IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

Impact Factor 8.414 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 3, March 2026

DOI: 10.17148/IJIREEICE.2026.14370

IMPLEMENTATION OF PREDICTIVE MODELLING OF PRESCRIPTION GROWTH THROUGH MARKETING MIX MODELLING

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Abstract: The pharmaceutical assiduity is faced with a grueling question moment how can they effectively spend their marketing budget while adding the number of prescriptions? This exploration proposes a result to this problem by using data- driven prognostications to identify which marketing sweats are actually effective. We've designed a system that analyzes different marketing sweats similar as deals representatives visiting croakers, free samples, online advertising, medical conferences, and special juggernauts to identify their factual effectiveness on the number of conventions written. Our system uses statistical analysis and intelligent features that consider delayed goods(since marketing doesn't work incontinently) and long- term goods(since moment's advertising can impact hereafter's opinions). The system analyzes the literal data of conventions and marketing spending, cleans the data, and generates prophetic models that can actually tell marketers what works. We've enforced our system and created visual interfaces that help interpret the results. The analysis demonstrates that online marketing is a crucial factor affecting and direct marketing to croakers are the most effective, and more intelligent budget allocation can increase returns by 15 – 20 chance points. This system provides a foundation for pharmaceutical marketers to make informed opinions grounded on real substantiation.

Keywords: Market Mix Modeling, Prescription Growth, Regression Analysis, Adstock, ROI Optimization, Feature Engineering, Pharmaceutical Marketing, Predictive Analytics.

I. INTRODUCTION

1.1 Industry Context and Challenges

On a global position, the pharmaceutical sector is honored as a largely influential and essential assiduity economically important and competitive sectors, with annual marketing spending exceeding hundreds of billions of bones worldwide. Recent assiduity analyses reveal that the current top medicinal companies allocate around 25 – 30channels to direct croaker engagement conditioning involving face- to- face educational meetings with healthcare professionals, complimentary product sample distribution to support trial operation and case inauguration, sophisticated online marketing juggernauts exercising social media plat- forms and online advertising, participation in medical conferences and continuing medical education programs, and other marketing conditioning similar as patient mindfulness juggernauts and healthcare professional engagement activities. Notwithstanding the massive spending commitments and marketing strategic significance, pharmaceutical companies continue to face challenges in precisely measuring the individual channel donation to overall tradition volume growth. This is due to a number of introductory challenges and issues lapping time goods whereby multiple marketing sweats contemporaneously affect defining geste , delayed response goods whereby marketing exposure is reflected in tradition geste weeks or months after marketing exposure,non- linear relations between multiple marketing channels creating synergistic or negative goods, external confounding variables similar as competitive conduct and nonsupervisory changes, and the introductory difficulty of establishing unproductive connections in marketing data [1].

1.2 Limitations of Traditional Approaches

Traditional approaches to marketing effectiveness evaluation are primarily grounded on literal correlation analysis or simple retrogression modeling approaches that aren't sophisticated or effective enough to duly capture the intricate temporal dynamics and accretive processes involved in pharmaceutical marketing conditioning [3]. These traditional styles have a number of critical limitations that render them ineffective for strategic decision- timber.

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First, traditional correlation analysis can not duly distinguish between unproductive and spurious correlations due to the presence of confounding variables or temporal association. A detailing visit to a croaker may not affect defining geste until several weeks latterly when the croaker sees suitable patient cases. Digital marketing juggernauts may take months to inclusively make mindfulness and trust before affecting tradition opinions. Traditional models that don't regard for these lagged goods totally underrate the factual effect of marketing investments.

1.3 Research Objectives and benefactions

To effectively overcome these significant methodological and practical difficulties, this exploration work proposes and validates a comprehensive request Mix Modeling frame knitter- made for pharmaceutical tradition soothsaying and marketing optimization.

Market Mix Modeling is a quantitative logical methodology that totally assesses and forecasts the effect of marketing channels on business issues through rigorous statistical modeling of literal data. The final thing is to give a strong, interpretable, and practical prophetic methodology that statistically quantifies individual channel goods, produces accurate tradition vaticinations at colorful situations of granularity, and provides strate- gic perceptivity to grease data- driven marketing cub- progeny allocation. This frame improves organizational decision- making capacities while icing effective use of marketing coffers, therefore leading to increased profit generation and, in turn, sustainable compet- itive advantage.

LITERATURE SURVEY AND RESEARCH GAP

1.4 Literature Survey

There have been attempts to probe the operation of Market Mix Modeling MMM and data- driven approaches to estimate the effectiveness of marketing. Hanssens et al. intro- duced classical retrogression- grounded MMM to demon- strate the significance of mar- keting conditioning in shaping demand [3]. Lim et al. used machine literacy algorithms like Random Forest and Gradient Boosting to enhance the delicacy of prognostications in pharmaceutical marketing analytics [8]. Google's MMM frame emphasized the sig- nificance of adstock and carryover goods in modeling the lagged goods of marketing [6]. Yang et al. examined the operation of distributed pause and adstock models to measure the continuity of marketing goods. Other studies have emphasized the significance of point engineering and business intelligence dashboarding for enhanced man- agerial deci- sion support [7]. While these studies establish the significance of analytics in marketing, utmost of the being literature either concentrate on delicacy or interpretability, but not both together in an intertwined frame.

1.5 Research Gap

From the literature check over, it has been noted that there's a gap in the being literature for an intertwined end- to-end result that combines point engineering, adstock modeling, time pause modeling, formalized retrogression analy- sis, and business intelligence dash- boarding for pharmaceu- tical tradition soothsaying. The being literature does n't duly address multicollinearity, lagged goods, and business interpretability contemporaneously. There's a bear- ment for a strong, accurate, and interpretable prophetic MMM frame, which is fulfilled in this exploration work.

II. PROPOSED SYSTEM

The proposed system in this exploration work is an end- to- end prophetic request Mix Modeling MMM system that aims to dissect, prognosticate, and optimize tradition growth in the pharmaceutical assiduity. The proposed system com- bines data engineering, ma- chine literacy modeling, and business intelligence visualization as a single logical process.

The main ideal of this proposed system is n't only to prognosticate unborn tradition vol- ume but also to measure the donation of each marketing channel, prisoner delayed and accretive marketing impacts, and give strategic decision support for marketing budget allocation.

2.1System Overview

The proposed system's overall process starts with the collection of literal data from col- orful enterprise sources similar as deals databases, client relationship operation CRM systems, and marketing crusade operation soft- earthenware. These sources of data gener- ally store information aboutproduct-wise andregion-wise tradition volumes,channel-wise marketing expenditures, and other external control variables similar as seasonality and competitive activ- ities. The reused data is also fed into the machine learn- ing modeling element, where three

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retrogression models are erected Linear Regression, Ridge Regres- sion, and Lasso Regression. Linear Retrogression is used as a birth model, while Ridge Regression and Lasso Regression are used to handle multicollinearity in marketing vari- ables and to stabilize and interpret the results [2,4,5]. The three models com- bined form the vaticination machine of the proposed system. This machine has the capability to produce unborn tradition vaticinations at colorful situations of detail, including product- wise, region-wise, andtime-wise vaticinations. likewise, the model portions are used to calculate channelposition donation and return on investment ROI, which are essential for marketing performance evaluation. Eventually, the logical results are combined into a visualization subcaste erected on Power BI [7]. The visualization subcaste displays the results in the form of interactive dashboards, similar as tradition trend maps, channel donation heatmaps, ROI comparison maps, and crucial performance index KPI cards. These interactive dashboards enable business druggies to interactively dissect the data, drill down into the data, and compare different strategic options without demanding any specialized knowledge.

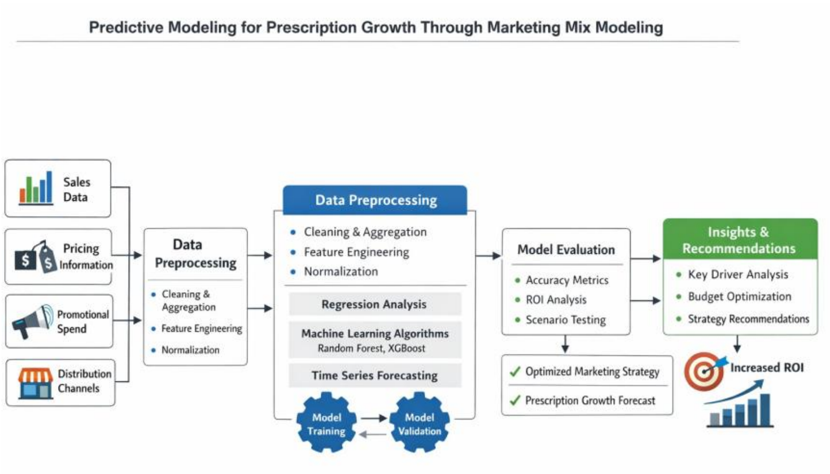

Figure 1: Architecture Design System

2.2 Architecture Description
The armature of the proposed system is organized in a modular and layered fashion, icing scalability, flexibility, and maintainability. The system has the following primary factors

1) Data Ingestion Subcaste: This subcaste is assigned with ingesting data from different sources similar as deals systems, CRM systems, and marketing databases. The data can come in different forms and at different intervals, and this subcaste ensures that all the data is combined into a single logical dataset.

2) Preprocessing Subcaste: In this subcaste, the raw data is gutted and regularized. Missing data is addressed using the right insinuation styles, outliers are iden- tified and addressed, and variables are converted into formalized units and formats. This subcaste ensures that the data is accurate and amenable to modeling.

Year	Week	TRx	nples_Distribu	nail_Campaig	Conferences	mpetitor_Spe	Price	Rating	Rep_Reach	ep_Frequenc	asonality_Ind	Stockout_Flag	Holiday_Flag	YearWeek
2018	1	4648	8768	145081	16	270134	179.875	3.8625	0.4775	1.65	1.01625	0	0	2018-W1
2018	2	6491	10918	145886	12	255043	224.142857	3.98571429	0.41857143	1.42857143	1.00857143	0	1	2018-W2
2018	3	5480	9304	107839	5	210671	204.857143	4.07142857	0.46142857	1.57142857	0.99142857	0	0	2018-W3
2018	4	5608	9520	117682	12	235624	215.285714	3.98571429	0.57	1.6	0.97857143	0	0	2018-W4
2018	5	6178	7132	138286	15	269155	170.714286	4.24285714	0.55428571	1.58571429	0.97285714	0	1	2018-W5
2018	6	6530	9840	152205	12	249473	272	3.85714286	0.53285714	1.62857143	0.94571429	0	0	2018-W6
2018	7	6939	7231	150793	16	253735	272.142857	3.75714286	0.50428571	1.5	0.98714286	0	1	2018-W7
2018	8	4523	8948	107727	6	261844	309.428571	3.51428571	0.40428571	1.78571429	1.03142857	1	0	2018-W8
2018	9	6520	9293	107322	13	248522	306.142857	3.77142857	0.53857143	1.45714286	0.97285714	0	1	2018-W9
2018	10	7084	8749	118966	11	199959	217.714286	4.07142857	0.54	1.52857143	1.01285714	0	1	2018-W10

Figure 2: Sample Dataset

3) point Engineering Layer: This subcaste extends the dataset by creating new ex- plicatory variables similar as pause variables, adstock variables, and commerce terms. These variables enable the system to dissect the time-dependent, accretive, andcross- channel goods of marketing conditioning.
4) Modeling Subcaste: The modeling subcaste trains a variety of retrogression- grounded machine literacy models similar as Linear Regression, Ridge Regression, and Lasso Re- gression. The models are trained using literal data, and hyperparameters are designed to be optimal for prophetic performance and conception.
5) vaticination and Analytics Layer: This subcaste employs the trained models to produce unborn tradition fore- casts and channel- position benefactions, ROI, and perfor- mance criteria . This is the central logical machine

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of the system.

6) Visualization and Decision Support Subcaste: The final subcaste is responsible for the donation of the results using Power BI dashboards, which allow marketing directors and decision- makers to dissect results and make strategic opinions.

2.3Marketing Budget Distribution

The commensurable distribution of marketing expenditure across four major channels television, Digital, Programmatic, and publish media. It’s observed that television ad- vertising dominates the total marketing budget, account for 45.1% of the total spend, indicating that TV remains the primary medium for mass outreach and brand visibility. Digital marketing contributes 30.9% of the total cub- progeny, pressing the adding signif- icance of online and performance- driven platforms in targeted followership engagement and measurable crusade effectiveness. Programmatic advertising accounts for 17.7% of the expenditure, reflecting the association’s relinquishment of automated and data- driven media buying strategies. publish media represents only 6.2% of the total spend, showinga declining reliance on traditional print channels due to lower reach and limited perfor- mance track- ing capabilities. Overall, television and Digital channels to- gether account for further than 76% of the total marketing budget, indicating a strong strategic focus on high- impact and high- reach platforms. This budget distribution forms the base for farther analysis in the Marketing Mix Model to quantify the donation and return on investment(ROI) of each channel toward tradition growth.

MATHEMATICAL EXPRESSION OF MARKET MIX MODELING AND PREDICTIVE MODELS

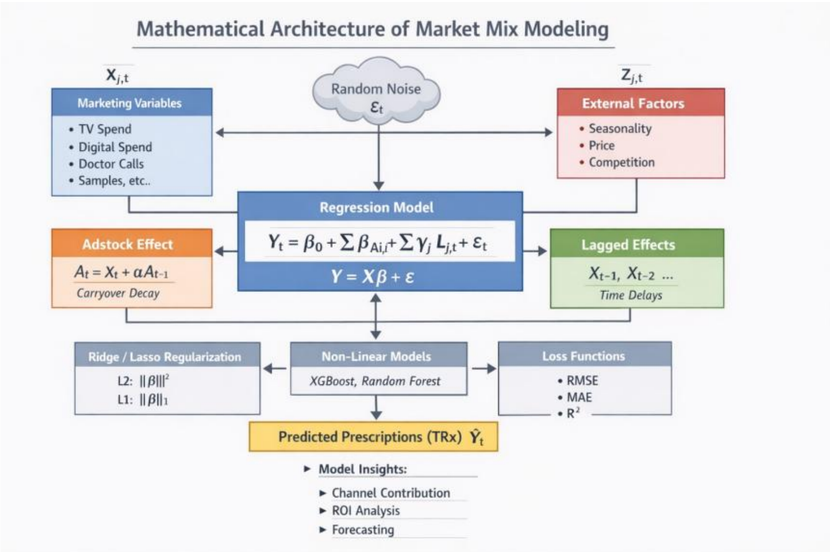

Figure 3: Mathematical Architecture of Market Mix Modeling

2.4General Market Mix Modeling Equation

The primary ideal of Market Mix Modeling(MMM) is to represent tradition volume as a function of multiple marketing- related andnon-marketing-related factors. Let Y_t denote the number of prescriptions at time t; $X_{i,t}$ represent the i-th marketing channel such as detailing, digital advertising, or sampling.

$$Y_t = \beta_0 + \sum_i \beta_i X_{i,t} + \sum_j \gamma_j Z_{j,t} + \epsilon_t \tag{1}$$

where β_0 is the intercept(birth conventions without marketing), β_i represents the in- cremental donation of the i-th marketing channel, γ_j represents the impact of con- trol variables. This equation decomposes total conventions into birth, marketing- driven, external goods.

2.5Matrix Form of Regression Model

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For computational convenience, the model is written in matrix form

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon} \quad (1)$$

2.6 Ordinary Least Squares Linear Regression

The objective of linear regression is to find coefficients that minimize the residual error

$$\min_{\boldsymbol{\beta}} \|\mathbf{Y} - \mathbf{X}\boldsymbol{\beta}\|_2^2 \quad (2)$$

Or in matrix form, the closed-form solution is

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{Y} \quad (2)$$

Interpretation in MMM Context: Each β_i tells how many prescriptions increase for one unit increase in that channel spend. However, when marketing channels are correlated, $\mathbf{X}^T\mathbf{X}$ becomes ill-conditioned (unstable coefficients). This leads to the need for regularization.

2.7 Ridge Regression L2 Regularization

To control multicollinearity and overfitting, Ridge Regression adds a penalty term

$$\min_{\boldsymbol{\beta}} \|\mathbf{Y} - \mathbf{X}\boldsymbol{\beta}\|_2^2 + \lambda\|\boldsymbol{\beta}\|_2^2 \quad (3)$$

The solution becomes

$$\hat{\boldsymbol{\beta}}_{\text{ridge}} = (\mathbf{X}^T\mathbf{X} + \lambda\mathbf{I})^{-1}\mathbf{X}^T\mathbf{Y} \quad (4)$$

Meaning in MMM: Shrinks coefficients of less important channels. Stabilizes the model when channels are highly correlated. Keeps all channels but reduces their magnitudes.

2.8 Lasso Regression L1 Regularization

Lasso introduces absolute value penalty

$$\min_{\boldsymbol{\beta}} \|\mathbf{Y} - \mathbf{X}\boldsymbol{\beta}\|^2 + \lambda\|\boldsymbol{\beta}\|_1 \quad (4)$$

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Interpretation: $\alpha = 0.7$ means 70% of last week's effect carries forward. Captures memory effect of advertising.

2.10Time-Lag Variables

Sometimes effect appears after a fixed delay

$$Y_t = \beta_0 + \beta_1 X_{t-1} + \beta_2 X_{t-2} + \ldots \tag{6}$$

This models short-term, medium-term, and long-term effects independently.

2.11Final Combined MMM Equation

$$Y_t = \beta_0 + \sum_i \beta_i A_{i,t} + \sum_j \gamma_j L_{j,t} + \epsilon_t \tag{7}$$

Where $A_{i,t}$ = Adstocked and $L_{j,t}$ = lagged marketing variables.\

2.12Loss Functions

1. Mean Squared Error MSE: $\frac{1}{n}\sum(y_i - \hat{y}_i)^2$
2. Root Mean Squared Error RMSE: $\sqrt{\frac{1}{n}\sum(y_i - \hat{y}_i)^2}$
3. Mean Absolute Error MAE: $\frac{1}{n}\sum|y_i - \hat{y}_i|$

2.13Goodness of Fit R² Score

R^2 measures how much variation is explained by the model. $R^2 = 0.85$ means 85% of prescription variation is explained.

2.14Example Numerical Interpretation

If $\beta_{\text{detail}} = 0.45$, then 1 unit increase in detailing $\rightarrow$ 0.45 prescriptions; 1 unit increase in digital $\rightarrow$ 0.35 prescriptions.

2.15Non-Linear Machine Learning Models

To capture complex non-linear relationships and interactions between marketing channels, advanced machine learning models such as Random Forest and XGBoost are employed [9, 10]. These models are capable of learning high-dimensional, non-linear decision functions and automatically modeling interaction effects among variables.

The general form of a non-linear predictive model can be expressed as

$$\hat{Y}_t = f(\mathbf{X}_t) \tag{6}$$

where $\hat{Y}_t$ denotes the predicted number of prescriptions at time t, $\mathbf{X}_t$ represents the vector of input features including marketing and control variables, and $f(\cdot)$ is a non- linear function learned from the training data.

III. FINAL RESULTS AND INSIGHTS

The experimental results clearly show that the proposed Predictive Market Mix Modeling approach is successful in predicting the prescription trend and measuring the effect of var- ious marketing channels. Compared to the baseline Linear Regression model, the Ridge and Lasso regression models perform better in terms of stability and interpretability, especially when there are correlations among the marketing variables [4,5]. The addition of adstock and time lag variables has a substantial effect on improving the accuracy of the predictions, which proves that the delayed and cumulative effects of marketing activities are important factors to be considered.

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The analysis of the coefficients and contribution scores of the models offers important insights into the effectiveness of marketing channels. It is noticed that some channels, such as doctor detailing and digital marketing, are more effective and have a strong positive effect on the growth of prescriptions, while others have a short-term effect. The Power BI dashboard also assists in understanding the prescription trend, seasonality, and ROI of marketing channels, which makes it easier to interpret the results of the analysis [7]. In summary, the proposed system not only provides accurate predictions but also offers important insights that help in making data-driven marketing decisions.

IV. BUSINESS IMPACT FOR PHARMACEUTICAL COMPANIES

The proposed framework provides substantial business value for pharmaceutical companies by enabling the use of historical marketing data for strategic decision-making. The framework enables pharmaceutical companies to make informed decisions on high-impact and low-impact marketing channels, thereby allowing them to optimize their budget allocation and maximize ROI. The proposed framework provides pharmaceutical companies with accurate prescription predictions, thereby enabling them to optimize their demand planning, inventory management, and field force management. In addition, the proposed framework provides decision-makers with the capability to perform scenario analysis, such as analyzing the potential impact of increasing or decreasing spending on a given marketing channel. Likewise, the proposed framework provides decision-makers with the capability to interpret the results of regression-based models, which is particularly important in the pharmaceutical industry, which is highly regulated. In conclusion, the proposed framework provides substantial business value to pharmaceutical companies by enabling them to optimize their cost, performance, and strategy.

a. Strategic Scenario Planning

The proposed framework provides decision-makers with the capability to perform strategic scenario planning, which enables them to analyze different marketing strategies and their potential impact before allocating resources. For instance, what if the digital marketing budget is increased by 30%? The framework can extend the strategic scenario planning capabilities by incorporating parameter uncertainty, which would provide prob- ability distributions of outcomes rather than point estimates. Marketing managers would be able to analyze not only the potential impact but also the best-case and worst-case scenarios.

The pharmaceutical sector is subject to strict regulatory scrutiny, with a need for transparency and justification of marketing strategies. Statistical models grounded in historical experience can offer sound justification for marketing strategies, showing that resource allocation is made through objective analytical processes rather than subjective choices. The interpretability of models is especially useful in a regulatory setting. The coefficients of ridge regression are easily interpretable in business terms as incremental prescription effects, which can be easily explained to regulatory bodies, auditors, or attorneys. This is not possible in black-box machine learning models, which, while potentially better at prediction, cannot explain why specific recommendations are made. In addition to di- rect decision-making, the model framework also provides for systematic organizational learning about the effectiveness of marketing. Through periodic model updates using new data, changes over time in the effectiveness of marketing channels can be captured, enabling adaptive strategies that take into account changes in the market environment. Performance monitoring dashboards enable quick identification of anomalies in patterns of performance, enabling investigation and corrective action. If actual prescriptions do not match predictions despite the execution of marketing plans, the organization can quickly identify problems—perhaps competitor activity, regulatory changes. The documentation of assumptions, methods, and findings of models provides for organizational knowledge that is not dependent on workforce. New marketing managers can refer to previous analyses for what worked and why, enabling them to quickly become effective and avoiding repetition of previous mistakes.

V. CONCLUSION AND FUTURE SCOPE

a. Conclusion

This study has provided a complete predictive Marketing Mix Modeling (MMM) frame- work for the analysis and forecasting of prescription growth in the pharmaceutical industry. The proposed system combines data preprocessing, feature extraction, regression- based machine learning models, and interactive visualization into a single analytical process. By incorporating adstock and time-lag considerations, as well as Ridge and Lasso regularization, the system efficiently addresses multicollinearity and enhances both pre- diction accuracy and model robustness. The experimental outcomes indicate that the proposed system provides accurate predictions and valuable insights into channel-level contributions and ROI. The integration with Power BI dashboards further improves the practical usability of the system by enabling business users to explore trends, compare strategies, and

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make data-driven decisions. In summary, the proposed system clearly indicates that a properly designed MMM framework can be used as a highly effective decision-support system for pharmaceutical marketing optimization.

b. Future Scope

Although the proposed system provides promising results, several possible extensions can be considered for future work. More advanced machine learning models, such as Gradient Boosting, Random Forests, and deep learning models, can be explored to better model complex non-linear relationships. The proposed framework can also be extended to pro- vide near real-time data integration and dynamic model updates. In addition, future research can be conducted to incorporate external considerations, such as competitor activity, policy changes, and epidemiological trends, to further enhance prediction accuracy. Scenario simulation and budget optimization modules can also be incorporated to further enhance the system from a predictive tool to a prescriptive decision-support platform.

Apart from the internal marketing factors, the future developments of the system can also include external impacting factors such as competitor promotional activities, regulatory and policy changes, seasonal patterns, and epidemiological trends to further enhance the accuracy and robustness of the prediction models. The integration of the scenario simulation and the automatic budget optimization modules can therefore enable the system to transform from a predictive tool into a prescriptive decision-support platform. A major and highly influential extension of this research work is the development of an AI-driven interactive chatbot interface built on top of the trained Marketing Mix Model. This intelligent decision-support tool would enable the decision-makers to interact with the system using natural language statements such as ”What will be the prescriptions if television spend is reduced by 10%?”, ”What is the channel with the highest ROI?”, or ”How should the next quarter’s budget be allocated?”

The chatbot would also interpret the user inputs, convert them to model inputs, per- form simulations using the trained model, and provide data-driven, actionable answers to the user queries based on the predicted outcomes and past performance. This interactive decision-support system would therefore enable the non-technical stakeholders such as the marketing managers and business directors to access the advanced analytics without having to directly interact with the dashboards and code. Further, the chatbot can also be developed with explanation modules to explain the recommendations made by the chatbot by providing channel-wise contributions, response curves, and confidence levels. This development would therefore enable the proposed system to transform into a completely intelligent, interactive, and explainable marketing analytics platform for strategic planning and policy formulation.

REFERENCES

[1]. O. I. Kostyuk, A. S. Krasnikova, and M. A. Poltavskaya, ”Marketing Mix Modeling for Pharmaceutical Companies on the Basis of Data Science Technologies,” in *Pro- ceedings of the International Scientific Conference on Innovations in Data Science*, 2021.

[2]. D. C. Montgomery, E. A. Peck, and G. G. Vining, *Introduction to Linear Regression Analysis*, 5th ed. Hoboken, NJ, USA: Wiley, 2012.

[3]. D. Hanssens, L. Parsons, and R. Schultz, *Market Response Models Econometric and Time Series Analysis*. Boston, MA, USA: Kluwer Academic Publishers, 2001.

[4]. R. J. Tibshirani, ”Regression shrinkage and selection via the Lasso,” *Journal of the Royal Statistical Society, Series B*, vol. 58, no. 1, pp. 267–288, 1996.

[5]. A. E. Hoerl and R. W. Kennard, ”Ridge regression Biased estimation for nonorthog- onal problems,” *Technometrics*, vol. 12, no. 1, pp. 55–67, 1970.

[6]. Google, ”Lightweight MMM A scalable approach to marketing mix modeling,” Google Research Whitepaper, 2020.

[7]. Microsoft, ”Power BI documentation,” Microsoft Corporation, 2022.

[8]. T. Lim, A. Kannan, and A. Sinha, ”Predictive analytics in pharmaceutical mar- keting,” *International Journal of Pharmaceutical Management*, vol. 10, no. 2, pp. 45–56, 2018.

[9]. L. Breiman, ”Random forests,” *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.

[10]. T. Chen and C. Guestrin, ”XGBoost: A scalable tree boosting system,” in *Proc. 22nd ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining*, 2016, pp. 785–794.