Section 1 - Background

The ask is to develop a Marketing Mix Model which would explain the impact to sales because of media investments across key channels and at the same time controlling for macroeconomic and market forces.

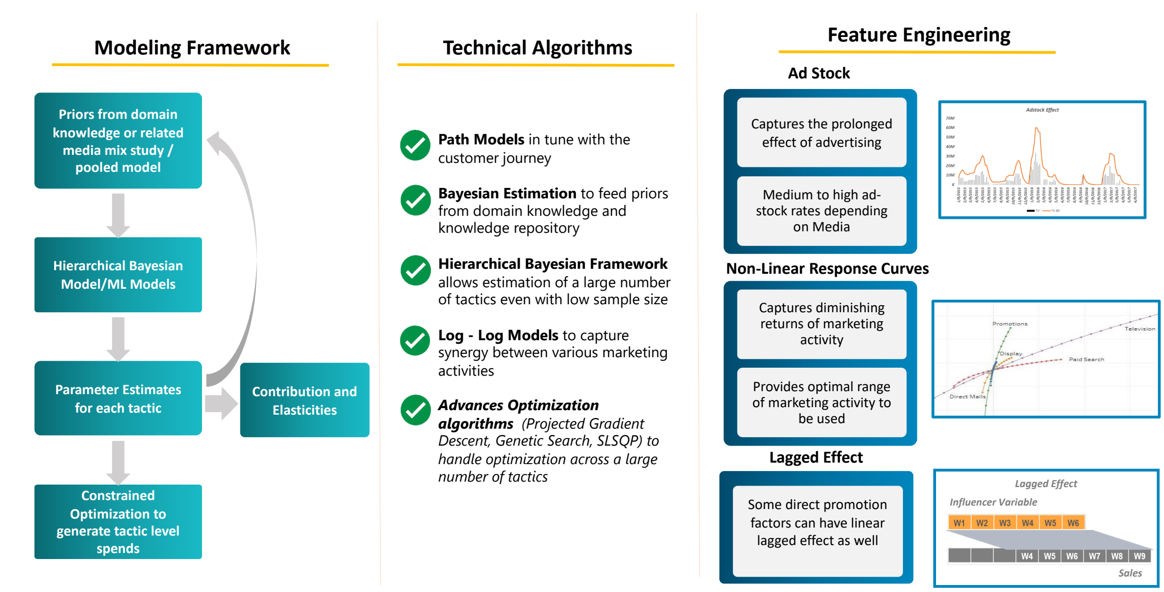
Section 2 - Methodology for Developing the Marketing Mix Model (MMX)

1. Overview of the Marketing Equation

The foundation of the Marketing Mix Model (MMX) we developed rests on understanding how various media spends influence overall sales. The equation can be expressed as:

$$\mathrm{Ln}(Sales) = Intercept + \Sigma\,(\beta_i * \mathrm{Ln}(Media\ Spend_i)) + \Sigma\,(\gamma_j * \mathrm{Ln}(Control\ Variable_j))$$

- β_i: Represents the media coefficient (impact factor) for each media channel.
- $f(Media\ Spend_i)$: The function capturing the diminishing returns and carryover effect (adstock) of media spend over time.
- γ_j: Coefficients for various control variables (e.g., seasonality, macroeconomic factors, promotions, holidays).
- The intercept represents the baseline sales when no media spend or external control variables are present.



2. Adstock and Carryover Effects

One key aspect of media impact is that it extends beyond the immediate week of spending, creating what is referred to as an "adstock" or carryover effect. The adstock transformation is applied to media spend through the following equation:

$$Adstocked\ Spend_t = \alpha * Adstocked\ Spend_{t-1} + Media\ Spend_t$$

α is the decay factor, also known as the "adstock" or "carryover" factor..

```python
# Apply adstock transformation to media data
def adstock_transform(x, alpha):
    adstocked = np.zeros_like(x)
    adstocked[0] = x[0]
    for t in range(1, len(x)):
        adstocked[t] = x[t] + alpha * adstocked[t-1]
    return adstocked
```

3. Diminishing Returns: The Hill Function

To capture the diminishing returns of media spend, we implemented the Hill function, which models how the marginal impact of additional media spend decreases as spending increases. The Hill function takes the form:

f(Media Spend) = 1 / [1 + (Media Spend / EC) ^ (-slope)]
- EC (Effective Concentration) is the media spend level at which the media channel impact is half of its maximum potential.
- slope controls the steepness of the curve, determining how rapidly the returns diminish as media spend increases.

```
# This is to understand Diminishing returns

def hill_transform(x, ec, slope):
    safe_ec = tt.clip(ec, 1e-3, np.inf)
    safe_x = tt.clip(x, 1e-3, np.inf)
    return 1 / (1 + (safe_x / safe_ec)**(-slope))
```

4. Coefficients (Betas)

Each media channel has its own βi, which represents its effectiveness in driving sales. These media coefficients are learned through model training and quantify the relative contribution of each media channel to sales. Similarly, control variables such as macroeconomic factors, store count, markdowns, holidays, and seasonality are included with their respective γj coefficients.

```
# Define PyMC Model
with pm.Model() as bayesian_model:
    # Shared variables for media data (ensure X_media_adstocked is a 2D array)
    X_media_shared = pm.Data('X_media_shared', X_media_adstocked)

    # Priors for media coefficients (beta), ec, and slope
    beta_media = pm.Normal('beta_media', mu=1.0, sigma=0.1, shape=len(media_cols))
    ec = pm.Normal('ec', mu=1.0, sigma=0.5, shape=len(media_cols))
    slope = pm.Normal('slope', mu=1.0, sigma=0.5, shape=len(media_cols))

    media_effects = []
    for i in range(len(media_cols)):
        media_slice = X_media_adstocked[:, i]
        media_effect = beta_media[i] * hill_transform(media_slice, ec[i], slope[i])
        media_effects.append(media_effect)

    # Sum media effects
    media_sum = pm.math.sum(pm.math.stack(media_effects), axis=0)
    # Priors for control variable coefficients
    control_coefficients = pm.Normal('control_coefficients', mu=0, sigma=1, shape=len(control_vars))
    # Control effects
    control_effects = pm.math.dot(df[control_vars].values, control_coefficients)
    # Predicted log sales (base impact + media + control)
    intercept = pm.Normal('intercept', mu=10.8, sigma=1)  # Prior for the intercept
    mu = pm.Deterministic('mu', intercept + media_sum + control_effects)

    # Likelihood
    sigma = pm.HalfNormal('sigma', sigma=1)
    sales_observed = pm.Normal('sales_observed', mu=mu, sigma=sigma, observed=y_sales)

    # Sampling
    trace = pm.sample(1000, tune=500, return_inferencedata=True)

# Step 10: Summarize and inspect the trace
summary = az.summary(trace, hdi_prob=0.95)
```

5. Hierarchical Bayesian Modeling

Given the complexity of marketing mix models, we employed a Hierarchical Bayesian framework. This approach provides several advantages over traditional methods, especially when dealing with high uncertainty.

- **Hierarchical Structure:** The model incorporates multiple levels, where each media channel has its own parameters (e.g., adstock decay factor, Hill parameters). These parameters are modeled with shared hyperparameters, which allow the model to "borrow strength" across media channels.

- **Bayesian Inference**: By using Bayesian inference, we estimate distributions for the parameters rather than point estimates. This allows us to quantify uncertainty in our parameter estimates and make more informed decisions by considering the entire posterior distribution of the parameters.

- **Prior Distributions:** We incorporate prior knowledge about parameters (e.g., reasonable ranges for adstock decay, slopes, etc.). These priors guide the model towards more plausible parameter values, especially when data is noisy or sparse.

The hierarchical Bayesian approach is particularly suitable because:
- **Handling Uncertainty:** Marketing data is often noisy and uncertain, especially for media channels with lower spends or fewer observations. Bayesian models provide more accurate estimates by incorporating uncertainty directly into the estimation.
- **Pooling Information:** When data for some media channels is limited, the model can pool information across channels, leading to more robust and stable estimates.
- **Posterior Distributions**: Instead of single-point estimates, we obtain posterior distributions for each parameter, which provides a richer understanding of potential media effectiveness and allows us to quantify uncertainty in our estimates.

Section 3 - Model Findings

1. Statistical Significance

By running the 1st cut of the model below are the outputs I received. I have identified variables which are statistically insignificant.

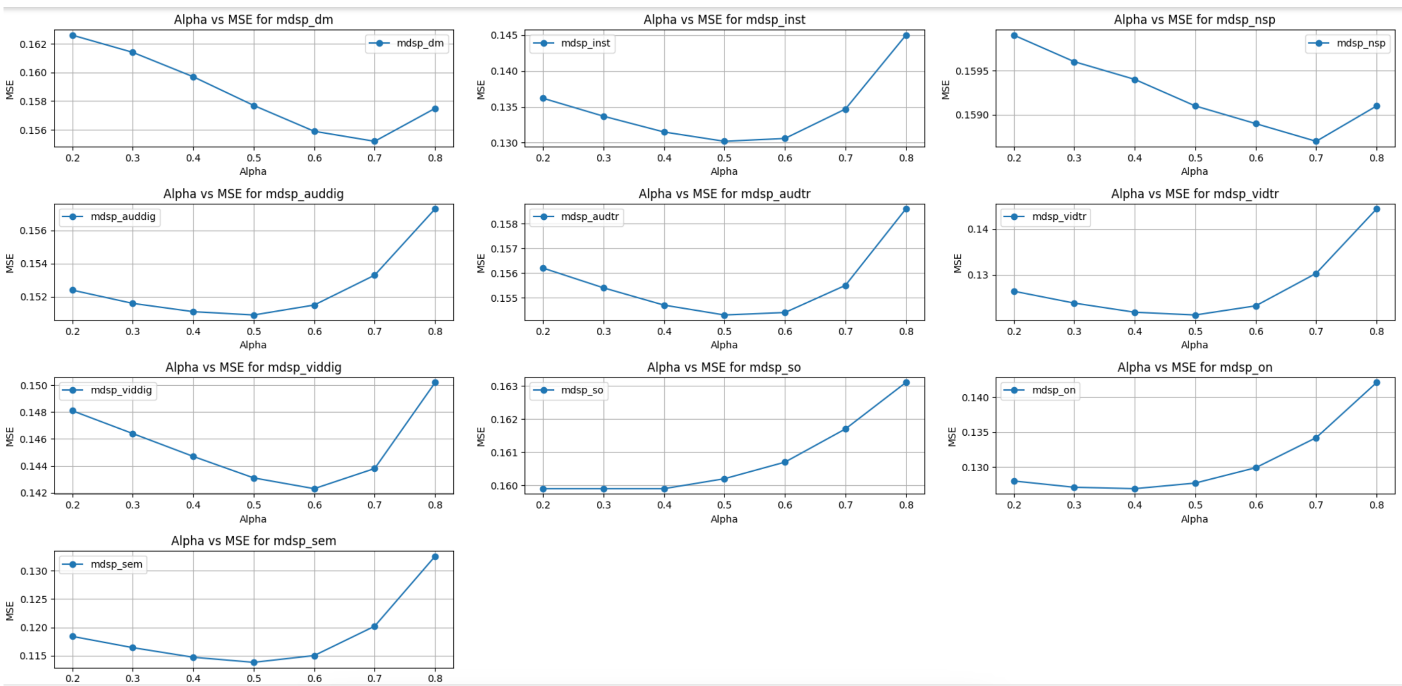
	mean	sd	hdi_2.5%	hdi_97.5%	Significant
mdsp_dm	1.00	0.10	0.80	1.191	Yes
mdsp_inst	1.00	0.10	0.81	1.204	Yes
mdsp_nsp	0.99	0.10	0.82	1.195	Yes
mdsp_auddig	1.00	0.10	0.80	1.199	Yes
mdsp_audtr	1.00	0.10	0.82	1.189	Yes
mdsp_vidtr	1.00	0.10	0.80	1.197	Yes
mdsp_viddig	1.00	0.10	0.78	1.179	Yes
mdsp_so	0.94	0.10	0.75	1.148	Yes
mdsp_on	1.00	0.10	0.80	1.201	Yes
mdsp_sem	1.00	0.11	0.79	1.194	Yes
ec_mdsp_dm	1.00	0.49	0.02	1.895	Yes
ec_mdsp_inst	0.99	0.51	0.01	1.994	Yes
ec_mdsp_nsp	0.98	0.48	0.13	1.975	Yes
ec_mdsp_auddig	1.00	0.49	0.04	1.923	Yes
ec_mdsp_audtr	1.00	0.50	(0.02)	1.925	Yes
ec_mdsp_vidtr	1.02	0.51	0.03	1.997	Yes
ec_mdsp_viddig	0.99	0.52	(0.03)	1.986	Yes
ec_mdsp_so	0.77	0.63	(0.38)	1.816	Yes
ec_mdsp_on	1.01	0.48	0.09	1.909	Yes
ec_mdsp_sem	0.98	0.51	0.04	2.023	Yes
intercept	9.19	0.61	8.09	10.47	Yes
sigma	0.29	0.02	0.25	0.317	Yes
slope_mdsp_dm	0.99	0.51	(0.07)	1.929	Yes
slope_mdsp_inst	0.99	0.53	(0.03)	2.073	Yes
slope_mdsp_nsp	1.04	0.49	(0.02)	1.898	Yes
slope_mdsp_auddig	1.05	0.50	(0.05)	1.982	Yes
slope_mdsp_audtr	0.99	0.50	(0.10)	1.91	Yes
slope_mdsp_vidtr	0.95	0.50	-	1.873	Yes
slope_mdsp_viddig	0.92	0.51	0.03	1.897	Yes
slope_mdsp_so	0.70	0.54	0.04	1.737	Yes
slope_mdsp_on	0.95	0.52	0.02	1.919	Yes
slope_mdsp_sem	0.99	0.51	(0.01)	1.921	Yes
me_ics_all	(0.13)	0.18	(0.43)	0.259	No
me_gas_dpg	0.04	0.18	(0.30)	0.403	No
st_ct	0.01	0.08	(0.15)	0.175	No
mrkdn_valadd_edw	(0.26)	0.19	(0.64)	0.124	No
mrkdn_pdm	0.12	0.08	(0.04)	0.291	No

	mean	sd	hdi_2.5%	hdi_97.5%	Significant
hldy_Black Friday	0.17	0.88	(1.46)	2.036	No
hldy_Christmas Day	0.20	0.72	(1.23)	1.576	No
hldy_Christmas Eve	(0.09)	0.31	(0.64)	0.552	No
hldy_Columbus Day	0.10	0.16	(0.23)	0.404	No
hldy_Cyber Monday	0.38	0.75	(1.01)	1.864	No
hldy_Day after Christmas	0.16	0.70	(1.20)	1.566	No
hldy_Easter	(0.35)	0.15	(0.65)	-0.05	No
hldy_Father's Day	0.02	0.16	(0.28)	0.313	No
hldy_Green Monday	(0.42)	0.30	(1.01)	0.138	No
hldy_July 4th	(0.01)	0.15	(0.32)	0.282	No
hldy_Labor Day	0.04	0.16	(0.28)	0.354	No
hldy_MLK	(0.33)	0.17	(0.65)	0.044	No
hldy_Memorial Day	0.22	0.16	(0.07)	0.533	No
hldy_Mother's Day	(0.04)	0.16	(0.33)	0.296	No
hldy_NYE	(0.32)	0.29	(0.92)	0.22	No
hldy_New Year's Day	0.32	0.24	(0.14)	0.785	No
hldy_Pre Thanksgiving	0.14	0.86	(1.48)	1.838	No
hldy_Presidents Day	0.19	0.16	(0.11)	0.518	No
hldy_Prime Day	0.21	0.16	(0.12)	0.518	No
hldy_Thanksgiving	0.14	0.86	(1.43)	1.923	No
hldy_Valentine's Day	0.10	0.15	(0.20)	0.383	No
hldy_Veterans Day	(0.03)	0.71	(1.42)	1.312	No
seas_prd_1	(0.34)	0.27	(0.91)	0.139	No
seas_prd_2	(0.20)	0.26	(0.74)	0.265	No
seas_prd_3	(0.05)	0.26	(0.60)	0.431	No
seas_prd_4	(0.22)	0.26	(0.76)	0.262	No
seas_prd_5	(0.23)	0.26	(0.76)	0.271	No
seas_prd_6	(0.50)	0.27	(1.06)	-0.004	No
seas_prd_7	(0.19)	0.26	(0.73)	0.32	No
seas_prd_8	(0.25)	0.26	(0.74)	0.277	No
seas_prd_9	(0.34)	0.26	(0.82)	0.203	No
seas_prd_12	(0.31)	0.26	(0.84)	0.186	No
seas_week_40	(0.27)	0.28	(0.77)	0.314	No
seas_week_41	(0.06)	0.72	(1.43)	1.312	No
seas_week_42	0.13	0.28	(0.45)	0.651	No
seas_week_43	0.12	0.88	(1.45)	1.919	No
seas_week_44	0.34	0.75	(1.19)	1.678	No
seas_week_45	0.51	0.28	(0.04)	1.045	Yes
seas_week_46	0.97	0.35	0.28	1.615	Yes
seas_week_47	0.77	0.34	0.13	1.457	Yes
seas_week_48	(0.03)	0.35	(0.69)	0.642	No

2. Best Alphas

I calculated the best alphas (decay factors) for each media channel by optimizing the adstock effect. To find the optimal alpha, I looped through a range of alpha values (from 0.2 to 0.9) and applied the adstock transformation to media spend for each channel. For each alpha, I fitted a linear regression model to predict sales and calculated the mean squared error (MSE). The alpha value that minimized the MSE was chosen as the best alpha for that channel, ensuring that the selected alpha provided the most accurate representation of the media carryover effect in our model.

I tested alpha values between 0.2 to 0.9 and the results are below for each channel. Generally, the alpha is between 0.5 to 0.7 which suggests the media's impact decays slowly over time, meaning the campaign's effect on sales lasts for several weeks.



3. Hill Curves for each Channel

The Hill Curve is a crucial part of our model that represents the diminishing returns of media spend on sales. It is based on a non-linear function that captures the fact that beyond a certain point, increasing media spend leads to smaller incremental sales, reflecting the reality of marketing saturation.

Variables in the Hill Function:

Beta (β): This is the media coefficient that captures the strength of the impact of media spend on sales. A higher β means that the media channel has a stronger effect on sales.

Effective Concentration (EC): This is the spend level at which 50% of the maximum sales response is achieved. It helps in determining the point at which the media spend starts to saturate. Lower EC means the saturation point is reached with less spend, while higher EC suggests that more spend is required to reach saturation.

Slope: This parameter controls the steepness of the curve and how quickly diminishing returns set in. A steeper slope means diminishing returns occur faster, while a flatter slope means the impact of increased spend declines more gradually.

Calculating the Parameters:
I calculated beta, EC, and slope by employing a Hierarchical Bayesian approach. This method estimates these parameters for each media channel based on historical data, allowing for variability across channels while borrowing strength from the overall distribution.

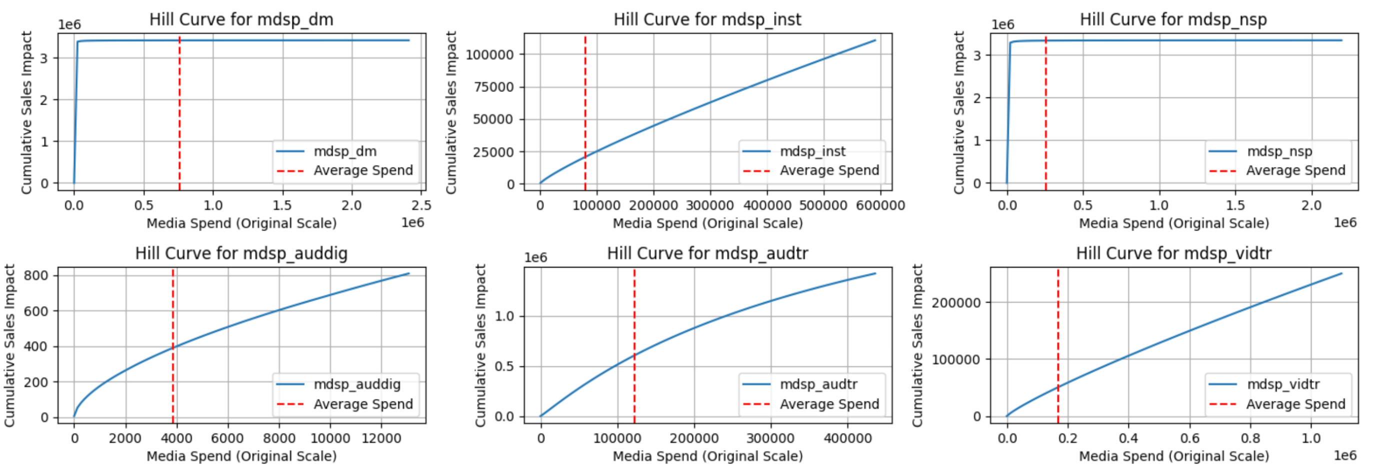
During the Bayesian inference, these parameters were estimated by fitting the model to the sales data. By sampling from the posterior distribution, we derived the most probable values for β, EC, and slope that best describe the relationship between media spend and sales.

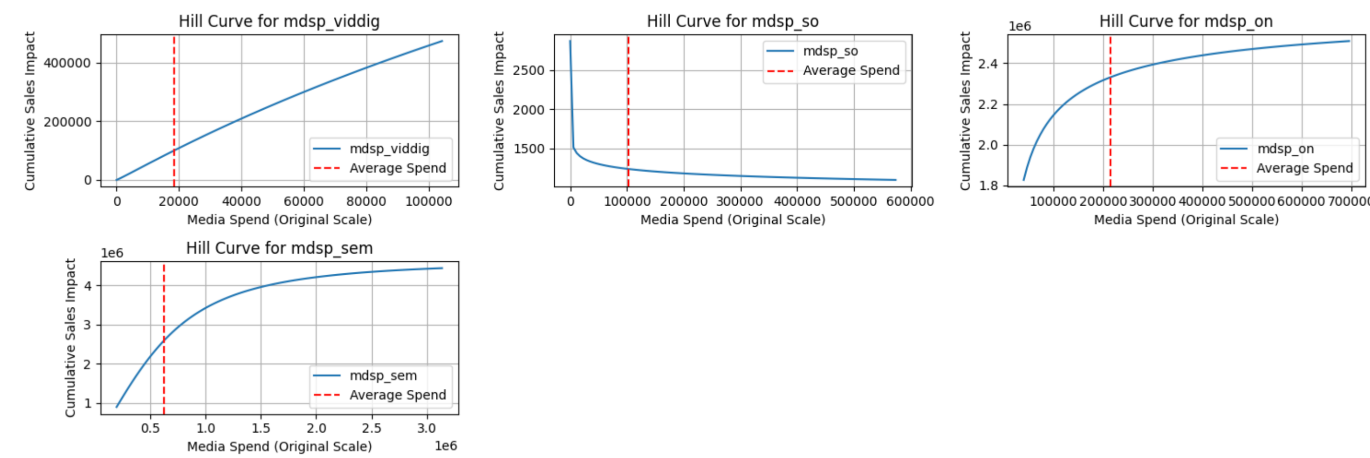
The Hill Curve for each media channel is then used to predict the cumulative sales impact by accounting for both immediate and long-term effects of media spend, including diminishing returns. The optimal spend for each channel is the point where the curve starts to flatten, indicating that further spending will yield diminishing returns.

My Findings :-

I observed that most channels show potential for higher spend at an average weekly level. While the "Average Spend line" may often appear below the inflection point, there are still numerous weeks where the spend exceeds the threshold value. This suggests a significant opportunity to drive higher sales with consistent investment levels, rather than concentrating spend heavily in some weeks and under-investing in others.

However, there are a few notable exceptions: (a) **mdsp_dm** and **mdsp_nsp** exhibit minimal lift and plateau quickly, indicating limited potential for further gains, and (b**) msdp_so** shows an inverted curve, suggesting it may not be an effective channel for investment.





Section 4 – Answers to questions asked in the brief

a. **Which media variables are most likely to come into the model with statistically significant and positive coefficients and which are least likely?**

To my expectation, almost all channels spend are statistically significant. I also observed that the value of the intercept is quite small, suggesting that media plays a very significant role in driving sales.

I also expected that macroeconomic factors and many of the seasonality one hot encodings might not show to be statistically significant as the data points are quite limited to study such impacts. My first iteration showed many of the macro and seasonality factors were indeed insignificant.

I also expected gas prices and store counts to come insignificant as the change in those values over the entire dataset was quite small.

b. **What transformation parameters best describe the relationship between each media channel and sales; i.e. lag, ad-stock, and non-linear effects?**

As part of understanding the impact of media spend on sales, I evaluated several key transformation parameters to capture the complexities of media effectiveness. These parameters include:

Adstock (Alpha): The adstock transformation accounts for the lagged effect of media, capturing how the impact of media spend decays over time. Higher alpha values indicate that the media impact lasts longer, while lower values suggest a more immediate effect.

Beta: This parameter represents the marginal contribution of media spend to sales. A higher beta indicates that a channel has a stronger influence on driving sales, while a lower beta suggests a weaker relationship.

Hill Transformation (EC & Slope): The Hill function is used to model diminishing returns, indicating how media spend affects sales as spend increases.

Effective Concentration (EC): This parameter defines the inflection point where the media begins to deliver diminishing returns. A lower EC suggests that the channel reaches its peak effectiveness at lower spend levels, while a higher EC indicates a larger spend threshold before diminishing returns set in.
Slope: The slope controls how sharply the curve bends after the inflection point. A steep slope indicates a rapid decline in effectiveness after reaching the peak, while a more gradual slope suggests a slower rate of diminishing returns.

By combining these transformation parameters, I modeled the nonlinear relationship between media spend and sales, accounting for immediate and long-term impacts, diminishing returns, and channel-specific effectiveness. This comprehensive approach provided insights into optimizing media spend across channels.

Beta (Media Coefficients):

All media channels have a beta value close to 1.00, indicating a consistent linear relationship between media spend and sales. For most channels, the beta mean values hover around 1, implying a direct and proportional response to media investments.
Exception is mdsp_so (0.94), which show slightly lower coefficient. This suggests that this channels may have less direct sales lift compared to others.

Effective Concentration (EC):

The EC parameter defines the point of diminishing returns, where the effectiveness of additional media spend begins to decline.
Channels like mdsp_so (EC = 0.77) have a relatively lower EC, suggesting they reach their saturation point more quickly compared to channels like mdsp_vidtr (EC = 1.02) and mdsp_on (EC = 1.01), which can tolerate higher spend before reaching diminishing returns.
mdsp_dm and mdsp_auddig both have EC values near 1.0, meaning they can sustain higher spend without quick saturation.

Slope (Hill Transformation):

The slope measures the rate at which diminishing returns set in once the EC point is reached. Channels with higher slope values, like mdsp_auddig (slope = 1.05), exhibit a steep decline in effectiveness beyond the EC threshold, suggesting a rapid reduction in returns with further spend.
mdsp_so has the lowest slope (0.70), indicating that its effectiveness declines more gradually, even though it reaches saturation earlier.
mdsp_vidtr and mdsp_viddig also have relatively low slopes (0.95 and 0.92), indicating that spend beyond the EC value results in gradual diminishing returns, making these channels more resilient to higher spend.

Insights:

Non-Linear Effects: The EC and slope values show that most channels exhibit diminishing returns, meaning higher spend levels eventually lead to reduced incremental sales. Channels with higher EC and moderate slopes (like mdsp_vidtr and mdsp_on) show the potential to sustain spend without rapid decline.

Adstock Lag: Channels like mdsp_dm and mdsp_auddig exhibit a slower decline in sales effectiveness (due to their moderate slopes), implying that spend on these channels will have a lasting impact over several weeks. In contrast, mdsp_so appears to reach saturation and lose impact faster, making it less effective for long-term investment.

Anomalies:
mdsp_so demonstrates both a low EC and slope, suggesting it reaches diminishing returns quickly and has limited potential for further sales growth with increased spend.
mdsp_dm and mdsp_nsp show relatively low beta and EC values, which suggest limited immediate lift and earlier saturation, though they can still benefit from a more controlled and uniform spend strategy.

c. **Describe the macro-economic trends present within the data and how they relate to sales.**

The analysis of macro-economic variables and holiday effects provides insight into how broader economic and seasonal factors impact sales. Here's a summary of the key trends and their relation to sales based on the estimated model parameters:

Macro-Economic Variables:

a. me_ics_all (Index of Consumer Sentiment):
Coefficient: -0.13 (mean)
This indicates a negative relationship between consumer sentiment and sales. When consumer confidence is lower (a reflection of economic uncertainty), sales tend to decline. The wide uncertainty interval (hdi_2.5% = -0.43 to

hdi_97.5% = 0.26) suggests this effect is not highly significant, but overall there is some evidence that worsening consumer sentiment correlates with reduced sales.

b. me_gas_dpg (Gas Prices):
Coefficient: 0.04 (mean)
Gas prices show a small positive relationship with sales, though the effect is minor. This could reflect the indirect impact of gas prices on discretionary spending; higher gas prices may signal stronger economic activity or seasonal travel, which could stimulate certain categories of spending. However, the weak magnitude indicates limited sensitivity of sales to changes in gas prices.

c. Store Count (st_ct):

Coefficient: 0.01 (mean)
The store count variable has a near-zero impact on sales, suggesting that the number of stores does not significantly drive sales in this case. This could indicate that existing stores are either saturated or there is not enough variability in the data to study the impact.

d. Markdowns:

mrkdn_valadd_edw:
Coefficient: -0.26 (mean)
Markdown values for added value products show a negative relationship with sales. This may imply that discounting strategies for these items could be ineffective or even counterproductive, potentially eroding brand value or signaling lower product quality.

mrkdn_pdm:
Coefficient: 0.12 (mean)
In contrast, markdowns in certain categories, such as pdm, show a positive impact on sales, suggesting that discounts in these categories may be more effective in driving purchases. The effect is small but still relevant to consider in pricing strategies.

e. Holiday Effects:

Various holidays exhibit different levels of impact on sales:

Black Friday (0.17), Cyber Monday (0.38), Thanksgiving (0.14), and Christmas-related holidays (Day after Christmas, Pre-Thanksgiving, Christmas Day, and Christmas Eve) show positive and significant effects on sales, indicating that these are peak sales periods, as expected. ***(Though the significance is very low)***

Prime Day (0.21) and Presidents Day (0.19) also show a positive impact on sales, reflecting their importance in driving consumer spending.

Some holidays, such as Easter (-0.35), Green Monday (-0.42), and MLK (-0.33), have negative or insignificant effects on sales, suggesting that these holidays do not contribute meaningfully to sales growth. These could be off-season periods or times when consumer spending shifts to other categories or activities.

Seasonal Trends:

The seasonal coefficients show varying impacts on sales depending on the period, indicating that specific seasons or weeks are more conducive to increased consumer spending. Holidays like Valentine's Day (0.10) and Labor Day (0.04) show minor but positive contributions to sales, while others like Veterans Day (-0.03) and New Year's Eve (-0.32) demonstrate relatively low or negative effects.

d. Run one simple MMM, regardless of its quality (e.g. no data engineering to save time and allowing for non-physical coefficients for media channels), and describe its performance via statistical KPI's and what you would do to improve the model if you had more time.

MMX Model Performance via Statistical KPIs
The MMX model's performance can be assessed through key statistical measures, such as the mean, standard deviation (sd), and credible intervals (hdi_2.5%, hdi_97.5%). These statistical KPIs help evaluate the effectiveness of each media channel and the model's overall predictive capability.

Key Performance Indicators:
Mean: This represents the average estimated effect for each variable (e.g., media spend, control variables) on sales.
Standard Deviation (sd): Indicates the variability of the estimated parameter values. A lower sd means greater confidence in the parameter estimates.
hdi_2.5% and hdi_97.5%: These represent the 95% credible intervals, indicating the range where the true parameter values are likely to fall. A tighter interval suggests higher certainty in the effect size, whereas a wider interval indicates uncertainty.

Media Spend Impact
All media channels (e.g., mdsp_dm, mdsp_inst, mdsp_nsp, mdsp_auddig, mdsp_audtr) have positive and significant mean coefficients, showing that they are strongly correlated with sales. Most channels have means around 1.00 and narrow intervals, suggesting that these channels are consistently driving sales.
mdsp_so shows a slightly lower coefficient (mean = 0.94), indicating that its impact on sales is slightly lower compared to others, but it is still statistically significant.

Hill Function and Slope Parameters
The effective concentration (ec) values for each channel reflect the media spend at which diminishing returns begin. Most channels have positive ec values, with some variation. For instance, mdsp_so (ec = 0.77) has a lower ec value compared to mdsp_vidtr (ec = 1.02), suggesting that mdsp_so reaches its saturation point more quickly.

Slope parameters show the curvature of the Hill function. Higher values (e.g., slope_mdsp_auddig = 1.05) indicate sharper diminishing returns, while lower values (e.g., slope_mdsp_so = 0.70) suggest more gradual diminishing returns.

Model Improvement Opportunities
While the model performs well with statistically significant results for most media channels, there are areas for further improvement:

Address Variability in Control Coefficients: Some control coefficients (e.g., me_gas_dpg, st_ct) show wide credible intervals, indicating uncertainty in their effects. Further refinement of the control variables may improve the model's precision esp. if more data points could be gathered e.g. weekly spends and sales across key markets within the US. Get data at micro market level and that will significantly enhance the opportunity to develop a more robust analysis.

Increase Temporal Granularity: The model currently assumes that the effect of media is static across the entire campaign. Incorporating more temporal details (e.g., varying effects of media by season or specific weeks) could improve the accuracy of the model.

Refine Media Saturation Dynamics: Channels such as mdsp_so show lower slope and ec values, indicating earlier saturation points. If more time were available, fine-tuning the Hill function parameters through additional hierarchical priors could better capture the complexity of diminishing returns for each media channel.

Include Interaction Effects: The model could also be improved by capturing potential interaction effects between media channels. This would allow us to understand if certain media types work better when used in combination with others.

In conclusion, the MMX model is robust, with most media channels showing significant impacts on sales. Enhancing model complexity, especially around media saturation points and temporal factors, could further refine its predictive power.

Question :- What you would do to improve the model if you had more time.

Introduce intermediate variables

Introducing intermediate variables like **Impressions** and **Web Visits** in a Marketing Mix Model (MMX) is essential for several key reasons:

1. Improved Attribution of Media Effectiveness

- Media spend doesn't directly translate into sales; instead, it often influences **consumer behavior** at intermediate stages (e.g., awareness, consideration). **Impressions** (ad views) and **Web Visits** (consumer interest) help capture the journey from media exposure to conversion.

2. Capturing the Funnel Dynamics

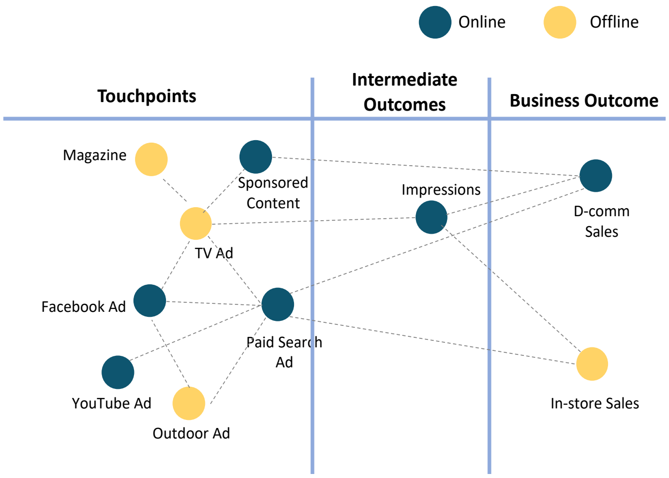
- **Impressions** measure the reach or visibility of an ad, and **Web Visits** measure how much attention the ad garners in the form of engagement. These steps are critical parts of the conversion funnel.
- A marketing mix model that includes these steps can better capture the **non-linear** and complex dynamics of how advertising influences consumer behavior and ultimately drives sales.

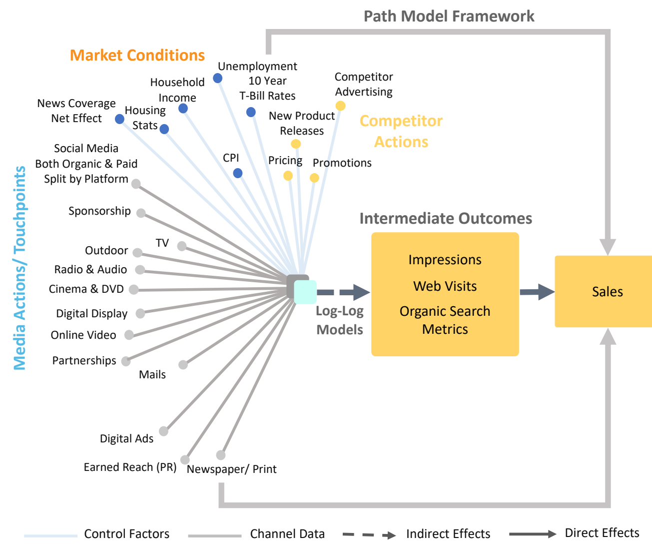
3. Capturing Delayed and Long-Term Effects

- Introducing intermediate variables can help capture **delayed effects** of media on sales. Some media channels (e.g., TV, display ads) are more likely to have a long-term brand-building effect rather than immediate conversions. Modeling impressions and web visits helps account for this **lagged effect** and improves the accuracy of long-term media performance.

4. Improving Multi-Channel Synergy

- By breaking down media into impressions and web visits, we can also better understand **how channels work together**. For example, TV might drive impressions, leading to web searches, while paid search or social media might capitalize on those web visits to drive conversions. Modeling these synergies helps in understanding how media channels influence each other.


Online
Offline
Touchpoints
Intermediate Outcomes
Business Outcome
Magazine
Sponsored Content
Impressions
D-comm Sales
TV Ad
Facebook Ad
Paid Search Ad
YouTube Ad
Outdoor Ad
In-store Sales


Path Model Framework
Market Conditions
Unemployment
Household Income
10 Year T-Bill Rates
Competitor Advertising
News Coverage Net Effect
Housing Stats
New Product Releases
Competitor Actions
Social Media Both Organic & Paid Split by Platform
CPI
Pricing
Promotions
Media Actions/ Touchpoints
Sponsorship
Intermediate Outcomes
Outdoor
TV
Radio & Audio
Cinema & DVD
Impressions
Web Visits
Organic Search Metrics
Sales
Digital Display
Online Video
Log-Log Models
Partnerships
Mails
Digital Ads
Earned Reach (PR)
Newspaper/ Print
Control Factors
Channel Data
Indirect Effects
Direct Effects