

Sales Forecasting Models for Direct Selling Business: A Data-Driven Approach to Predictive Analytics

PREPARED BY: SIVARAJAN ESVARAN - MSC241051



PREPARED BY:





SIVARAJAN ESVARAN
MCS241051
Master in Data Science Student



ASSOC. PROF. DR. MOHD SHAHIZAN BIN OTHMAN
Lecturer
University Teknologi Malaysia

TABLE OF CONTENTS



- Background Study
- Problem Statement
- Research Question and Objective
- Scope of Study
- Literature Review Research
- Methodology
- Data Collection Method

- Data Cleaning Process
- Exploratory Data Analysis
- Initial Finding & Result
- Feature Engineering
- Key Business Insights
- Summary
- Future Work



BACKGROUND STUDY





The direct selling industry, valued at USD 175.19 billion in 2024 and projected to reach USD 207.36 billion by 2034 Direct Selling Overview in 2024: Thriving Industry | MLM Trend org, faces significant operational challenges that hinder business growth and strategic planning Independent distributors in direct selling companies encounter particularly difficult circumstances in anticipating future sales performance due to highly unpredictable consumer demand patterns, seasonal fluctuations, and complex customer relationship dynamics. Individual distributors typically rely on intuitive decision-making rather than data-driven forecasting models and leading to missed sales opportunities. While predictive analytics have brought tremendous success to retail and e-commerce industries, the direct selling sector, particularly at the individual distributor level, has been slow to adopt advanced forecasting technologies, creating a critical gap between available analytical capabilities and practical business applications that this research aims to address.

PROBLEM STATEMENT



FORECASTING TOOLS

Independent
distributors in direct
selling companies do
not have access to
sophisticated sales
forecasting models
that can predict future
performance and
guide strategic
business decisions.

SUBOPTIMAL BUSINESS OPERATIONS

Without accurate
forecasting
capabilities,
distributors face
inefficient inventory
management, missed
sales opportunities,
and poor planning for
promotions.

COMPLEX SALES DYNAMICS

The direct selling environment presents unique forecasting challenges due to highly variable consumer demand, seasonal fluctuations, customer lifecycle changes, product launches, and economic factors.

STRATEGIC DECISION-MAKING LIMITATIONS

Distributors struggle
to set achievable
targets, plan
promotional activities,
and make informed
decisions about
market segment
development.

RESEARCH QUESTIONS & OBJECTIVES



RESEARCH QUESTIONS

- What are the dominant temporal patterns in direct selling transactions, and how do seasonal variations affect sales forecasting accuracy across different time horizons?
- How do traditional statistical models (ARIMA) compare to machine learning approaches (LSTM, Random Forest, Linear Regression) in terms of forecasting performance for direct selling businesses with highly variable sales patterns?
- What factors contribute to the superior performance of ARIMA models in achieving acceptable forecasting criteria compared to machine learning approaches in this specific business context?
- How can the identified customer demographics patterns and purchasing behaviours be leveraged to improve sales forecasting models?

RESEARCH OBJECTIVES

- To conduct comprehensive exploratory data analysis
- To analyse temporal sales patterns
- To develop and implement multiple forecasting models
- To establish comprehensive model evaluation criteria
- To identify optimal forecasting approaches

SCOPE OF STUDY





Data Source and Timeframe

The study utilizes detailed transaction and customer data from a single Amway distributor which provides granular insights into customer purchasing patterns, product performance, and sales trends for developing robust forecasting models.

Forecasting Model Development

The research implements and compares four distinct forecasting approaches to ensures comprehensive evaluation of different forecasting methodologies suitable for direct selling business contexts.

Multiple Prediction Horizons

The study develops forecasting systems capable of predictions across representative time scales to meet different business planning requirements from short-term operational decisions to long-term strategic planning.

04

02

Technology Stack and Deployment Considerations

The research focuses on Python-based model development using scikit-learn, TensorFlow/Keras, and specialized forecasting libraries like Prophet and statsmodels.



INDUSTRY CHARACTERISTICS AND CHALLENGES

The literature examines the unique operational challenges faced by direct selling organizations, particularly those functioning within network marketing relationships like Amway.

MODELS AND METHODOLOGIES

The literature review covers
the evolution of forecasting
approaches from traditional
statistical models (ARIMA,
exponential smoothing, Bass
diffusion models) to modern
machine learning
techniques (LSTM, Random
Forest, SVM).

CUSTOMER SEGMENTATION AND BEHAVIORAL ANALYSIS

Studies highlight the importance of customer profiling and segmentation using advanced techniques like RFM analysis (Recency, Frequency, Monetary) combined with clustering algorithms.





| Author / Year | Title | Research Focus | Machine Learning Methods |
|----------------------|----------------------------------|---|--|
| Liu et al. (2023) | A combination model based on | Developing a hybrid forecasting model | MEMD decomposition, Sentiment analysis, |
| | multi-angle feature extraction | integrating multi-angle feature extraction | Combination forecasting |
| | and sentiment analysis: | and sentiment analysis for electric vehicle | |
| | Application to EVs sales | sales prediction | |
| | forecasting | | |
| Elalem et al. (2023) | A machine learning-based | Forecasting sales of new short life cycle | ARIMAX, LSTM, GRU, CNN |
| | framework for forecasting sales | products using deep learning and | |
| | of new products with short life | ARIMAX with cluster-based data | |
| | cycles using deep neural | augmentation | |
| | networks | | |
| Yan et al. (2025) | A novel sales forecast framework | Hierarchical sales forecasting with | LSTM (for time-dependent features), MLP (for |
| | based on separate feature | separate feature extraction and | static features) |
| | extraction and reconciliation | reconciliation to improve supply chain | |
| | under hierarchical constraint | planning | |



| Author / Year | Title | Research Focus | Machine Learning Methods |
|----------------------|--|---|--|
| Liu et al. (2025) | An electric vehicle sales hybrid forecasting method based on improved sentiment analysis model and secondary | Combining sentiment analysis and secondary decomposition for electric vehicle sales forecasting | BERT-BiLSTM sentiment analysis, decomposition + ML hybrid |
| Wu et al. (2023) | decomposition Bayesian non-parametric method for decision support: Forecasting online product sales | Developing PoissonGP, a Bayesian non- parametric model for online sales forecasting with uncertainty quantification | Poisson Gaussian Process (PoissonGP) |
| Rahman et al. (2025) | Enhancing sustainable supply chain forecasting using machine learning for sales prediction | Using ML algorithms to improve demand prediction and supply chain decision-making | Linear Regression, Elastic Net, KNN, Random Forest, Voting Regressor |



| Author / Year | Title | Research Focus | Machine Learning Methods |
|--------------------|-----------------------------------|--|--|
| Hu et al. (2025) | Grid-based market sales | Combining AutoML and geospatial | AutoML, regression models |
| | forecasting for retail businesses | intelligence for grid-level market sales | |
| | using automated machine | forecasting and site selection | |
| | learning and geospatial | | |
| | intelligence | | |
| Shao et al. (2025) | New energy vehicles sales | Integrating media sentiment indices into | ML models with sentiment analysis (exact |
| | forecasting using machine | machine learning models for NEV sales | algorithms not detailed but includes ML hybrid |
| | learning: The role of media | forecasting | models) |
| | sentiment | | |



RESEARCH GAP

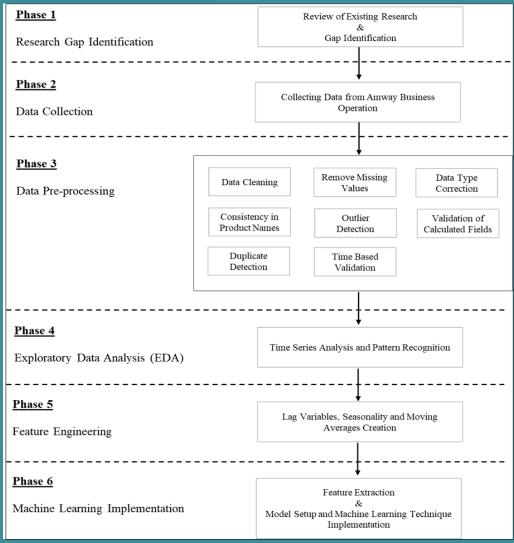
- Spatial and Geographic Limitations
- Limited Direct Selling Analytics
- Inadequate Time-Horizon Analysis
- Multi-Modal Data Integration Gap

SOLUTION

- Comprehensive Forecasting Framework
- Data-Driven Decision Making Tools
- Practical Business Application
- Scalable Analytics Platform

RESEARCH METHODOLOGY





The framework for this research includes the following stages:

- 1. Identifying the Research Problem and Reviewing Existing Literature.
- 2. Data Collection from Amway Business Operations.
- Preprocessing the Data: Preparing and cleaning data for detailed analytical tasks
- 4. Exploratory Data Analysis (EDA): Time Series Analysis and Pattern Recognition
- 5. Sales Forecasting Models: Implementing multiple forecasting algorithms (Linear Regression, Random Forest, LSTM and ARIMA)
- Model Evaluation: Comparing model performance using forecasting evaluation metrics.

DATA COLLECTION METHOD

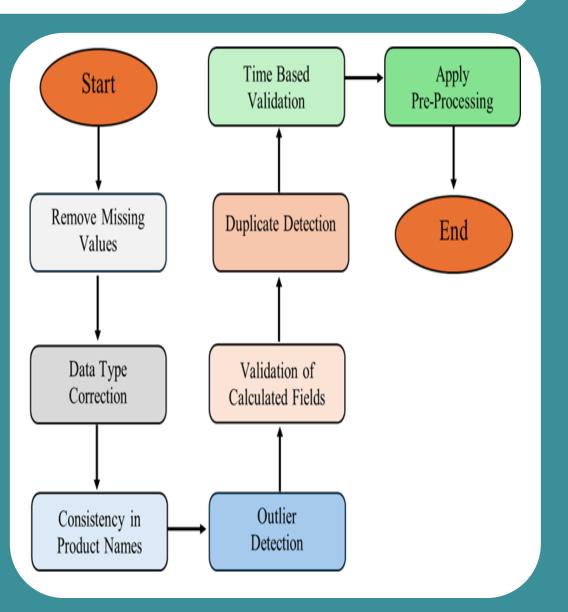




The data collection process involved acquiring actual sales transaction data from a single Amway distributor covering a 24-month period from April 2023 to April 2025. The primary data source consisted of monthly PDF sales reports downloaded directly from the official distributor portal. To facilitate analysis and model building, a systematic Python-based conversion methodology was implemented to transform these PDF files into structured CSV format. The conversion process utilized specialized Python libraries (pandas, PyPDF2, tabula, pdfplumber) for PDF data extraction and processing

DATA CLEANING PROCESS





Data cleaning is a vital process in sales forecasting to ensure the dataset is accurate, consistent, and ready for machine learning models. The comprehensive cleaning pipeline involved removing missing values, correcting data types, standardizing product names, detecting outliers using statistical methods, validating calculated fields, and eliminating duplicate transactions.

Data Cleaning Process

EXPLORATORY DATA ANALYSIS



Exploratory Data Analysis (EDA) serves as the foundation for identifying temporal patterns, key business insights, and customer behaviors that directly influence sales performance in direct selling environments. The EDA process systematically explores relationships, underlying patterns, and dataset characteristics before model development, focusing on two critical components:

Time Series Analysis

 Time series analysis identifies temporal patterns such as trends, seasonality, and cyclical behaviors through time series decomposition, separating underlying trends from seasonal variations and random noise to provide insights into long-term business growth patterns and recurring seasonal effects.

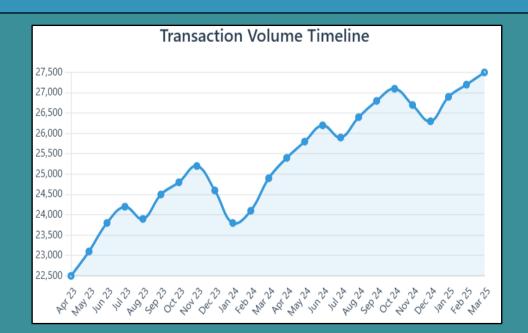
Pattern Recognition Analysis

 Pattern recognition analysis encompasses behaviour evaluation. product customer performance assessment, and geographic market analysis to identify actionable business intelligence, including RFM analysis (Recency, Frequency, Monetary) for customer segmentation, cross-selling pattern identification, and regional market performance analysis that reveals opportunities for business expansion and optimization

INITIAL FINDING & RESULT



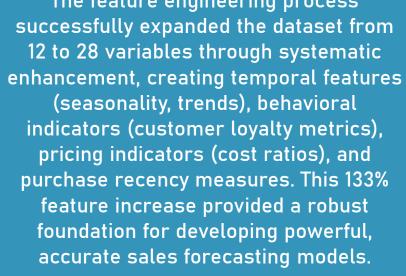
The research demonstrates exceptional data quality and substantial business scale, providing a robust foundation for comprehensive sales forecasting analysis. The dataset encompasses 553,542 real-world transactions collected over a 24-month period from April 2023 to April 2025, achieving remarkable 100% data completeness across all 12 core features with no missing values identified during the quality assessment process. This pristine data quality is particularly notable in direct selling business analytics, where complete and accurate transaction records are often challenging to obtain. The substantial scale of the dataset is further emphasized by the total sales volume of RM 335.8 million generated during the study period, with an average transaction value of RM 606.31, demonstrating significant business impact and commercial relevance.



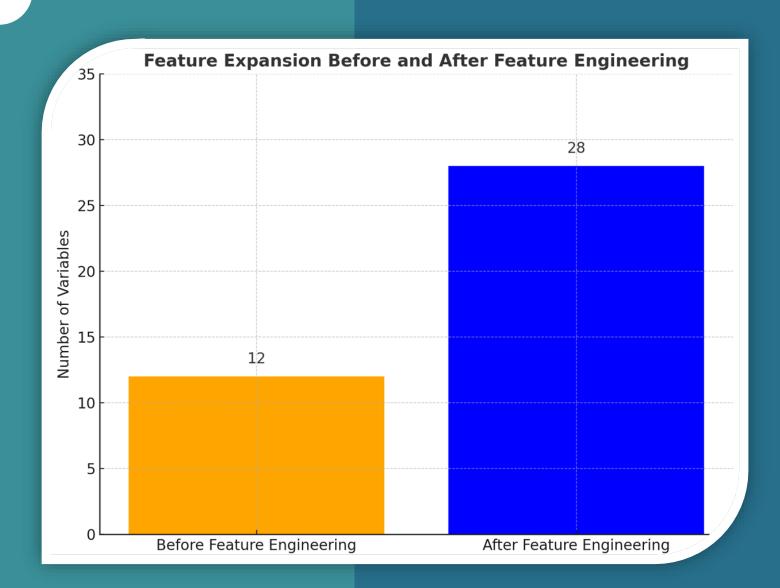


FEATURE ENGINEERING

The feature engineering process successfully expanded the dataset from 12 to 28 variables through systematic (seasonality, trends), behavioral indicators (customer loyalty metrics), pricing indicators (cost ratios), and purchase recency measures. This 133% feature increase provided a robust foundation for developing powerful, accurate sales forecasting models.



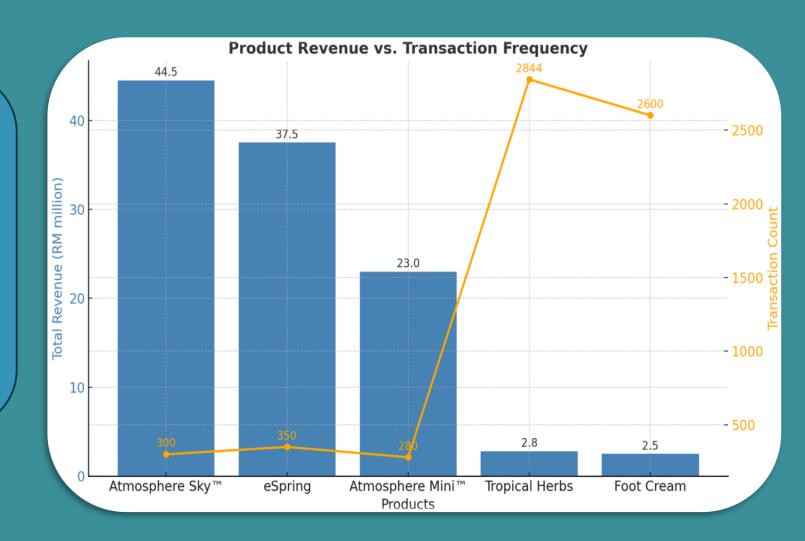




KEY BUSINESS INSIGHTS

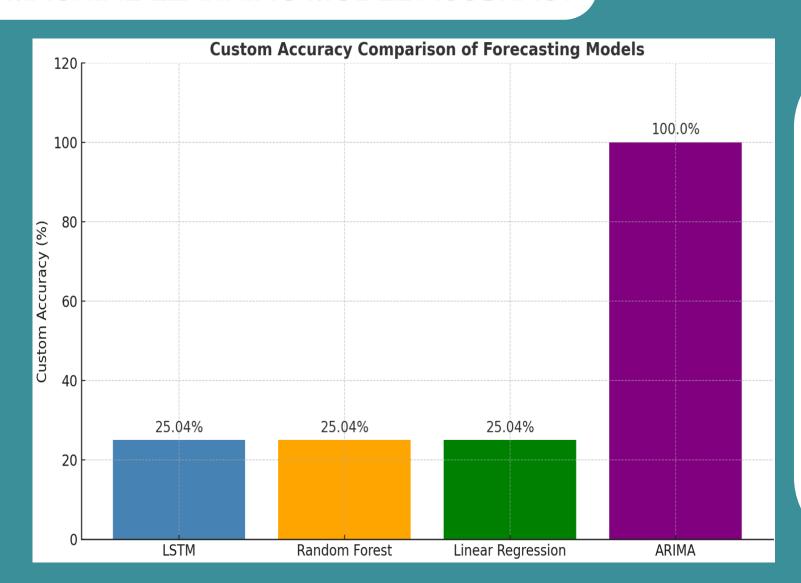


The analysis revealed significant business insights including product performance disparities where Atmosphere Sky™ generated RM 44.5 million in revenue despite lower transaction frequency, while consumables led in transaction volume. Customer demographics showed a mature base averaging 47.8 years with substantial purchasing power reflected in RM 606.31 average transactions, demonstrating clear revenue concentration patterns.



MACHINE LEARNING MODEL ACCURACY





Model evaluation revealed unexpected results where LSTM, Random Forest, and Linear Regression achieved identical performance with $R^2 = 0.964$ but critically high MAPE = 52.68% and only 25.04% custom accuracy, severely limiting practical utility. ARIMA demonstrated paradoxical performance with negative R² (-0.106) yet achieved 100% custom accuracy, highlighting that high explanatory power doesn't guarantee business forecasting utility.

SUMMARY



01

Research Achievement and Dataset Quality

Successfully analyzed 553,542 transactions over 24 months with 100% completeness, generating RM 335.8 million in real Amway sales data

Critical Model Performance Insights

03

High R² (0.964) didn't guarantee business utility with 52.68% MAPE. Only 25.04% predictions met acceptable accuracy thresholds.

02

Comprehensive Forecasting Model Development

Implemented four forecasting approaches (LSTM, Random Forest, Linear Regression, ARIMA) and expanded features from 12 to 28 variables systematically.

Business Impact and Future Research
Directions

Revealed gap between statistical success and practical utility, establishing framework for democratizing analytics in direct selling businesses.

FUTURE WORK



Model Architecture Refinement and Optimization

Investigate advanced LSTM architectures with attention mechanisms, ensemble techniques, and address potential data leakage issues for improved performance.

Enhanced Evaluation Framework Development

Resolve ARIMA
performance
contradictions through
detailed methodological
reviews, crossvalidation methods, and
business-sensitive
scoring measures for
operations.

Customer-Level Predictive Analytics Expansion

Develop individual customer behavior models predicting lifetime value, purchase propensity, and product preferences for enhanced relationship management.

Real-Time Integration and Automation Systems

Enable automated model retraining pipelines, live dashboard monitoring, geographic analysis, and scalable deployment for comprehensive business intelligence.



