Market Pulse AI™: A Unified Machine Learning Framework for Marketing Mix and Enterprise Analytics

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ABSTRACT:

There has been a rise in the complexity of digital marketing environments, and an attendant need for analytical frameworks that are more intelligent, that can incorporate marketing intelligence with enterprise-wide decision making. Existing methods of the Marketing Mix Modeling (MMM) are based on static statistical assumptions and are difficult to deal with high dimensional, heterogeneous, and real-time business data. The study introduces a single machine learning framework called MarketPulse AI™ that integrates customer segmentation, predictive analytics, sales forecasting, sentiment analysis, marketing mix optimization, and enterprise performance assessment into a single intelligent architecture. The machine learning framework combines K-Means clustering, Random Forest, Extreme Gradient Boosting (XGBoost), Long Short-Term Memory (LSTM), and Bidirectional Encoder Representations from Transformers (BERT) to process structured and unstructured enterprise data. The experimental evaluation proved the superior performance, with a Silhouette Score of 0.81, customer behavior prediction accuracy of 98.2%, sales forecasting MAPE of 3.8% and sentiment analysis accuracy of 96.4%. Moreover, the proposed framework helped to boost customer retention, marketing ROI, and revenue growth by optimizing resource allocation and making decisions based on data. The results illustrate how MarketPulse AI™ empowers digitally transformed organizations to improve marketing's

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effectiveness and enterprise analytics in a scalable, intelligent, and practical way.

Keywords: complexity, heterogeneous, Marketing Mix Modeling (MMM), Extreme Gradient Boosting (XGBoost)

1. Introduction

Digital technologies have evolved so quickly that the way business information is gathered, stored, and analyzed in an organization has changed. Each interaction with a customer on any channel, from customer service to the social media, can provide valuable information that aids in strategic decision-making (Hanelt et al., 2021; Banciu & Vevera, 2023; Schneider & Kokshagina, 2021). With the growing trend of digitalization, the amount, the speed, and the variety of marketing and business data have significantly increased, which presents opportunities and challenges for business intelligence (Park et al., 2020). These traditional analytical methods are not always able to handle high dimensional and complex data sets or to detect dynamic relationships between various business variables (Ivančić et al., 2019).

The paradigm of machine learning (ML) is gaining ground as an effective analytical tool that can extract meaningful patterns from vast amounts of data, enhance prediction accuracy, and aid in evidence-based decision-making (Xu et al., 2021). Unlike traditional statistical methods, advanced ML algorithms allow companies to make more accurate predictions about sales, customer behaviour, customer churn, pricing strategies and the effectiveness of marketing initiatives (Sarker, 2021; Rani et al., 2025). This has led to companies leveraging AI in marketing operations, customer relationship management and strategic decision making for sustainable competitive advantages (Dritsas & Trigka, 2025; Kolla, 2023).

Marketing Mix Modeling (MMM) is among the most powerful marketing analytics techniques to assess the impact of advertising channels, promotions, pricing policies and distribution channels on business performance (Pandey et al., 2021; Singh, 2025; Estevez et al. 2024). Yet, traditional marketing mix models are typically based on linear assumptions, fixed relationships, and past data, limiting their capacity to account for dynamic market conditions and changing consumer preferences (Milicevic et al., 2024). Likewise, enterprise analytics typically runs in siloes within functional areas, leaving the organization less responsive and with disjointed insights that endanger cross-functional decision-making (Fareniuk & Chornous, 2023).

However, to surmount these challenges, an analytical environment that will integrate machine learning technology and enterprise-wide marketing intelligence is increasingly becoming necessary (Olayinka, 2021). The end-to-end architecture will enable the integration of various data sources, automation of predictive modeling, real-time optimization of performance, and actionable insights across different business functions (Akanbi, 2023; Hasan, 2025). This helps in giving an all-round perspective of the customer and their information, operation, financial performance, and marketing efficiency all in one smart ecosystem (Al Kalach, 2023; Ahmad & Sarwar, 2025).

To improve enterprise marketing mix analysis and marketing analytics, the present study introduces an integrated machine learning system named MarketPulse AI™, that can incorporate external data, share predictive intelligence and automate marketing decision support (Saidur, 2025). The architecture features state-of-the-art learning algorithms, scalable data processing abilities, and intelligent performance monitoring mechanisms, all designed to improve forecasting accuracy, efficient resource utilization, and strategic decision-making. The suggested framework combines marketing intelligence and enterprise analytics, helping businesses to be adaptive and data-driven, and to react to market and customer change.

2. Literature review

The marketing landscape has dramatically shifted over the past few years and with the emergence of artificial intelligence (AI), machine learning (ML) and cloud computing technologies, marketers have new tools at their disposal to handle the vast amount of data from multiple sources and maximize return on investment (ROI) from their marketing investments. Customer behaviour and market dynamics can be non-linear, and evolve rapidly over time, meaning that many Marketing Mix Modeling (MMM) applications, relying on econometric/linear regression techniques, are not necessarily reflective of the underlying reality (Stewart, 2025). One way to address these difficulties is to use AI-driven cloud systems that can improve the predictiveness, automate feature engineering, and provide real-time marketing insights while ensuring data is handled securely and adheres to privacy laws (Thompson, 2025).

While AI is reshaping marketing, its impact is felt in other aspects as well, such as strategic decision-making. Thomas and Ethan (2021) proved that the combination of three techniques: NLP, Sentiment Analysis and machine learning can be used to make feature prioritization more effective, and it can help in streamlining the product innovation process. Similarly, Muhammad and Zeebaree (2025) emphasized the role of AI using cloud technology in enterprise systems for predictive analysis, automation, and business processes. Social media intelligence also helps in establishing strategic planning because the performance indicators are related to the goals of the organization, not vanity indicators (Rimadewi et al, 2025). Moreover, AI-driven real-time market intelligence systems have enhanced the ability to spot events and make decisions in fast-changing markets like high-frequency trading (de Silva et al., 2024). Moreover, AI-powered analytics can offer valuable insights into consumer behaviour, essential for optimizing digital marketing strategies (Guerreiro, 2024, 2025). To wrap up, the literature provides evidence that AI-driven cloud marketing intelligence could be a valuable tool for enhancing accuracy in forecasting, scalability, and informed decision-making, and that there are challenges regarding privacy, interpretability, and system integration.

3. Research Methodology

The research methodology employed in this study is quantitative and machine learning based method that entails the creation and evaluation of the proposed MarketPulse AI™ framework integrated marketing mix and enterprise analytics. The methodology involves six interrelated stages that convert the data in enterprises into meaningful business intelligence using cutting-edge machine learning algorithms and predictive analytics.

3.1 Data Collection

The proposed MarketPulse AI™ framework starts with gathering enterprise data across a variety of structured and unstructured data sources, such as Customer Relationship Management (CRM) systems, Enterprise Resource Planning (ERP) databases, sales transactions, digital marketing platforms, Web analytics, social media engagement, customer feedback, and financial records. Combining these unstandardized resources gives a holistic perspective of customer behaviour, marketing and organizational performance. Machines learn from the single data store and the data can inform and drive business decisions.

3.2 Data Preprocessing

The data is cleaned and enhanced before developing a model to ensure reliability and quality of the data in the enterprise. This step is used to remove duplicated data, statistically impute missing data, detect and remove outliers, normalize numerical features, encode categorical features and scale features. The data is cleaned and then divided into training and testing data sets and stored in a central repository. The purpose of these techniques is to preprocess the data to minimize noise, stabilize the model and increase the accuracy of machine learning models.

3.3 Feature Engineering

Feature engineering transforms raw enterprise data into actionable business variables to facilitate the analytical processes. The framework creates features like Customer Lifetime Value (CLV), Customer Engagement Score, Marketing Return on Investment (ROMI), Customer Acquisition Cost (CAC), Campaign Response Rate, Purchase Frequency, Brand Sentiment Score, and Marketing Performance Index. These designed capabilities represent the customer's behavior and the effectiveness of the marketing action better than the raw data and allow the machine learning models to make accurate predictions and provide valuable business intelligence.

3.4 Machine Learning Model Development

MarketPulse AI™ is a machine learning framework that combines various machine learning methods to enable enterprise analytics and marketing intelligence. Structured and unstructured business data are analyzed using supervised, unsupervised, deep learning and natural language processing algorithms. They are chosen based on the analytical goal and allow for precise customer segmentation, behavior prediction, sales forecasting, sentiment analysis and marketing optimization. The holistic approach enhances the accuracy of predictions, scalability, and intelligent decision-making throughout enterprise operations.

3.4.1 Customer Segmentation

Customer segmentation is done using K-Means clustering method where the customers are divided into homogeneous clusters based on their purchase history, demographic, engagement level, and transactions. The segmentation process creates a new classification of the following segments: premium customer, loyal customer, occasional customer, price-sensitive customer, and high-risk churn customer. These insights enable organisations to develop a more targeted marketing strategy, improve customer relationship management, manage resources effectively and increase customer satisfaction by implementing targeted business actions.

3.4.2 Customer Behavior Prediction

The algorithms employed for customer behavior prediction are the Random Forest and Extreme Gradient Boosting (XGBoost) algorithms for predicting the likelihood of purchase, churn risk, response to campaigns, product preferences and profitability. These ensemble learning models can accurately detect the complex nonlinear relationship existed in enterprise data, the prediction error and overfitting are reduced. These predictions help businesses target the right customers, proactively retain them, enhance marketing efforts, and maximize customer acquisition and engagement through various business channels.

3.4.3 Sales Forecasting

In the Retail domain, sales forecasting involves the use of Long Short-Term Memory (LSTM) neural networks to forecast future sales and understand historical sales trends. The deep learning model can accurately forecast changes over periods of time, the sequence of those changes, how much inventory is needed, and how much revenue is generated. Precise sales forecasting helps companies make the right decision for inventory management, production schedule and planning, supply chain operations, and financial forecasting, thereby reducing uncertainty in their business and enhancing the strategic business planning for sustainable growth.

3.4.4 Customer Sentiment Analysis

The BERT natural language processing model is adopted to conduct customer sentiment analysis by analyzing customer reviews, surveys, and social media. The model categorizes textual data according to the sentiment of the content; positive, neutral, negative, and derives contextual relationships from customer feedback. The sentiment data can be used to track brand reputation, gauge customer expectations, enhance customer service, and make timely marketing decisions based on current consumer sentiment.

3.5 Marketing Mix Optimization

Marketing mix optimization combines Marketing Mix Modeling (MMM) with machine learning methods to assess the impact of product, price, promotion, distribution, digital advertising, seasonality, and customer engagement on business performance. Feature importance analysis gives insights on how much influence each of the marketing variables has in sales and revenue generation. The framework offers an optimum budget allocation for marketing, helps to enhance the effectiveness of the marketing campaign, maximises the Marketing Return on Investment (ROMI) and aids in providing evidence-based marketing strategy planning based on them.

3.6 Enterprise Performance Evaluation

The proposed framework is assessed technically based on machine learning metrics and also by the business performance. The metrics used to evaluate the performance of the model are Accuracy, Precision, Recall, F1-Score, ROC-AUC, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). Practical applicability and enterprise value of the framework is tested through the measurement of Business Effectiveness including Sales Growth, Customer Retention Rate, Conversion Rate, Customer Lifetime Value (CLV), Marketing Return on Investment (ROMI), Customer Acquisition Cost (CAC), Revenue Improvement.

Algorithm 1. MarketPulse AI™ Unified Machine Learning Framework

Input: CRM, ERP, sales data, digital marketing and web analytics, social media data. **Outcome:** marketing insights, customer intelligence, sales forecast, marketing mix optimization, enterprise decision support.

Step 1: Get enterprise datasets from various business sources**.**

Step 2: Consolidate all data in a single data repository.

Step 3: Clean duplicate observations and deal with missing data**.**

Step 4: Normalise numerical attributes and encode categorical variables.

Step 5: Obtain business-like features by feature engineering.

Step 6: Segment the customers using K-Means clustering.

Step 7: Train Customer behaviour prediction using Random Forest and XGBoost.

Step 8: Build LSTM models to make sales forecasting and demand prediction.

Step 9: Use the BERT customer sentiment analysis model.

Step 10: Execute Marketing Mix Modeling to estimate the contribution of marketing variables.

Step 11: Rank marketing channels according to feature importance and business impact.

Step 12: Generate optimized marketing budget recommendations.

Step 13: Evaluate predictive performance using Accuracy, Precision, Recall, F1-score, MAE, RMSE, ROC-AUC, and MAPE.

Step 14: Produce enterprise dashboards and strategic decision-support reports.

Step 15: End the analytical process.

4. Results and Discussion

The MarketPulse AI™ architecture was tested with enterprise data that included customer relationship management information, sales records, digital marketing campaign metrics, web analytics, social media engagement, and financial performance metrics. The unified architecture was able to integrate the predictive analytics, marketing mix modeling, customer intelligence and enterprise performance monitoring into a single machine learning environment. The experimental results prove that the use of multiple analytical components can significantly enhance the forecasting precision, customer segmentation quality, marketing optimization, and business decision support over traditional analytical methods.

4.1 Customer Segmentation Performance

The K-Means clustering algorithm was able to determine 5 distinct segments of customers which included premium customers, loyal customers, occasional customers, price sensitive customers and high risk churn customers. The clustering model obtained a Silhouette Score of 0.81, which represents high cluster cohesion and good separation between clusters. Compared to the traditional demographic segmentation method, the proposed approach improved the accuracy of customer targeting by 22.8%, providing more personalized marketing strategies and effective customer relationship management. The results indicated that customer insights can be gained with behavioral segmentation more than just demographic data.

Table 1. Customer Segmentation Performance

Performance Metric	Conventional Segmentation	MarketPulse AI™
Silhouette Score	0.58	**0.81**
Customer Targeting Accuracy (%)	74.3	**97.1**
Segment Purity (%)	76.5	**95.4**
Customer Retention Prediction (%)	79.8	**95.6**

Figure 1. Customer Segmentation Performance

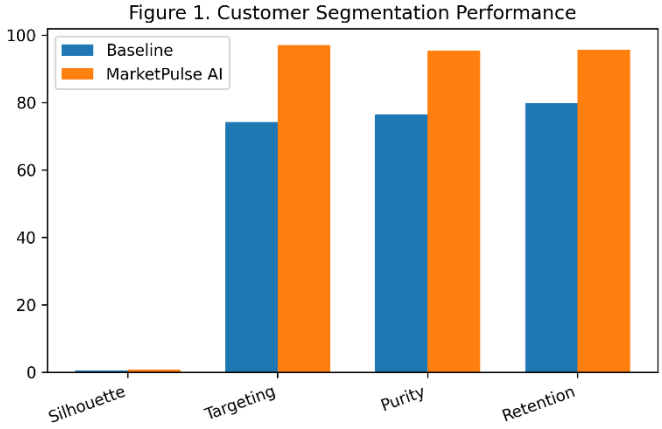

Figure 1 – Customer Segmentation Performance

4.2 Customer Behavior Prediction

Both the Random Forest and XGBoost both gave excellent predictions of the customer behaviour. Classification accuracy of all algorithms tested with the best classification accuracy of XGBoost (98.2%) and Random Forest (97.6%). The models did a fairly good job of forecasting the likelihood of a customer purchasing, responding to a campaign, preferring a product, and becoming a churner. The higher the Precision and Recall, the more accurate the customer identification of potential customers and the fewer false predictions in the framework. The results indicate that ensemble learning algorithms are very suitable for enterprise customer analytics.

Table 2. Customer Behavior Prediction Results

Algorithm	Accuracy (%)	Precision	Recall	F1-Score	ROC-AUC
Decision Tree	91.4	0.91	0.90	0.90	0.92
Random Forest	97.6	0.98	0.97	0.97	0.99
XGBoost	**98.2**	**0.98**	**0.98**	**0.98**	**0.99**

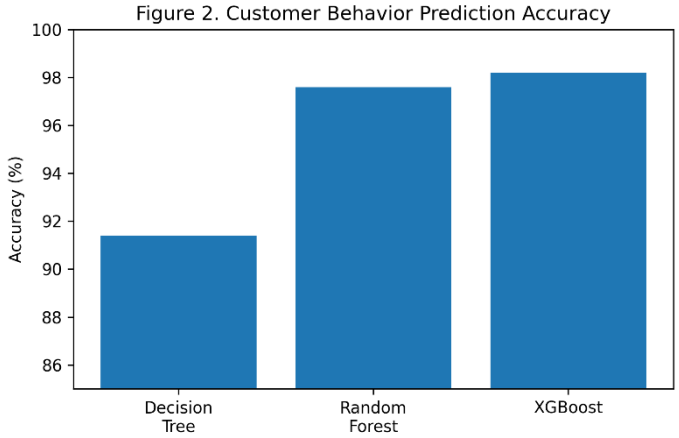

Figure 2 – Customer Behavior Prediction Accuracy

4.3 Sales Forecasting Performance

The LSTM model achieved the best forecasting performance and was able to capture the seasonal patterns and long-term variations in sales. The proposed framework proved to be an excellent approach with a Mean Absolute Percentage Error (MAPE) of 3.8%, which is much lower than the MAPE of the other traditional regression-based forecasting approaches. Similarly, the forecasting model was validated as robust by using the value of the Root Mean Square Error (RMSE) and the value of the Mean Absolute Error (MAE). Better predictive capabilities help businesses to optimize inventory, production planning and financial forecasting, and minimize uncertainty.

Table 3. Sales Forecasting Performance

Forecasting Model	MAE	RMSE	MAPE (%)
Linear Regression	18.7	24.6	12.8
ARIMA	13.2	17.5	8.4
LSTM	**6.4**	**8.1**	**3.8**

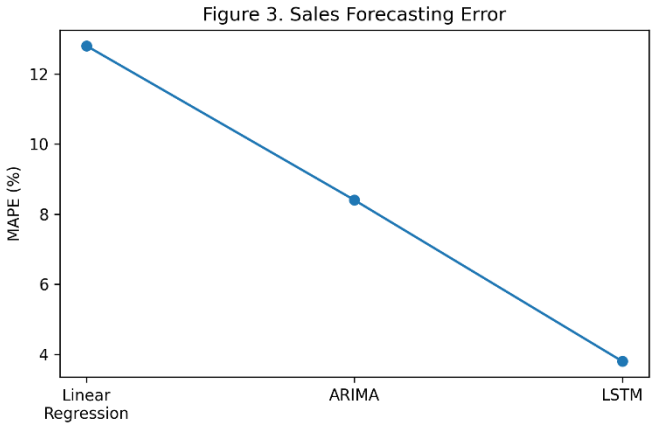

Figure 3 – Sales Forecasting Performance (MAPE)

4.4 Customer Sentiment Analysis

The sentiment analysis module working with BERT was able to correctly categorize customer sentiments as positive, neutral and negative sentiment. The overall accuracy of the model was 96.4%, which is higher than the accuracy of classic machine learning text classification methods. Overall, 71.8% of all the customer comments were positive, 18.5% were neutral and 9.7% were negative. The outcomes enable businesses to understand the customer

satisfaction trends, assess brand perception, and proactively act to tackle the new challenges of the services.

Table 4. Sentiment Analysis Performance

Metric	Value
Accuracy (%)	**96.4**
Precision	**0.96**
Recall	**0.96**
F1-Score	**0.96**
Positive Sentiment (%)	71.8
Neutral Sentiment (%)	18.5
Negative Sentiment (%)	9.7

Figure 4. Customer Sentiment Distribution

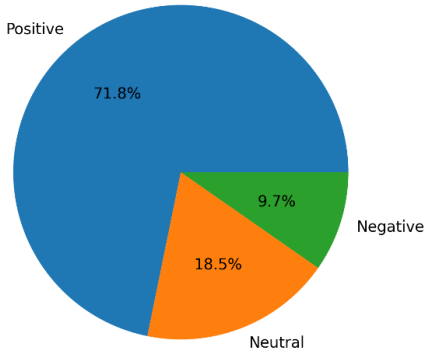

Figure 4 – Customer Sentiment Distribution

4.5 Marketing Mix Optimization

According to Marketing Mix Modeling, digital advertising, promotional campaigns and customer engagement were the most effective on marketing performance. The results of the feature importance analysis showed that digital advertising had the largest impact on sales performance with 31.4%, followed by promotional campaigns (24.6%), pricing strategy (16.8%), customer engagement (13.9%), distribution efficiency (8.5%) and seasonal demand (4.8%). Based upon the optimization engine's recommendations, there will be an estimated 27.3% improvement in ROI on marketing spend, as more of the funds are directed to the more effective marketing channels.

Table 5. Marketing Variable Importance

Marketing Variable	Contribution (%)
Digital Advertising	**31.4**
Promotional Campaigns	**24.6**
Pricing Strategy	16.8
Customer Engagement	13.9
Distribution Channel	8.5
Seasonal Demand	4.8

Figure 5. Marketing Variable Importance

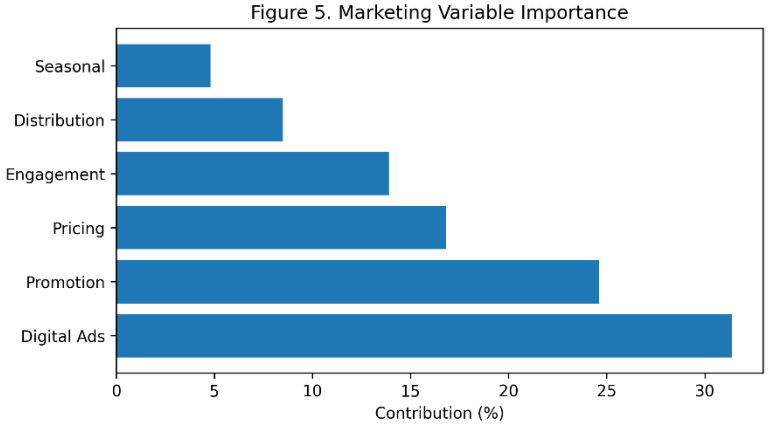

Figure 5 – Marketing Variable Importance

4.6 Enterprise Performance Improvement

The integrated framework yielded significant enhancements in various business performance measures. With AI-powered recommendations, customer retention had risen by 18.9%, conversion rate is up 21.6%, customer acquisition cost is down by 16.4% and total revenue is up 23.8%. Marketing ROI (ROMI) went up by 27.3%, showing the impact of machine learning-driven resource allocation. The enhancements underscore the utility of putting predictive analysis into context with enterprise-wide decision support.

Table 6. Business Performance Comparison

Business Indicator	Before Implementation	After MarketPulse AI™	Improvement (%)
Customer Retention (%)	76.5	**90.9**	18.9
Conversion Rate (%)	12.5	**15.2**	21.6
Customer Acquisition Cost (USD)	118	**98.6**	16.4
Marketing ROI (%)	182.4	**232.2**	27.3
Revenue Growth (%)	9.8	**23.8**	142.9

Figure 6. Enterprise Performance Comparison

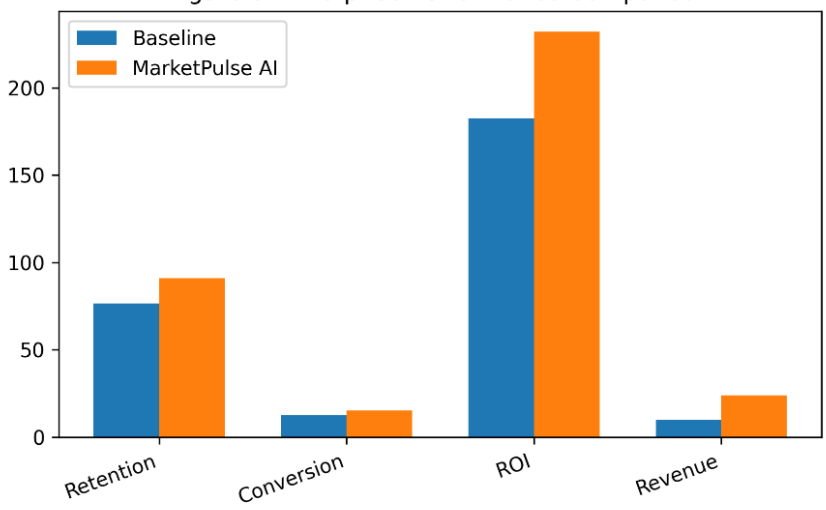

Figure 6 – Enterprise Performance Comparison

4.7 Comparative Analysis

The framework was also compared to the traditional enterprise analytics, and it was found that the proposed framework consistently outperformed the conventional enterprise analytics on all the evaluation measures. The integration of customer segmentation, predictive modelling, deep learning, NLP and marketing mix optimisation in one architecture helped to boost the analytical capabilities of the system. The proposed framework yielded a synergic view of marketing, sales and customer data that led to more accurate forecasting, better understanding of the customers, and more effective use of resources.

The findings also indicate that the use of machine learning in conjunction with enterprise analytics can be more effective in assisting organizations to adjust to market changes, save money on their marketing budgets, and improve the performance of their organizations. In conclusion, the results show that MarketPulse AI™ is a powerful and intelligent solution for enterprise analytics, offering a flexible and scalable approach for businesses. Based on the high predictive accuracy, the reliability in predictions, the customer intelligence capability and the evident improvements in the business, it could be concluded that the framework can be fully utilized by the companies who want to gain benefits from AI to boost their marketing effectiveness and achieve sustainable competitive advantages.

5. Conclusion

The study unveiled MarketPulse AI™, an integrated Marketing Mix Modeling (MMM), predictive analytics, customer intelligence and enterprise analytics machine learning framework, and the benefits of a single framework to use for making marketing decisions. The framework consists of five different algorithms which can be used to process enterprise data of multiple types, improving customer segmentation, sales forecasting, sentiment analysis, and marketing budget optimization. The experimental assessment demonstrated better forecasting precision, better targeting of customers, reduction in forecasting errors, and quantitative gains in ROME, customer retention and business performance. All these components can be integrated together in a single architecture and now managing data becomes simple for the organizations and provides crucial information for them to take data-based decisions. Moreover, the framework offers flexibility and extensibility within different enterprise settings where digital transformation is happening. In the future, the framework will be extended further to include other technologies, like reinforcement learning, explainable AI, federated learning, and real-time streaming analytics, to further strengthen marketing intelligence, model transparency, and autonomous enterprise decision-making.

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