Marketing Mix Modeling (MMM) Project Analysis

1. Aim of the Project

The aim of this project is to build a Marketing Mix Model (MMM) that explains and quantifies the impact of different marketing channels on sales (kpi_val_sales_mn). The model also derives Return on Investment (ROI) and provides recommendations for future budget allocation.

2. Objectives

The key objectives of the MMM analysis were:

• To explore the dataset through detailed Exploratory Data Analysis (EDA).

• To check modeling assumptions including multicollinearity, heteroscedasticity, and stationarity.

• To apply Adstock and Saturation (Hill function) transformations for marketing spends.

• To fit an Ordinary Least Squares (OLS) regression model and evaluate its performance.

• To derive channel-level contributions, ROI, and marginal ROI.

• To generate response curves and provide actionable recommendations for budget reallocation.

3. Procedure

The MMM analysis was carried out in the following steps:

1. Data Preparation: Loaded the dataset from Excel (48 rows, 41 columns). Identified the dependent variable (kpi_val_sales_mn), media variables, and control variables.

2. Exploratory Data Analysis (EDA): Generated descriptive statistics, missing value counts, and correlation analysis. This helped understand distribution, variability, and initial relationships.

3. Assumption Checking:

- Variance Inflation Factor (VIF) was used to identify multicollinearity among predictors.
- Augmented Dickey-Fuller test was conducted for stationarity of the dependent variable.

• Breusch-Pagan test checked heteroscedasticity of residuals.

4. Data Transformation: Applied Adstock to capture carryover effects and Hill function (saturation) to model diminishing returns in marketing spends.

5. Model Building: Built an OLS regression model with robust (HC3) standard errors after iterative VIF filtering.

6. Model Evaluation: R-squared and Adjusted R-squared were computed. Final model achieved $R^2 \approx 0.478$ and Adjusted $R^2 \approx -0.021$ (indicating predictors added little explanatory power beyond the mean).

7. Contributions & ROI: Derived channel-level contributions to sales and calculated ROI for each channel.

8. Response Curves: Generated curves showing predicted sales response vs. spend for top media channels. Due to adstock + saturation, curves exhibit diminishing returns.

9. Recommendations: Computed marginal ROI and proposed reallocation of 10% budget from least efficient channel to most efficient channel.

4. Results and Key Insights

• The model explains ~47.8% of variance in sales, though Adjusted R^2 is negative, reflecting the small dataset and many predictors relative to observations.

• Several media channels show concave response curves, indicating diminishing returns after certain spend levels.

• ROI varies significantly across channels, with some channels providing higher marginal ROI than others.

• Marginal ROI analysis suggested reallocating budget from low-performing channels to higher-performing ones to maximize impact.

5. Recommendations

• Focus incremental budgets on channels with higher marginal ROI (steeper response curve at current spend levels).

• Reduce spend in saturated channels where additional investments yield minimal incremental sales.

• Periodically re-estimate the model as new data becomes available, to capture changing media effectiveness.

• Consider combining MMM with digital attribution models for more granular insights.

• Improve data quality and increase observation periods for more reliable model estimates.

6. Limitations

• Small sample size (48 observations) limits model robustness and increases risk of overfitting.

• Adjusted R^2 being negative indicates that the predictors added limited explanatory power relative to the mean.

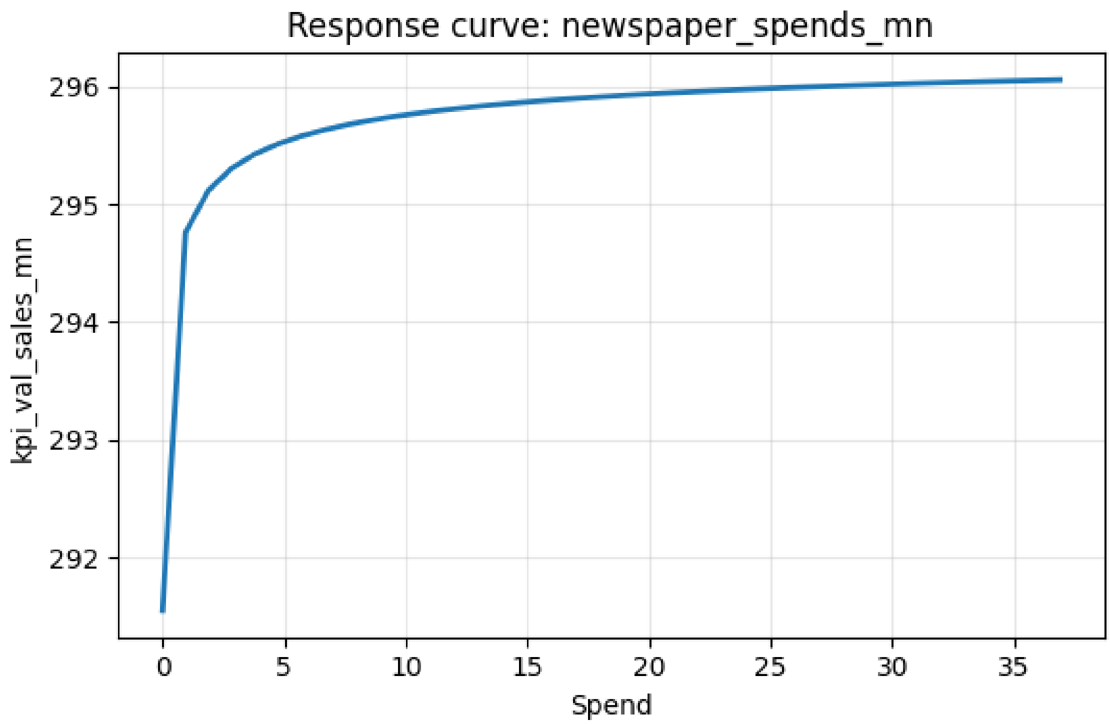
• Model assumes linear-additive structure after transformations, which may oversimplify real-world dynamics.

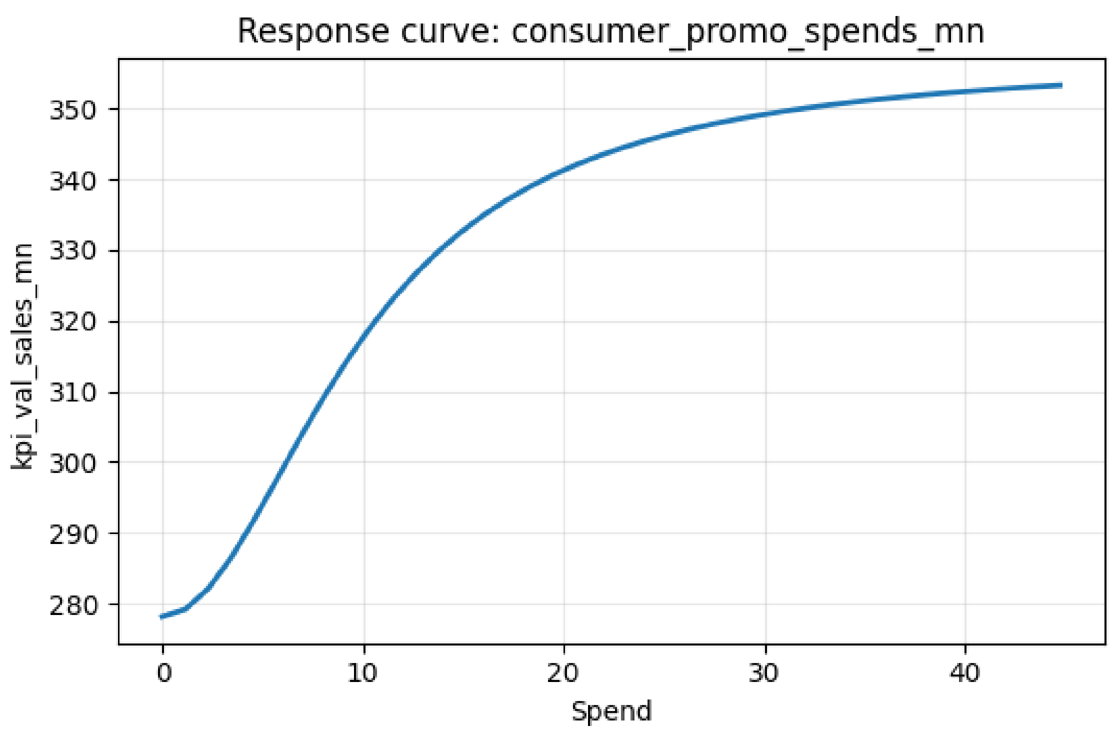
• External factors (seasonality, macroeconomic shocks, competitor actions) may not be fully captured.

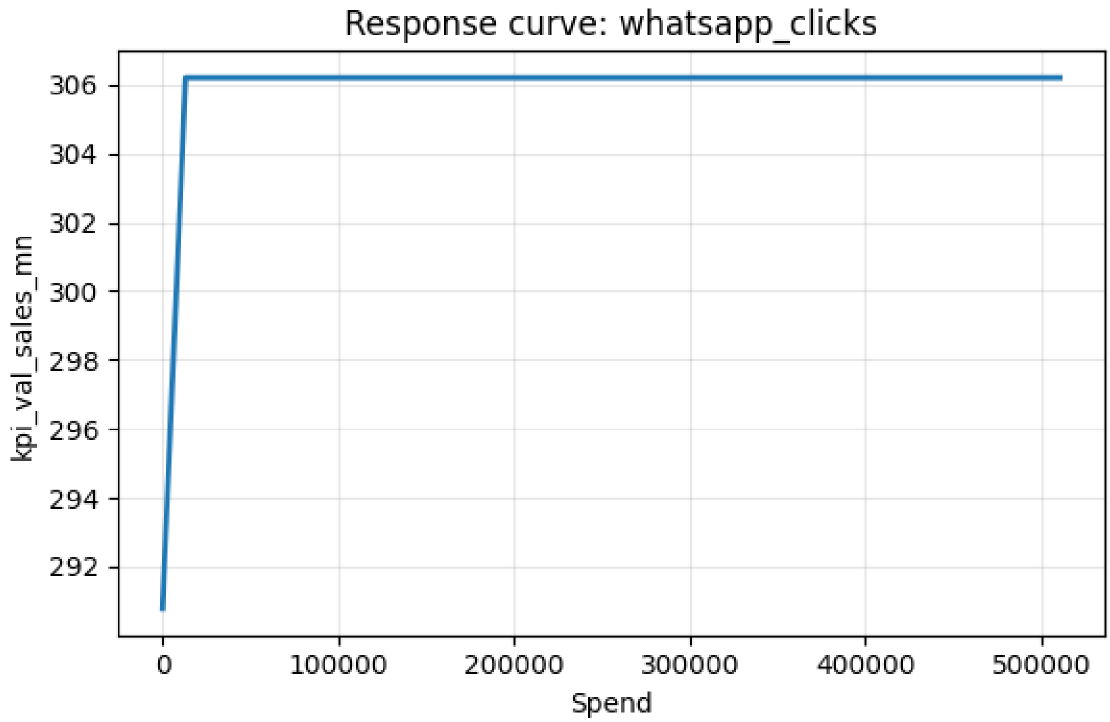
• The greedy parameter search for Adstock and Hill parameters may not find the global optimum.

7. Conclusion

The MMM project successfully demonstrated the use of Adstock and Saturation transformations in a regression-based framework. While the R^2 is moderate and Adjusted R^2 is negative due to data constraints, the model still provides useful directional insights into channel effectiveness, ROI, and budget allocation strategies. The analysis highlights the importance of data scale and quality in MMM and suggests that with more observations and refined feature engineering, stronger explanatory power can be achieved.


Response curve: newspaper_spends_mn
296
295
294
293
292
kpi_val_sales_mn
0
5
10
15
20
25
30
35
Spend


Response curve: consumer_promo_spends_mn
350
340
330
320
310
300
290
280
kpi_val_sales_mn
0
10
20
30
40
Spend



Response curve: whatsapp_clicks
kpi_val_sales_mn
306
304
302
300
298
296
294
292
0
100000
200000
300000
400000
500000
Spend