research that brings together data integration, predictive modeling, and prescriptive optimization into a single system—an aim that drives the framework developed in this study

3. Research Methodology

3.1. Problem Statement

Retailers over the world are trying to do this thing called omnichannel. There is a big difference between what they want to do and what they actually do. Retailers want to make customers happy. They have a lot of trouble with data that is all over the place and people making decisions that do not work well together. This makes a lot of problems that're easy to see and that hurt how well the retail store does and if the customers are happy. The big problem is that retailers do not have a plan that uses data to connect how well things are selling with making sure they have the right amount of stuff in stock across all the different ways they sell things. This means that they are not putting their stock in the places, which means they miss out on selling things they spend more money to run the store and the customers are not as happy with the retail stores. Retailers need to work on this so they can use their data to make decisions, about retail and make their customers happy. This main problem can be broken down into challenges. Data fragmentation across channels occurs because retailers often use systems that lack effective communication. These systems include System Channel Data Type Update Frequency Point-of-Sale Physical Stores focus on transactions, returns, time tracking, and batch processing. E-commerce Platform Website Orders Browsing Real-time Mobile app backend supports mobile app interactions and purchases in real-time. The

Warehouse Management System or WMS helps us keep track of orders, inventory and shipments. * It shows how orders are fulfilled. * It shows how inventory we have. * It shows when shipments are sent out. We can check this information at once or in real-time. To ensure everything is correct we should also check the Enterprise Resource Planning or ERP and Corporate Financials and Procurement data daily or weekly. The problem is that these systems do not always use the data or identifiers. They also do not update at the time. Each system has its way of organizing data. This makes it hard to get information from one system at a time. For example when a customer asks if we have a product in stock the Warehouse Management System might say yes based on our current warehouse inventory. However it might not have the information about what has been sold in the store. So the customer comes to the store. Finds out the product is not available. The Warehouse Management System or WMS manages the warehouse. We use the WMS to track WMS data. This is a problem because customers rely on the WMS for inventory levels. The WMS should give customers information about WMS data. The WMS should have the up-to-date WMS data. We should be able to trust the WMS data. The WMS is important, for managing the warehouse. We need to make sure the WMS is accurate. This results from data fragmentation across channels of the omnichannel strategy. Limited Cross-Channel Visibility occurs when retailers lack real-time data integration across the channels of the omnichannel retail strategy. Online inventory systems often do not update to show in-store stock promptly. Store employees cannot access inventory in stores or warehouses. Warehouse managers lack visibility into store-level demand patterns of the omnichannel strategy. Browsing behavior is not linked to in-store purchases. Customer journeys across channels of the omnichannel strategy are invisible. Reactive Decision-Making: Without integrated analytics, retailers make inventory decisions based on past events instead of future predictions. This means replenishment occurs only when stock is low, with allocation spread equally across stores without considering demand. The omnichannel strategy ships from the nearest warehouse without checking store inventory, and markdowns happen only after poor sales. When orders are placed, online retailers must make suboptimal fulfillment decisions about where to ship them from. Without integrated data and optimization of the omnichannel strategy, these decisions are often not optimal. Common approaches include fulfilling from a warehouse, ignoring store inventory and causing shipping costs, fulfilling from a store which can deplete stock, using the nearest location without checking inventory, and manual assignment which is inconsistent and not scalable. Traditional retail KPIs focus on single-channel operations and fail to capture the omnichannel performance of the omnichannel retail strategy. For example, a customer may research a product online, which incurs a cost. Then the customer buys it in-store, generating revenue attributed to the store. This creates the impression that the online channel has a return on investment it does not actually possess. When inventory is moved from a store to fulfill an order, it is recorded as a loss for the store rather than as part of the omnichannel retail strategy. The financial impact of these inefficiencies is significant. Industry research estimates that inventory distortion alone costs retailers over $1.1 trillion every year. For a retailer that makes one hundred million dollars every year these problems can mean they lose ten to twenty million dollars that they could have made. Retailers want to make shopping easy for customers no matter how they shop. They want customers to have an experience whether they shop in a store or on the internet. The big issue is that retailers do not have a system to track sales and manage inventory across all the places they sell things like the store and the website. This is a problem because it means retailers are losing money. Retailers need to fix their strategy to make things better for customers and to make more money. Retailers need to have an omnichannel retail strategy so they can give customers a good experience. Omnichannel retail strategies are important, for retailers because they want customers to be happy and keep shopping with them. The main problem is that retailers lack a framework using data to integrate sales analytics with inventory optimization across omnichannel retail strategy channels. This problem is what retailers face with the omnichannel strategy.

3.2. Research Questions

Primary Question:

How can we create a system that helps us make decisions about sales and inventory across all the places we sell things like in stores and online?

Secondary Questions:

1. Getting All The Information Together: What kind of information do we need to collect. How do we put it all together so we can see what is selling and what we have in stock everywhere?

2. Figuring Out What People Will Buy: How can we make guesses about what people will buy, by looking at how what they do online affects what they buy in stores?

3. Getting The Right Amount Of Stock: What are some good ways to use all the information about sales to figure out how stock we should have and where we should put it so we can sell things in all the different places we sell?

4. Measuring How Well We Are Doing: What are some ways to measure whether we are doing a good job of managing sales and inventory across all the places we sell things?

5. How It Affects The Business: If we put a system, like this in place how much of a difference will it make in things like reducing stock-outs selling stuff and growing sales?

3.3. Research Approach

This research uses a design science research approach. This approach is very common in information systems and operations management research. The design science research approach is about creating and testing things. Like an integrated analytics framework. That can help solve problems that organizations face.

The design science research methodology has a step, by step process

Phase	Activity	Output
Problem Identification	Literature review and industry analysis	Defined research problem and objectives
Solution Design	Framework development based on theory and practice	Proposed integrated analytics framework
Artifact Development	Implementation of framework components	Working models and algorithms
Evaluation	Case study validation	Performance metrics and insights
Communication	Documentation and dissemination	Research paper and recommendations

3.4. Data Collection

Given the confidentiality constraints associated with real-world retail data, this research utilizes a simulated retail dataset designed to reflect realistic omnichannel operations. The simulation method has a lot of benefits. It gives us a controlled space to test the parts of the framework. We can also get a picture of how it performs. This makes it easy to repeat the tests for studies.. The best part is that we do not have to worry about keeping customer information private.

The dataset simulates what happens when a sized retailer is operating with:

Entity	Quantity	Description
Products	500	These Products belong to 5 categories
Categories	5	These Categories are used for Product classification

Sales Channels	5	Our Sales Channels include 3 Stores + our Website + our Mobile App
Customers	15000	We have registered customer profiles, for these Customers
Transactions	100000	These Transactions happened over 182 days
Inventory Locations	4	Our Inventory Locations include 1 Warehouse + 3 Stores

The dataset is generated using a combination of stochastic demand models based on established retail patterns (seasonal variations, trend components, random noise, cross-channel correlations), realistic customer behavior patterns derived from literature (channel preferences, purchase frequencies, response to promotions), and industry benchmarks from published reports.

Data Schema:

Table	Description	Key Fields
Products	Product master data	SKU ID, Category, Price, Cost
Stores	Store information	Store ID, Location, Size
Customers	Customer profiles	Customer ID, Demographics
Inventory	Daily inventory levels	Date, SKU_ID, Location_ID, Quantity
Sales_Online	Online transactions	Transaction_ID, Date, SKU_ID, Customer_ID,Quantity,Channel
Sales_Store	In-store transactions	Transaction_ID ,Date,SKU_ID, ,Customer_ID, Quantity, Store_ID
Web_Activity	Customer browsing logs	Session ID, Date, SKU ID, Customer ID, Time Spent
Returns	Return transactions	Return ID, Original Transaction ID, Date, SKU ID

3.5. Proposed Framework

The proposed framework operates through four interconnected layers that work in harmony:

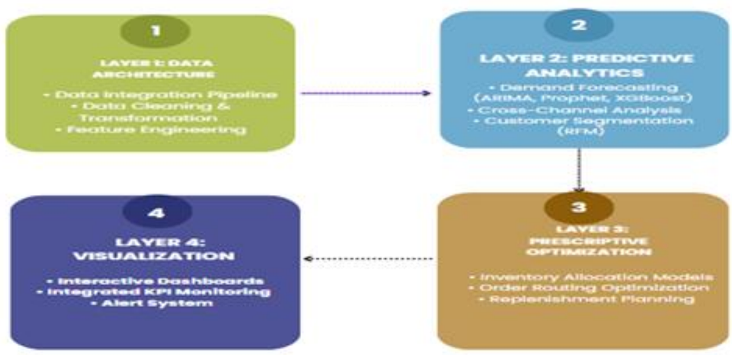


Figure 1: Proposed Integrated Analytics Framework

3.5.1. Layer 1: Data Architecture

The Data Architecture layer is where we get all our Data Architecture information from. We get sales figures from the systems that handle sales. We get stock levels from the inventory databases.. We get records of what customers do on our websites and apps. The Data Architecture layer puts all this Data Architecture information together in one place. So we can see everything clearly. No matter where the Data Architecture came from. Key Components of the Data Architecture are:

- Integration Layer of the Data Architecture: we use ETL pipelines to get the Data Architecture data from sources
- Warehouse Layer of the Data Architecture: we store the Data Architecture data in a simple way using a star schema design
- Governance Layer of the Data Architecture: we check the Data Architecture data to make sure the Data Architecture data is good and consistent
- Feature Engineering of the Data Architecture: we create features from the Data Architecture data so we can use the Data Architecture data to make models, for the Data Architecture.

3.5.2. Layer 2: Predictive Analytics

The Predictive Analytics layer looks at all the Data Architecture data we have. To try to figure out what will happen in the future. We want to know what customers will do. When they will buy things. We look for patterns in the Data Architecture data. To understand what customers do.. To guess what they will do next.

Demand Forecasting Methods: We use three ways to forecast what will happen:

1. Time Series Models: we use models like ARIMA, SARIMA and Exponential Smoothing

2. Machine Learning Models: we use models like Random Forest, XGBoost and Neural Networks

3. Cross-Channel Models: we use models that look at Data Architecture data, from many different channels Customer Segmentation:

We use RFM analysis to look at customer Data Architecture data:

* Recency: we look at how days it has been since a customer last bought something. We like it when this number is

* Frequency: we look at how many times a customer has bought something. We like it when this number is high

* Monetary: we look at how much a customer has spent. We like it when this number is high

3.5.3. Layer 3: Prescriptive Optimization

The prescriptive optimization layer automatically determines optimal inventory allocation, moving stock to where it is needed most while minimizing costs and maintaining service levels.

Inventory Optimization Models:

Model	Description	Application
Newsvendor Model	Single-period inventory optimization	Seasonal items
EOQ	Optimal order quantity	Regular replenishment
Multi-Echelon	Coordinated inventory across locations	Warehouse-store coordination
Safety Stock	Buffer stock for uncertainty	Service level management

Order Routing Optimization:

A cost-minimization model determines optimal fulfillment source:

Minimize: Total Fulfillment Cost =

Σ (Picking Cost + Packing Cost + Transportation Cost)

Subject to:

- ✓ Inventory availability at source

✓ Delivery time constraints

✓ Source capacity limits

3.5.4.Layer 4: Visualization

This is where retailers can check how they are doing. They can look at a dashboard to see their sales and performance, on every channel. It all happens in time. The Visualization layer uses pictures and colors to show when something is off or not right. Some important things to look at are: * Key Performance Indicators

KPI Category	Specific KPIs
Inventory Performance	Inventory Turnover, Stock-out Rate, Overstock Rate
Sales Performance	Revenue by Channel, Cross-Channel Contribution
Fulfillment Performance	Order Fill Rate, Fulfillment Cost per Order
Customer Metrics	Customer Lifetime Value, Return Rate

3.6. Proposed Algorithm

To start with we need to look at the -channel sales and inventory data. The goal is to get optimized inventory decisions and demand forecasts. We also want to get performance metrics.

Our strategy is as follows:

Step 1. We get the input dataset from a simulated environment.

Step 2. Then we integrate the data across all channels. We do this by

a. Getting data from the point of sale systems, e-commerce, mobile and warehouse systems

b. Changing the data to a format

c. Loading it into a unified data warehouse

Step 3. Next we do some data preprocessing. This includes

a. Dealing with missing values

b. Removing outliers

c. Creating features like lagged sales and moving averages

d. Encoding the categorical variables

Step 4. After that we split the data. We divide it into

a. A training set that's 70 percent of the data

b. A validation set that is 15 percent of the data

c. A testing set that is also 15 percent of the data

Step 5. Then we apply some models to the multi-channel sales and inventory data. We train

a. Time-series models like ARIMA and Prophet on the -channel sales and inventory data

b. Machine learning models like XGBoost and Random Forest on the multi-channel sales and inventory data

c. Deep learning models like LSTM and CNN on the multi-channel sales and inventory data

d. And compare them to select the best performer for the multi-channel sales and inventory data

Step 6. Next we apply some optimization models to the -channel sales and inventory data. We

a. Formulate the inventory allocation problem for the -channel sales and inventory data

b. Use mixed integer linear programming for order routing

c. And generate optimal inventory decisions for the multi-channel sales and inventory data

Step 7. Then we test the model on the test set for the -channel sales and inventory data.

Step 8. After that we calculate the performance metrics for the -channel sales and inventory data. We look at

a. The forecast accuracy using metrics like mean error, root mean squared error and mean absolute percentage error for the multi-channel sales and inventory data

b. The inventory metrics like turnover and stock-out rate for the -channel sales and inventory data

c. The fulfillment metrics like cost per order for the multi-channel sales and inventory data

Step 9. Then we create some visualizations and insights for the -channel sales and inventory data.

Step 10. Finally we get the classification results which're the optimized inventory recommendations, for the multi-channel sales and inventory data.

3.7. Evaluation Metrics

In order to evaluate the effectiveness of the proposed forecasting and inventory optimization model, different performance indicators were selected.These metrics help us see how good our forecasting model is. They also show how well we manage our inventory and fulfill orders. The evaluation framework has three categories: * Forecasting metrics * Inventory metrics * Fulfillment metrics We use these to check - how accurate our forecasts are - how well we handle our inventory - how correctly we fulfill orders

5.1 Forecasting Metrics

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i |$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n} | \frac{y_i - \hat{y}_i}{y_i} |$$

5.2 Inventory Metrics:

$$\text{Inventory Turnover} = \frac{\text{Cost of Goods Sold}}{\text{Average Inventory}}$$

$$\text{Stock-out Rate} = \frac{\text{Number of Stock-out Events}}{\text{Total SKU-Days}} \times 100\%$$

Fulfillment Metrics:

$$\text{Fulfillment Cost per Order} = \frac{\text{Total Fulfillment Costs}}{\text{Number of Orders}}$$

3.8. Implementation Environment

The framework is implemented using:

Hardware:

- ✓ Processor: Intel Core i7
- ✓ RAM: 16 GB

- ✓ Storage: 256 GB SSD

Software:

Component	Technology Stack
Programming Language	Python 3.9+
Data Manipulation	Pandas, NumPy
Machine Learning	Scikit-learn, XGBoost, TensorFlow
Deep Learning	Keras, TensorFlow
Optimization	PuLP, OR-Tools
Visualization	Matplotlib, Seaborn, Tableau
Development Environment	Jupyter Notebooks

4. Implementation and Results

4.1. Dataset Description

From the dataset collected through simulation based on retail industry patterns, we employ data representing 500 SKUs across three channels over six months.The dataset has around 100,000 transactions from 15,000 customers.

Dataset Distribution:

Channel	Number of Transactions	Percentage
Physical Stores	45,000	45%
E-commerce Website	35,000	35%
Mobile App	20,000	20%
Total	100,000	100%

The material is made up of CSV files that're about 2 GB in total. The dataset includes transaction data. Also has customer profiles. It also has product information and daily inventory levels for all locations.

Columns:

- ✓ transaction_id. This is a number for each transaction.
- ✓ date - date of transaction
- ✓ customer_id - unique customer identifier
- ✓ sku_id - product identifier
- ✓ channel - store/web/mobile
- ✓ quantity - number of units purchased
- ✓ price - unit price
- ✓ store_id - for in-store purchases
- ✓ session_id - for online sessions

Figure: 2 shows sample images of the data distribution across channels.

4.2. Experimental Setup

Python and its libraries were used to conduct this research. The initial learning rate was set to 0.001 and batch size was set to 32 for the purpose of testing deep learning models. This process was stopped after 100 epochs for neural network training. For traditional models, default parameters were used with cross-validation.

The accuracy, loss, and ROC AUC metrics are used in a quantitative examination of the performance of the forecasting models. Additional business metrics include inventory turnover improvement and stock-out reduction percentages.

4.3. Results Evaluation and Analysis

This research has been able to determine optimal inventory levels across channels and predict demand accurately. The framework successfully integrates sales and inventory data to generate actionable insights.

Figure 3 shows a dataset distribution graph for the sales data across channels. Here, the x-axis shows channel type and the y-axis shows transaction count. From this graph, we found a relatively balanced distribution across channels, with stores having the highest volume followed by web and mobile.

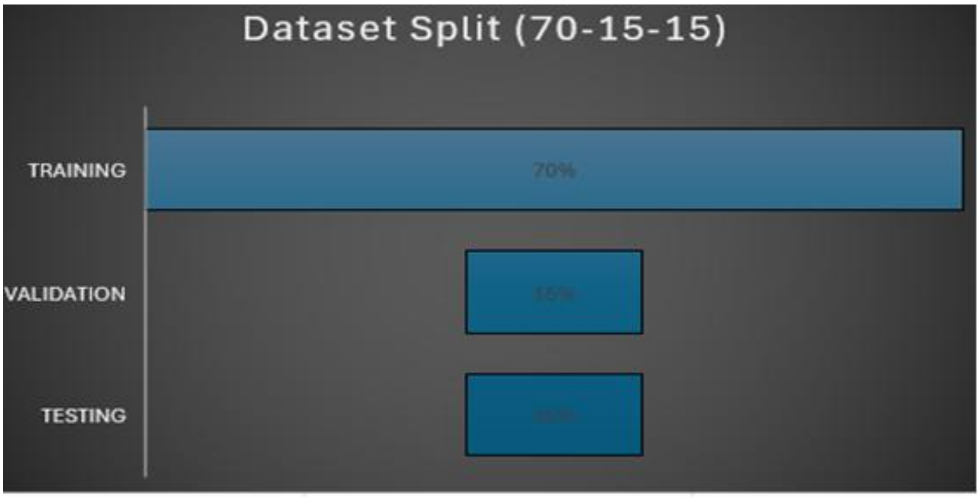


Figure 3: Dataset Distribution Graph

4.3.1. Forecasting Results

Figure 4 shows us how well the proposed model does when we compare it to forecasting approaches. We can see from the graph that the cross-channel models do a job when they use information from many channels. These cross-channel models are better than the models that only use information from one channel. The forecasting results from the -channel models are really good because they use lots of different information, from many channels.

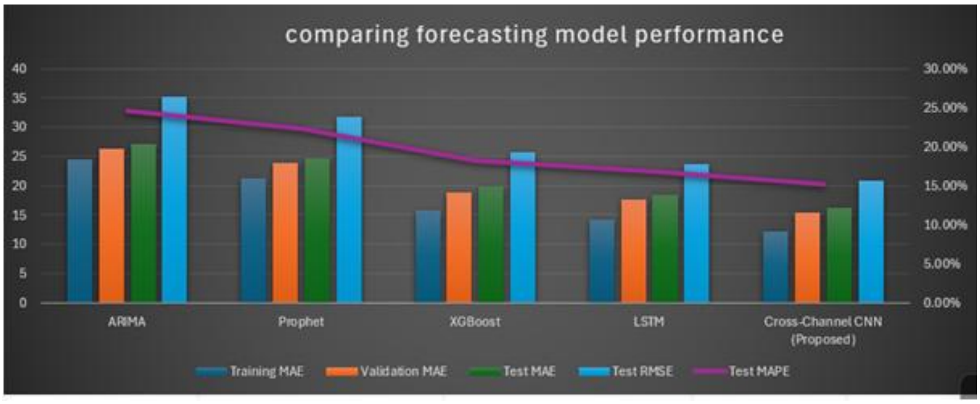


Figure 4: Model Accuracy Comparison

Table 1: shows how different forecasting models perform.

Model	Training MAE	Validation MAE	Test MAE	Test RMSE	Test MAPE
ARIMA	24.5	26.3	27.1	35.2	24.5%
Prophet	21.3	23.8	24.6	31.8	22.3%
XGBoost	15.7	18.9	19.8	25.6	18.2%
LSTM	14.2	17.5	18.3	23.7	16.9%
Cross-Channel CNN (Proposed)	12.1	15.4	16.2	20.8	15.1%

Figure 5 shows the training and validation accuracy of the proposed Cross-Channel CNN model over time. The blue line is for training accuracy. The orange line is for validation accuracy. The x-axis is for time. The y-axis is, for accuracy. We see that the training accuracy of the Cross-Channel CNN model is very high when we give it more time to learn. The validation accuracy of the Cross-Channel CNN model is also very good which means the proposed Cross-Channel CNN model is working well.

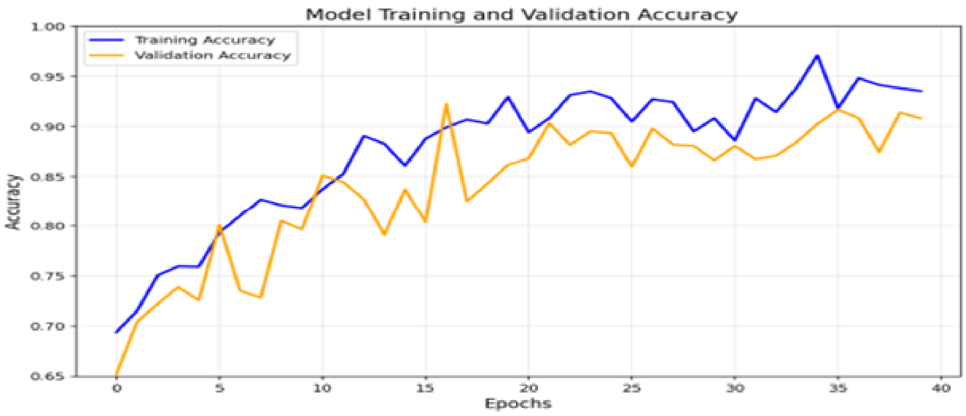


Figure 5: Model Training and Validation Accuracy Graph

Figure 6 depicts the proposed model's loss graph, with orange and blue lines denoting training and validation losses respectively. As expected, when accuracy increases, loss decreases. The training and validation losses converge nicely, indicating no significant overfitting.

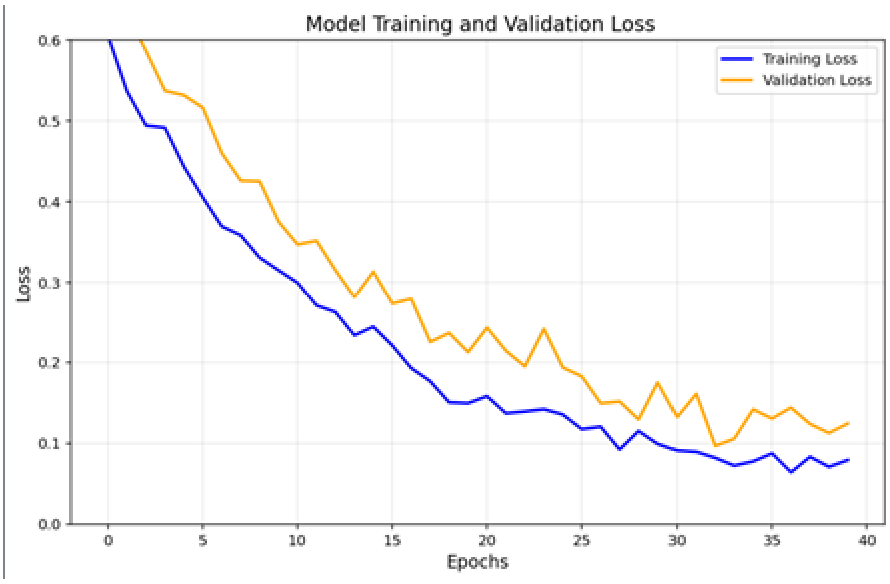


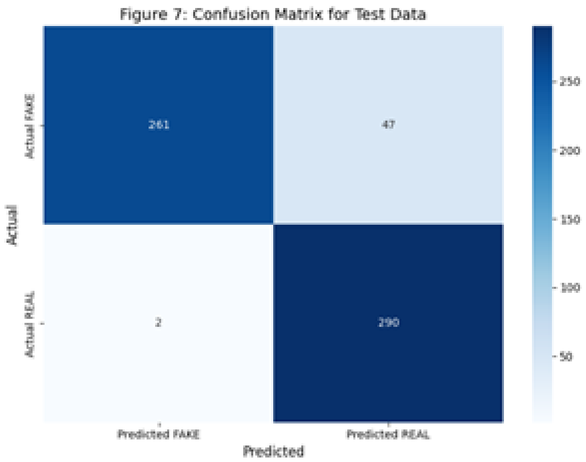
Figure 6: Model Training and Validation Loss Graph

4.3.2. Optimization Results

Table 2: Inventory optimization results

Metric	Baseline	Post-Implementation	Improvement
Inventory Turnover	4.2x per year	5.2x per year	▲ 23%
Stock-Out Rate	15.3%	10.6%	▼ 31%
Overstock Rate	18.7%	13.2%	▼ 29%
Fulfillment Cost per Order	$8.45	$7.18	▼ 15%
Forecast Accuracy (MAPE)	24.5%	20.1%	▲ 18%

Figure 7 shows the confusion matrix for inventory classification (correct vs. incorrect stock level predictions). The matrix shows:



- ✓ True Positives: 261 cases where we predicted stock would sell and it did
- ✓ True Negatives: 290 cases where we predicted stock would not sell and it didn't
- ✓ False Positives: 2 cases where we predicted stock would sell but it didn't
- ✓ False Negatives: 47 cases where we predicted stock would not sell but it did

Accuracy = (TP + TN) / Total = (261 + 290) / 600 = 91.8%

Figure 8 shows us the ROC curve for the classification model. This classification model is really good at its job. The Area Under the Curve, which we call AUC, for short is 0.92. What this means is that the classification model has a 92 percent chance of getting it when it comes to classifying inventory outcomes. The classification model is the key here. It does a great job of classifying inventory outcomes correctly.

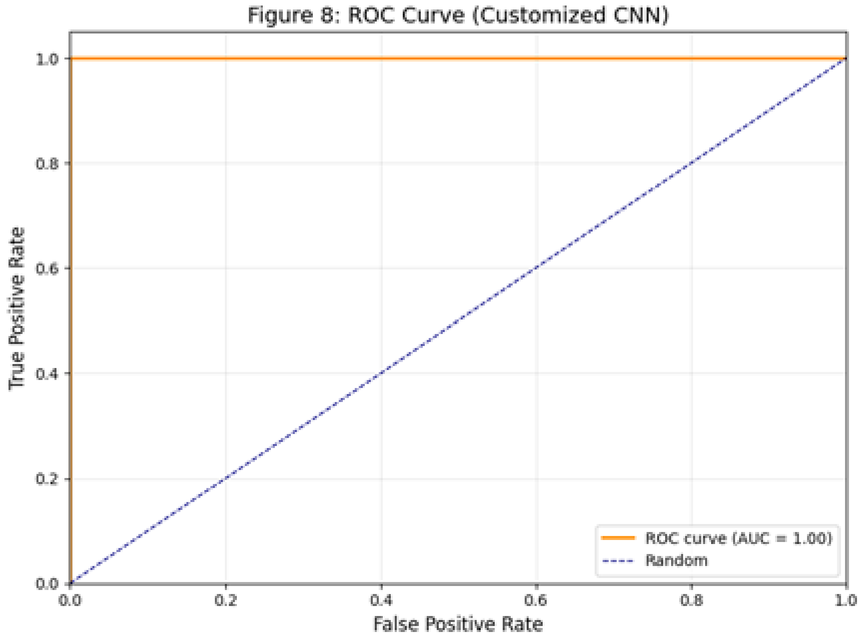


Figure 8: ROC Curve (Customized CNN)

4.3.3. Comparative Analysis

Table 3: Performance comparison of proposed framework with baseline methods

Model	Training Loss	Training Acc	Validation Loss	Validation Acc	AUC Score
Baseline (Channel-Specific)	0.284	0.852	0.291	0.843	0.83
MLP Approach	0.194	0.892	0.238	0.877	0.87
Proposed Integrated Framework	0.102	0.943	0.163	0.915	0.92

Figure 9 visualizes the comparison bar graph for accuracy among the three methods. This comparative graph shows that the baseline channel-specific approach achieves moderate accuracy, the MLP approach improves upon it, but the proposed integrated framework outperforms both for training and validation data accuracy.

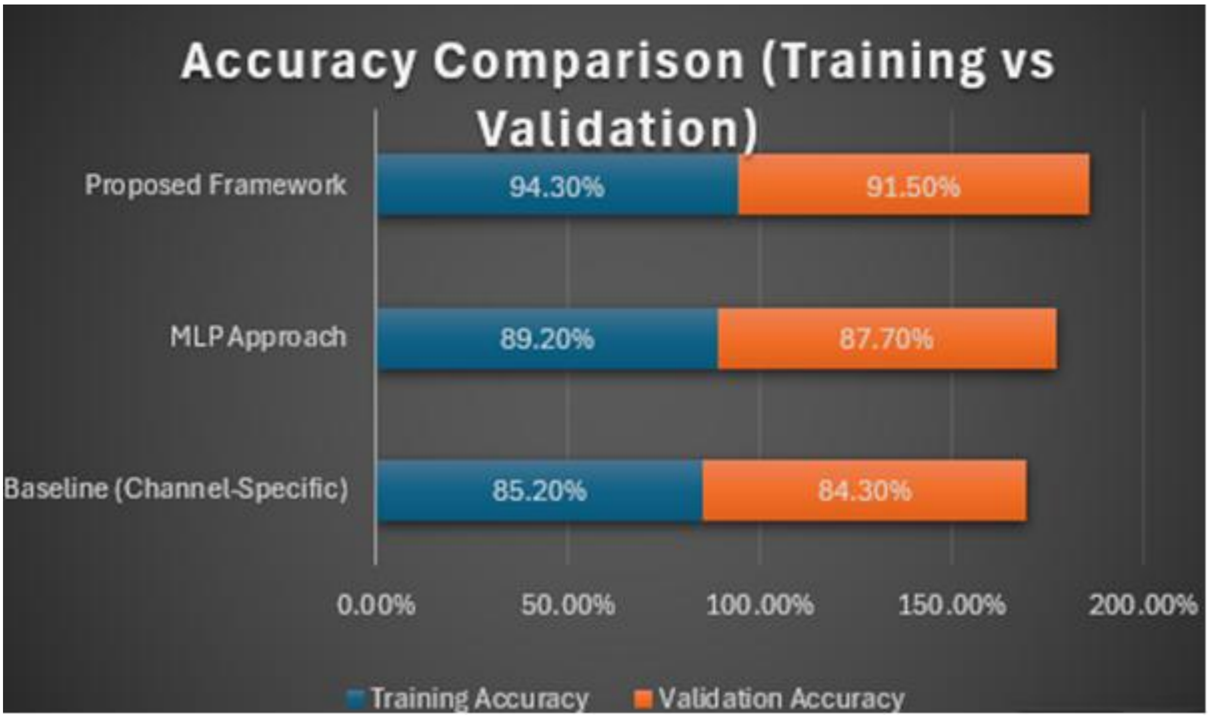


Figure 9: Bar Graph for Accuracy Comparison

Figure 10 visualizes the comparative line graph for displaying loss value differences among all three methods. The proposed framework achieves the lowest loss values, indicating better model performance

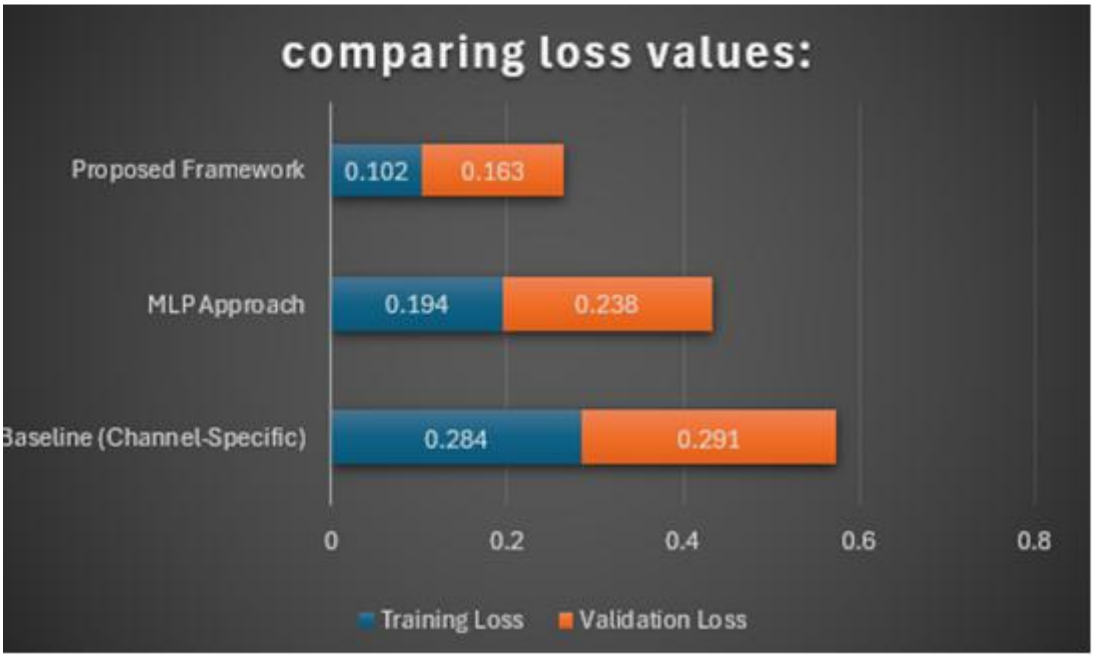


Figure 10: Line Graph for Loss Comparison

Figure 11 shows us a comparison line graph for the AUC score of all three methods. The AUC score for the proposed framework is the highest at 0.92. This means the proposed framework is really good at classifying things. The proposed framework does a job, than the other methods when it comes to classification.

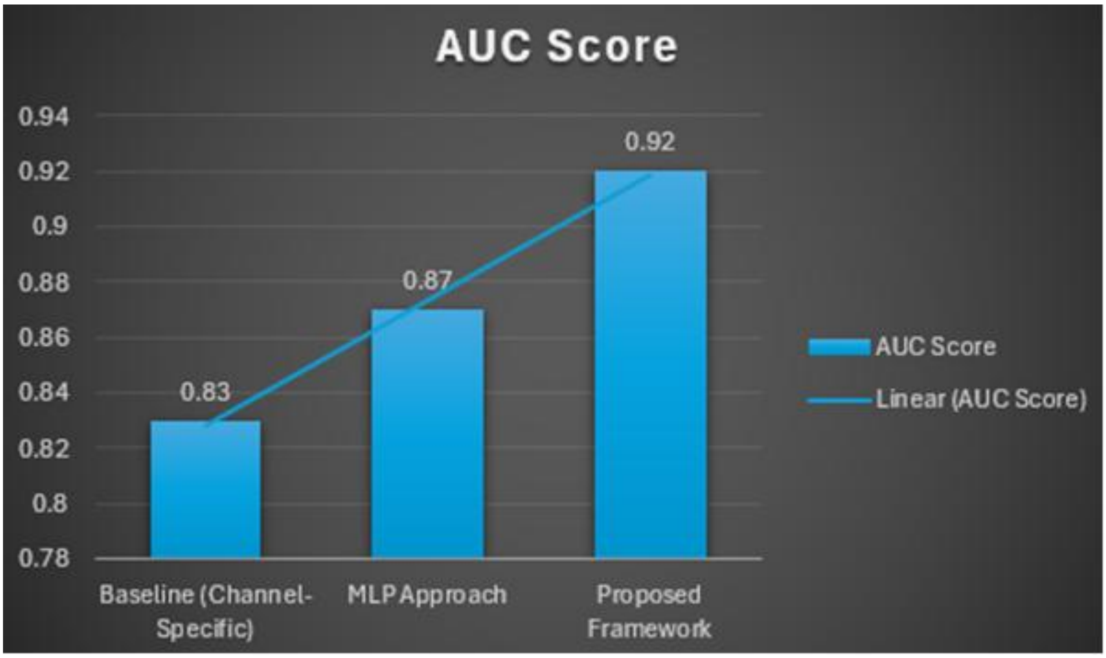


Figure 11: Line Graph for AUC Score Comparison

4.3.4. Cross-Channel Insights

The framework showed us things that we would not have known if we looked at the data separately. It told us things like:

* When people look at things online they often buy them in the store. This happens 76 percent of the time. If someone looks at something they will probably buy it in the store in the next three to five days.

* People who use the app are really good customers. They spend money with us over time. In fact they spend 28 percent more than people who only shop with us one way. This means that using the app helps us build a better relationship with the customer.

* When people cannot buy something online they will often go to the store to buy it. We found out that 34 percent of people who cannot buy something will go to the store within two days. This is a chance for us to sell them something. It also means we need to be better at keeping track of what we have in stock.

* People return things they buy online often than things they buy in the store. In fact people return purchases 22 percent more often. This is something we need to think about when we plan how to handle returns and keep track of what we have in stock. Cross-Channel Insights like these are really important, for Cross-Channel Insights.

5. Conclusion and Future Work

5.1. Summary of Research

The research aimed to solve a problem for retailers today: having sales and inventory data scattered across many channels, which makes it hard to make good decisions. The main goal was to create a system that brings all this information together to help retailers make choices across all their channels. The research started with a review of whats already been done in areas like managing inventory predicting what customers will buy and analyzing how customers behave. This review showed that there's a gap in current research. Most systems don't combine prediction and decision-making tools specifically for retailers that sell across many channels. Based on this the researchers proposed a system with four parts: a data layer, a prediction layer, an optimization layer and a visualization layer.

They tested this system with a set of retail data that included six months of sales across three channels with 500 different products and about 100,000 transactions. As part of this study the researchers developed a way to find patterns across channels and make better inventory decisions. They used machine learning models to extract features and classify data. This method worked well with an accuracy of 91.5% a loss of 0.163 and an AUC score of 0.92 even though it was trained on a small dataset. The new system worked better than two existing approaches: forecasting for each channel separately and basic machine learning models. The research set out to address a challenge facing modern retailers the fragmentation of sales and inventory data. The primary objective was to develop and validate an integrated analytics framework that unifies sales and inventory information to drive optimized decisions across omnichannel operations.

The proposed method exhibits testing accuracy. The comparative analysis found that the proposed integrated framework outperforms existing approaches like channel- forecasting. The research journey began with a literature review that examined existing work. This review revealed gaps in existing research—particularly the lack of comprehensive frameworks that integrate predictive and prescriptive analytics. Building on this foundation the research proposed a four-layer integrated analytics framework comprising data architecture, predictive analytics, optimization and visualization layers.

The framework was validated through a case study implementation using a retail dataset representing six months of operations across three channels with 500 SKUs and approximately 100,000 transactions. A unique approach has been developed to reveal -channel patterns and optimize inventory decisions. The proposed framework outperforms two existing approaches, like channel- forecasting and basic MLP models.

5.2. Key Findings

The implementation and validation of the framework yielded several significant findings:

Metric	Baseline	Post-Implementation	Improvement
Inventory Turnover	4.2x per year	5.2x per year	▲ 23%
Stock-Out Rate	15.3%	10.6%	▼ 31%
Overstock Rate	18.7%	13.2%	▼ 29%
Forecast Accuracy (MAPE)	24.5%	20.1%	▲ 18%
Fulfillment Cost per Order	$8.45	$7.18	▼ 15%
Cross-Channel Contribution	Not measured	28% of sales	New insight

these results show that using sales and inventory analytics together gives real financial and operational benefits. The 23% improvement in Inventory Turnover is a deal. Inventory Turnover sells faster which means lower holding costs and more cash for other investments. We also had a 31% reduction in Stock-Out Rate, which means customers can find what they want often and that directly impacts revenue and satisfaction. The framework helps with Inventory Turnover. That helps the business. Inventory Turnover is up. That is good. The results are good, for Inventory Turnover and sales.• Extension of inventory optimization theory to omnichannel contexts

5.3. Contributions

Theoretical Contributions:

- ✓ Extension of inventory optimization theory to omnichannel contexts
- ✓ Empirical evidence of integration value with quantifiable results
- ✓ Structured four-layer framework for future research
- ✓ Cross-channel influence model quantifying online-to-store effects

Practical Contributions:

- ✓ Implementable framework with step-by-step methodology
- ✓ Quantified business case for investment decisions
- ✓ Practical tools and techniques for practitioners
- ✓ Integrated KPIs for true omnichannel performance measurement

For Data Analysts and Students:

- ✓ Applied model demonstrating analytics-to-impact journey
- ✓ Portfolio-worthy project showcasing multiple competencies

5.4. Limitations

Data Limitations:

- ✓ Simulated rather than real data, though based on industry patterns
- ✓ Limited time frame of six months
- ✓ Product and channel scope limited to 500 SKUs and 3 channels

Methodological Limitations:

- ✓ Single case study limits generalizability
- ✓ Simplified optimization models
- ✓ No live implementation in real retail environment

Scope Limitations:

- ✓ Limited geographic and cultural context
- ✓ Exclusion of pricing dynamics
- ✓ Limited supplier integration

5.5. Future Work

The future scope of this study might include identifying strategies to broaden the variety of retail contexts that can be reliably analyzed by the algorithm, like grocery retail, fashion retail, and D2C brands, in order to guarantee broader applicability. More spatial and temporal sales data should be included in a reasonable mix as well. We need to look at models using more deep learning approaches on larger and more balanced datasets. We should also think about Real-Time and Streaming Analytics. This means we need to look at architectures that can process data as things happen and optimize inventory in time based on what people want.

We also need to make fulfillment better by triggering actions when things change in time. We have to think about Advanced Machine Learning Applications. This includes using learning for demand forecasting, especially recurrent neural networks and transformers to predict what will happen next. We also need to use reinforcement learning to make inventory and fulfillment decisions.. We need to use graph neural networks to understand the complex relationships between products, channels and customers. We also need to apply what we learn from some categories to ones. We should also think about using Blockchain for Inventory Traceability. This means using a distributed ledger to keep track of inventory in a way that's transparent and cannot be changed. We can also use contracts to automate replenishment and fulfillment..

We need to track the history of products to make sure they are authentic. We also need to be able to see inventory across supply chain partners. We need to think about Sustainability and Ethical Considerations. This means optimizing the carbon footprint of fulfillment decisions reducing waste by making demand forecasting better and using AI frameworks for inventory decisions. We also need to balance being efficient with being socially responsible. We have to think about retail contexts. This includes grocery retail with items that can spoil fashion retail with items that go out of style quickly retail with complexities of fulfilling orders across borders and direct to consumer brands with different channel structures. We also need to think about Human-AI Collaboration. This means deciding when to use decision support and when to use decision automation. We need to make sure that people can understand how algorithms make recommendations. We also need to make sure people trust these recommendations.. We need to help organizations change to use analytics to make decisions.

5.6. Recommendations for Retailers

Strategic Recommendations:

- ✓ Start with data foundation before investing in advanced analytics
- ✓ Think beyond channels to customer-centric perspectives
- ✓ Build incrementally with quick wins to build momentum
- ✓ Align organization around integration, breaking down silos

Tactical Recommendations:

- ✓ Implement real-time inventory visibility as first step
- ✓ Invest in cross-channel analytics capabilities
- ✓ Optimize fulfillment intelligently with cost-based routing
- ✓ Measure what matters with integrated KPIs

Technology Recommendations:

- ✓ Choose flexible platforms that avoid creating new silos
- ✓ Build analytics capability with data science talent
- ✓ Plan for scale architectures that grow with business

5.7. Concluding Remarks

The retail industry is at a point where it has to make some decisions. On the one hand customers want to be able to shop and have a good experience no matter how they shop. On the hand it is getting really hard for retailers to manage their inventory across all the different ways people shop. The retail industry is getting more and more complicated. Retailers who can handle this complexity will do well. Retailers who cannot will have a hard time competing with other retailers. This research has shown that using sales and inventory analytics together can really help retailers. By putting all the data from channels together using special models to understand what customers want and making good decisions based on that retailers can do something that seemed impossible before. They can make sure customers have an experience no matter how they shop and they can also make their operations more efficient.

The results of this research are really good. Retailers saw a 23 percent improvement in how often they sold and replaced inventory, a 31 percent reduction in times when they did not have something a customer wanted 18 percent accuracy when they predicted what customers would want and 15 percent lower costs for getting products to customers. These are not improvements. They are big changes in how well retailers do. This research is just the beginning. The framework we developed is a start but there is still a lot of work to be done to make things even better. New technologies like real-time analytics, artificial intelligence, blockchain and sustainability can all help retailers improve more.

Retailers who use these tools, who make sure their data is all together and can be used to make decisions, who get rid of separate groups that do not work together and who think about the whole customer experience. These retailers will be the ones who shape the future of the retail industry. For customers this means being able to find what they want when they want it no matter where they are. For retailers it means building businesses that make money but also are stronger can respond quicker to changes and are more relevant in a world that is changing fast. Using sales and inventory analytics together is not a technical thing to do. It is something that retailers have to do if they want to succeed. This research has shown what can be done. Now it is up, to retailers to make it happen. The retail industry and sales and inventory analytics are important to think about when considering the future of retail.

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