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Predicting ROI On Market Attribution Using Market Mix Modelling (MMM)

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Abstract

This dissertation explores the implementation of Marketing Attribution Modeling with a focus on Market Mix Modeling (MMM). By leveraging historical customer data and advanced machine learning tools such as Robyn, this study aims to predict the Return on Investment (ROI) for marketing campaigns. The research delves into various attribution models, analyzing the effectiveness of touchpoints like Meta, Google, and TikTok, while accounting for seasonality, holidays, and external factors. The methodology includes comprehensive data collection, exploratory analysis, and Pareto optimization to evaluate marketing efficiency. Key insights reveal the impact of carryover and immediate advertising effects, enabling businesses to make informed decisions on budget allocation. This study highlights the importance of machine learning techniques in modern marketing science, offering a scalable and interpretable framework for ROI prediction and strategy optimization.

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List of Abbreviations

MMM	Market Mix Modelling
DTC	Direct To Customer
MA	Market Attribution
FTA	First Touch Attribution
LTA	Last Touch Attribution
TDA	Time Decay Attribution
PBA	Position-Based Attribution
RMSE	Root Mean Square Error

Chapter 1

Introduction

1.1 Background

1.1.1 Market Attribution

Market Attribution is the process of identifying and assigning value to the various marketing touchpoints that influence a customer's decision to make a purchase or take another desired action. It helps businesses understand which marketing efforts are most effective in driving conversions. By evaluating the impact of different channels, such as social media, websites, and emails, companies can optimize their strategies and allocate resources more efficiently to maximize their return on investment.

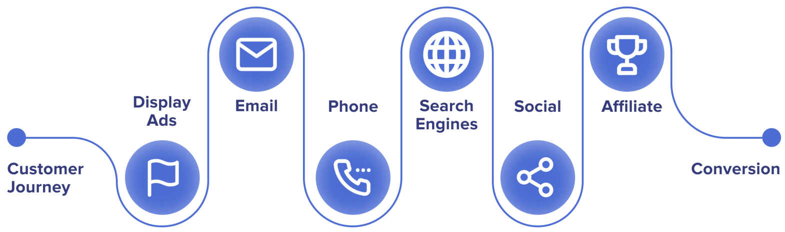

Figure 1.1: Customer Touchpoint journey

The customer touchpoint journey refers to the series of interactions a customer has with a brand as they move from awareness to making a purchase. It starts when a customer first learns about a brand, often through advertising or recommendations. From there, they may engage with the brand further by visiting a website, reading product reviews, or interacting with customer service. As they continue to explore, they move closer to making a decision, ultimately taking action, such as buying a product or signing up for a service. Each of these interactions is a touchpoint, and each one plays a role in shaping the customer's experience and influencing their decision to purchase.

1.1.2 Direct-to-consumer

Direct-to-consumer (DTC or D2C) is a way for companies to sell their products straight to customers, skipping stores and other middlemen. This approach has really gained traction with the boom in online shopping, allowing brands to reach people directly through their websites and social media platforms. In contrast to traditional retail, where other businesses dictate how and where products are sold, DTC brands have the freedom to set their own prices, manage their branding, and interact with customers on their own terms.

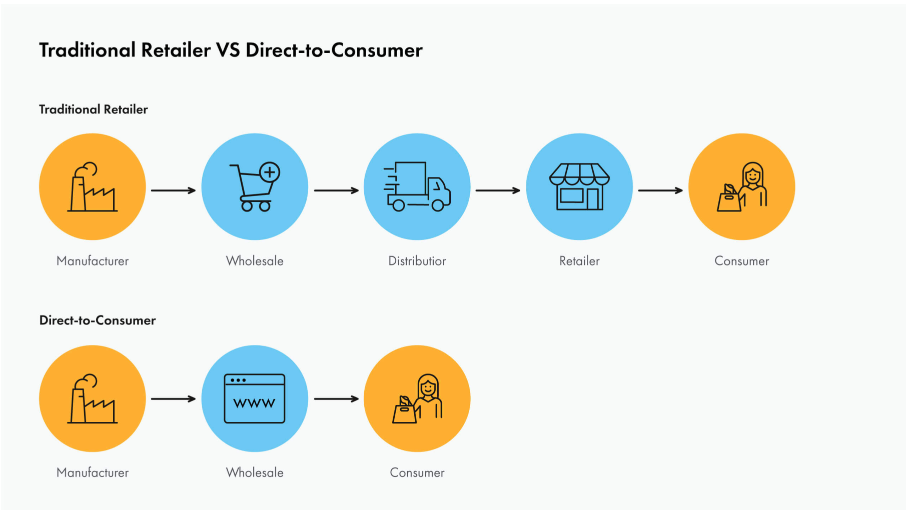

Figure 1.2: DTC VS Non-DTC

There are several reasons why DTC is becoming increasingly important. It allows companies to create closer relationships with their customers, building loyalty and trust. It also helps brands understand customer behavior that helps them know want and how they shop (Hillerborn & Eriksson, 2022). With this kind of information, businesses can tailor their marketing efforts, enhance their products, and quickly respond to new trends. Plus, by selling directly, DTC companies can often avoid the extra costs that come from working with retailers, which means they can offer better prices or make more money on each sale. In a world where people want convenience and personalized experiences, DTC gives brands a flexible way to meet those expectations.

As more consumers turn to online shopping and look for unique shopping experiences, the DTC model is becoming a key strategy for brands that want to connect with their customers. By taking charge of their interactions with buyers and being able to quickly develop new products, DTC brands are in a strong position to compete in today's fast-moving market.

1.1.3 Attribution Modeling

Marketers apply attribution models to understand how different touchpoints in customer's conversion pathways contribute. It will give company insights on most effective marketing channels (whether it be social media, email or paid ads) in terms of sales. This allows companies to understand how different interactions along the customer journey impact buying decisions and in turn make more informed marketing budget plans. Businesses in the US alone brought in USD 107.5 billion in revenue in 2018, according to the Internet Advertising Bureau, with a 21.8% inter-annual gain (Romero Leguina et al., 2020).

1.2 Problem Stetement

The objective of this research is to predict the return on investment (ROI) generated from new customers by leveraging historical customer data. The dataset includes detailed information about customer touchpoints, specifically identifying the platforms through which customers have arrived. The predictive model will provide insights into the business's marketing investments across various platforms and the corresponding returns. This analysis will enable a comprehensive understanding of ROI contributions from new customers and the aggregated returns from both new and existing customers.

To achieve this, the study will employ the Marketing Mix Modeling (MMM) technique, utilizing Robyn libraries. These libraries are widely recognized for their application in marketing attribution and will be instrumental in building a robust and data-driven predictive model.

1.3 Aims and Objectives

This project aims to Market Attribution Modelling to provide predictions for Returns on Investment (ROI) or revenue. The resulting model can be used to understand the customer touch point journey to know which marketing platforms are generating the most revenue. To achive this, the following objectives will be met:

- Explore previous work in predicting Market Attribution, using various Market Attribution models.

- Discovering correlations between customer clicks and impressions.
- What is the media's contribution to new customer orders.
- Understanding How much does seasonality play a role compared to media in driving new customer orders.
- Propose further work based on the results of Market Attribution modelling.

1.4 Scope and Delimits

This study aims to develop a Market Mix Model (MMM) to predict return on investment (ROI) by analyzing the contribution of various marketing activities to overall business outcomes. In addition to MMM, other modeling techniques used in market attribution will be researched to understand advancements in the field and to provide context for the choice of MMM as the preferred approach. A detailed analysis will be conducted to evaluate why MMM offers distinct advantages over alternative models, such as its ability to incorporate both online and offline marketing efforts and its interpretability for decision-making.

While areas such as direct-to-customer (DTC) marketing and the impact of seasonality on new customer acquisition will be considered as part of the broader discussion, they fall outside the core scope of this study. These factors will serve as supporting contexts rather than primary focus areas, ensuring that the study remains centered on developing an effective MMM for ROI prediction.

Chapter 2

Literature Review

2.1 Market Mix Modeling (MMM)

2.1.1 Introduction to Market Mix Modeling

Market Mix Modeling (MMM) is a quantitative method employed to evaluate the effectiveness of various marketing activities, such as promotions and media campaigns. It provides insights into how different marketing channels influence sales and other key performance metrics (ref1, ref2). The core objective of MMM is to optimize marketing budgets, assess the return on investment (ROI) for specific initiatives, and facilitate data-driven strategic decisions by mitigating uncertainty (ref2, ref3)

Historical Evolution of MMM

The development of MMM dates back to the 1950s, where it began as a straightforward approach utilizing simple regression models to assess the impact of marketing efforts (ref4). Over time, as digital marketing emerged and media channels diversified, MMM evolved to incorporate more sophisticated methods, including artificial intelligence (AI) and machine learning, to address the growing complexity of marketing data and analysis (ref4, ref5). Additionally, the need to adapt to emerging challenges such as privacy laws and the integration of multi-channel marketing strategies has driven significant advancements in MMM methodologies (ref4, ref6).

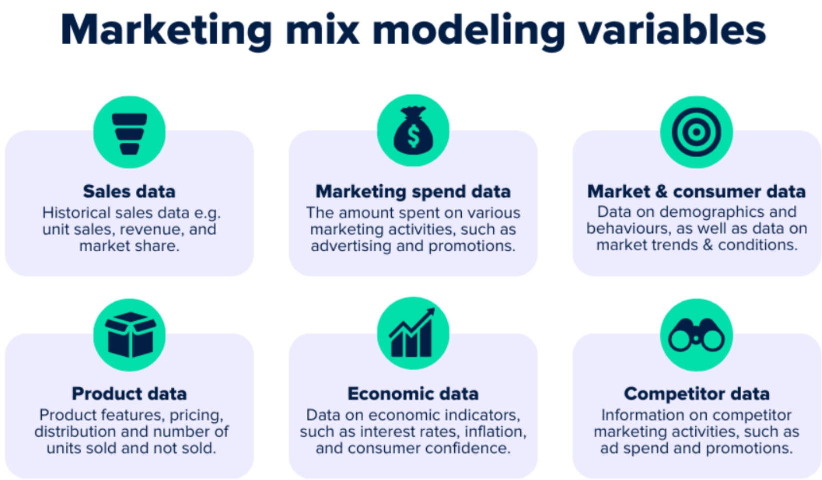

Figure 2.1: Market Mix Modelling

Key Applications in Marketing

1. **Budget Allocation:** MMM is widely recognized for its ability to optimize marketing budgets by identifying the most impactful channels and activities. This ensures that resources are allocated efficiently to maximize returns on investment (ref2, ref3, ref7). Advanced MMM approaches, particularly those leveraging AI, enable dynamic and real-time analyses, offering even greater precision in budget allocation decisions (ref5).

2. **ROI Estimation:** Another critical application of MMM is determining the ROI of marketing initiatives. By quantifying both immediate and long-term effects on sales and brand value, MMM provides actionable insights for marketing teams (ref8). The analysis of historical data allows organizations to anticipate the financial implications of various strategies, enabling more confident decision-making (ref2, ref9).

3. **Sales Forecasting:** MMM plays a pivotal role in sales forecasting by analyzing the effects of marketing efforts and external factors on sales performance. This predictive capability is essential for designing future strategies that align with organizational goals (ref10, ref11). Techniques such as causal MMM and machine learning improve the precision of forecasts by identifying dynamic relationships and patterns in data (ref5, ref10).

2.1.2 Data Requirements and Challenges

Data Requirements in MMM

- **Comprehensive Data Collection:** Market Mix Modeling (MMM) relies heavily on the collection of comprehensive data from a variety of marketing activities, such as promotional efforts, media advertisements, and other marketing channels, in order to assess their effectiveness (Chen et al. 2021). Essential data for accurate modeling includes historical sales figures, marketing spend, and other relevant performance metrics, as these variables are critical to understanding the impact of each element of the marketing mix (Luan and Sudhir 2010).

- **Granular and High-Quality Data:** For MMM to provide reliable and accurate results, it requires high-quality, granular data. This entails detailed insights into customer interactions, sales transactions, and specific marketing expenditures (Rosário and Dias 2023). To ensure the robustness of the model's outputs, the data must be meticulously cleaned, accurate, and free from any biases that could distort the analysis (Rosário and Dias 2023).

- **Integration of Multiple Data Sources:** An effective MMM approach often involves the integration of diverse data sources. These can include data from digital marketing channels, traditional media, and point-of-sale systems, offering a comprehensive view of marketing performance across platforms (Stürze et al. 2022). By consolidating data from multiple touchpoints, MMM captures a more complete picture of the customer journey, enabling a better understanding of how different marketing efforts interact and contribute to sales outcomes (Gujar et al. 2024).

Challenges in Market Mix Modeling

- **Endogeneity Issues:** A key challenge in MMM is addressing endogeneity, which occurs when marketing decisions are influenced by unobserved factors that also impact sales, leading to biased estimates if not properly handled (Luan and Sudhir 2010). Various methods, such as structural equation modeling and control function approaches, are employed to mitigate these endogeneity concerns and ensure more accurate model results (Kaur and Arora 2015).

- **Causal Inference and Heterogeneity:** Establishing causal relationships between marketing activities and sales can be difficult, as these relationships may vary significantly across products and markets. The heterogeneity in causal structures further complicates the process (Gong et al. 2024). Techniques like Granger causality and variational inference frameworks are used to dynamically uncover and adapt to specific causal relationships in different contexts (Gong et al. 2024).

- **Complexity and Scalability:** Traditional MMM methods may struggle to keep pace with the complexity and scalability demands of modern marketing, particularly with the rise of big data and the expansion of digital marketing platforms (Gong et al. 2024). To address these challenges, more advanced approaches, such as Hamiltonian Monte Carlo algorithms and AI-driven MMM tools, are being developed to handle the growing complexity of marketing data and to scale effectively (Chen et al. 2021).

- **Privacy and Regulatory Constraints:** With the evolving landscape of privacy regulations and data protection laws, collecting and utilizing data for MMM has become more challenging. Marketers must navigate these constraints while maintaining the quality and granularity of the data used for analysis (Gujar et al. 2024). Ensuring compliance with these regulations is essential for the continued reliability and validity of MMM processes.

- **Interpretability and Adoption of AI Models:** While AI and machine learning models offer significant advancements in the capabilities of MMM, their complexity often hinders interpretability and widespread adoption among marketers. Striking a balance between the sophistication of AI-driven models and the need for transparency and ease of use is a key challenge in ensuring their successful implementation and acceptance.

2.1.3 Applications of MMM

Marketing Mix Modeling (MMM) is a vital tool for assessing and optimizing the effectiveness of marketing activities across multiple channels. A significant application of MMM is budget allocation and optimization, where it analyzes the effectiveness of different marketing channels, ensuring that resources are allocated to the most impactful areas, thereby improving return on investment (ROI) (Stürze et al. 2022)(Estevez, Ballestar, and Sainz 2024). MMM also supports scenario planning, allowing marketers to simulate various budget allocation strategies and predict their potential outcomes, which aids in strategic decision-making (Gujar et al. 2024).

MMM is also used for measuring marketing effectiveness, such as determining the return on advertising spend (ROAS) by evaluating how marketing activities affect sales and other key performance indicators (**de Morais2024520**). Additionally, in the context of online advertising, MMM can predict gross merchandise volume (GMV) for brand shops, helping businesses optimize budget allocations across different digital channels (Gong et al. 2024).

In complex marketing environments, MMM can automatically uncover causal structures through advanced approaches like CausalMMM, improving the precision of predictions and deepening understanding of marketing dynamics (Gong et al. 2024). The integration of machine learning with MMM further enables dynamic and real-time analysis, enhancing the ability to make rapid decisions based on current marketing performance (Chaudhary, Afshar Alam, and Zafar 2025).

For businesses leveraging digital marketing, MMM can be integrated with multi-touch attribution (MTA) models, providing a comprehensive analysis of the effectiveness of both traditional and digital marketing channels (Stürze et al. 2022). Additionally, MMM incorporates social media activities, transforming static advertisements into interactive channels that influence consumer behavior through multimedia engagement (Pantano, Priporas, and Migliano 2019).

MMM also provides long-term strategic insights, helping businesses align their marketing strategies with overarching business goals by analyzing market responses to various marketing mix variables (Gujar et al. 2024). By conducting market response analysis, MMM reduces uncertainty in decision-making, fostering the development of effective and data-driven marketing strategies (Estevez, Ballestar, and Sainz 2024).

Finally, MMM addresses challenges in the marketing landscape, such as privacy and regulatory changes, adapting to evolving regulations and media fragmentation to maintain marketing effectiveness (Gujar et al. 2024). Furthermore, tools like PromotionLens use MMM to model and assess the impact of various promotional strategies, enabling businesses to conduct "what-if" analysis and respond effectively to customer demand shifts (Zhang et al. 2023).

2.2 Other Market Attribution Models

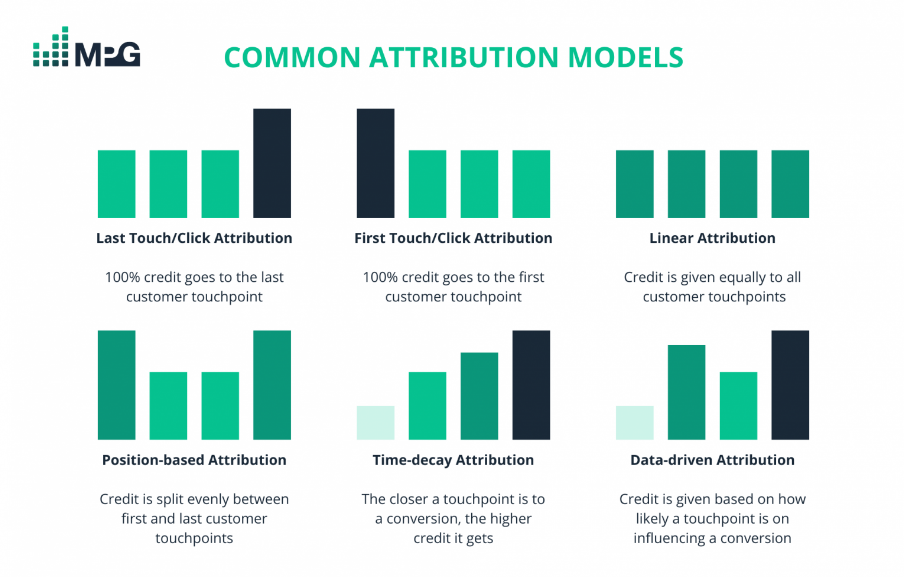

Figure 2.2: Other Market Attribution Models

2.2.1 Multi-Touch Attribution (MTA)

Multi-Touch Attribution (MTA) is a marketing measurement method by which credit for a conversion or customer action is assigned to multiple touchpoints along the customer journey. In contrast to traditional attribution models that might attribute all credit for the sale or conversion either to the initial or final interaction, multitouch can account for a range of touchpoints along a potential customer's marketing journey — e-mail newsletters, social media campaigns, search ads and display banner advertising (Pattanayak et al., 2022). A more sophisticated analysis of how varying marketing touchpoints interact to drive conversions, MTA recognizes the capability of algorithms for assessing each and channeling them into a refined view on which channels are actually doing better, helping companies in making a stronger allocation over their marketing budgets while also optimizing strategic areas so as per actual user behavior (Yang et al., 2020).

After the data has been collected, MTA uses different attribution models to consider how much value each touchpoint deserves. Linear attribution (where credit is shared equally among all touchpoints), time decay attribution (which places more value on closer-to-the-conversion interactions) and algorithmic or data-driven/econometric multi-touch models use machine learning to determine the influence each type of interaction has had. Google Analytics uses six basic models, made available through vendor data collection (Rabinovitch, 2020). It is essential for marketers to learn which channels are working and how they not only impact, but actually convert a potential consumer.

Thus, implementing Marketing Mix Modeling (MTA) enables businesses to generate useful insights on how their marketing expended seeing the world and advertise them in a more targeted manner(Pattanayak et al., 2022). This might manifest as the business investing more in that channel say if MTA highlights a particular social media campaign, which is shown to generate conversions. Furthermore, MTA enables marketers optimize the targeting and messaging they employ in order to focus on what touchpoints are most effective so,in turn higher return (ROI) will be earned from marketing campaigns.

2.2.2 Last-Touch Attribution

The last touch attribution model, or last-click attribution, is widely used in digital marketing to credit the final interaction before a conversion. This model is the default in platforms like Google Ads and Facebook Ads, where full credit is assigned to the last clicked ad. While convenient, this approach often overlooks the role of earlier touchpoints, leading to potential inefficiencies in marketing budget allocation (Sriram et al. 2022a).

A case study on a jewelry brand's campaigns revealed that ROI varied significantly under the last touch model, particularly during the "action" stage of the AIDA framework. This emphasizes how the model influences the assessment of marketing effectiveness, potentially misrepresenting the impact of multi-touch customer journeys (Sriram et al. 2022a).

Despite the availability of more advanced attribution methods, many marketers continue to rely on last-touch or first-touch models due to their simplicity and limited familiarity with alternative techniques. This reliance can obscure the true contributions of diverse marketing channels and touchpoints, hindering holistic campaign optimization (Burton and Powers 2019a).

Critics argue that the last touch model unfairly credits the final interaction, often disregarding earlier efforts that drive conversions. Alternatives like the Shapley value model and logistic regression offer more equitable credit distribution and improved optimization potential (Mahboobi, Usta, and Bagheri 2018).

To address these limitations, the Enhanced Last Touch Interaction (ELTI) model has been proposed. By incorporating game theory and synergistic effects, the ELTI model more accurately distributes revenue across channels, achieving prediction accuracy exceeding 75% and addressing key shortcomings of traditional last-touch attribution Yuvaraj et al. 2018a.

2.2.3 First Touch Attribution

First touch attribution is a marketing model that assigns full credit for a conversion to the first interaction a customer has with a brand. This approach is primarily used to identify which initial marketing efforts are most effective at attracting new customers and bringing them into the sales funnel. By focusing on the customer's first touchpoint, it provides insight into acquisition strategies (Jayawardane, Halgamuge, and Kayande 2016).

In the broader context of marketing attribution, first touch attribution stands apart by simplifying the process. Unlike multi-touch attribution, which distributes credit across all interactions in the customer journey, or last-touch attribution, which credits the final interaction, first-touch attribution exclusively emphasizes the starting point of the customer's engagement (Burton and Powers 2019b). This simplicity makes it particularly appealing to marketers with limited resources or technical expertise, though it often sacrifices depth for ease of use (Burton and Powers 2019b).

Despite its popularity, first touch attribution has notable limitations. It provides only a narrow view of the customer journey, ignoring the impact of subsequent interactions that nurture and convert leads. This can lead to an overvaluation of initial touchpoints while undervaluing the significant contributions of middle and later stages in the funnel. In contrast, multi-touch attribution offers a more balanced perspective by considering the cumulative effect of all touchpoints (Prantner 2019)(Yao et al. 2022).

Nevertheless, first touch attribution has its advantages. It is easy to implement and understand, making it accessible for marketers looking to quickly identify effective acquisition channels. Its focus on the starting point of engagement can help businesses refine their strategies for attracting new customers. However, its inability to provide a holistic view of the customer journey underscores the need for more sophisticated models, such as multi-touch attribution, when a comprehensive understanding is required (Shao and Li 2011).

2.2.4 Linear Attribution

Linear attribution is a marketing model that equally assigns credit to each touchpoint a customer encounters before converting. This means that every interaction, from the initial click to the final purchase, is considered equally influential in the conversion process.

However, the linear attribution model has several drawbacks. It oversimplifies the customer journey by assuming all touchpoints are equally important. In reality, some interactions have a more significant impact on decision-making than others, which this model fails to recognize (Sinha, Andrus, and Paulsen 2020). Moreover, by giving equal weight to each touchpoint, it does not provide valuable insights into which interactions are most effective. This limits a marketer's ability to allocate resources efficiently and optimize marketing strategies (Sinha, Andrus, and Paulsen 2020).

The model also ignores the complexity and non-linear nature of customer journeys. Customers often interact with multiple channels in various sequences, and certain touchpoints may be more critical at different stages of the decision-making process (Zhang, Wei, and Ren 2014). Additionally, the equal distribution of credit can lead to misleading data, causing incorrect conclusions about the effectiveness of marketing strategies and resulting in poor decision-making (Sinha, Andrus, and Paulsen 2020). Lastly, linear attribution may unintentionally favor channels with more frequent interactions, regardless of their actual contribution to conversions, skewing the perceived effectiveness of certain marketing efforts (Zhang, Wei, and Ren 2014).

2.2.5 Time Decay Attribution

Time decay attribution is a marketing model that assigns credit to touchpoints based on their proximity to the conversion event. Interactions occurring closer to the time of conversion are given more weight, under the assumption that these interactions have a greater influence on the final decision.

This model helps marketers identify which touchpoints are most influential in the final stages of the customer journey, enabling more informed decisions about budget allocation and strategy adjustments (Danaher and Heerde 2018). Unlike models like first or last touch attribution, which give all credit to the first or last interaction, time decay attribution distributes credit more evenly but prioritizes recent interactions (Yuvaraj et al. 2018b). It differs from linear attribution, which assigns equal credit to all touchpoints, and position-based models that emphasize the first and last interactions (Yuvaraj et al. 2018b).

However, implementing time decay attribution can be challenging due to the need for accurate temporal data and the computational resources required to adjust weights dynamically (Cormode et al. 2009). Additionally, marketers may face difficulties with data integrity and the complexity of the buyer's journey, making it harder to use this model effectively.

Despite these challenges, time decay attribution offers several advantages. It provides a more nuanced understanding of the customer journey by recognizing that recent interactions play a more significant role in influencing conversions (Cormode et al. 2009). This model is particularly useful in fast-paced digital environments where customer decisions are heavily influenced by recent interactions. It is also beneficial in scenarios like flash sales or time-sensitive promotions, where recency is a key factor in driving conversions.

2.2.6 Position-Based Attribution

Position-based attribution, also known as U-shaped attribution, is a model that assigns significant credit to the first and last touchpoints in a customer's journey, while distributing the remaining credit across the middle interactions. This model highlights the importance of both the initial engagement and the final conversion point, making it valuable for understanding key moments in the customer journey (Yuvaraj et al. 2018b).

Compared to other attribution models, position-based attribution provides a more balanced approach. Unlike the last-touch model, which attributes all credit to the final touchpoint, or the linear model, which gives equal weight to all interactions, position-based attribution acknowledges the critical roles of both the first and last interactions (Danaher and Heerde 2018). This balance makes it especially useful for marketers seeking to understand both customer acquisition and conversion.

However, position-based attribution faces challenges related to data integrity. Accurate attribution requires high-quality data, and issues with data quality can lead to misguided strategies and incorrect conclusions (Oloyede 2022). Furthermore, the growing complexity of customer journeys, involving multiple touchpoints across various channels, makes it difficult to fully trust or implement attribution models effectively (Hosahally and Zaremba 2023). Additionally, position-based attribution may not fully account for the synergistic effects between channels, potentially leading to an incomplete understanding of overall channel performance (Méndez-Suárez and Monfort 2021).

To address these limitations, newer models have been developed. The Enhanced Last Touch Interaction (ELTI) model, for example, incorporates game theory and synergistic effects to improve the accuracy of traditional attribution methods (Yuvaraj et al. 2018b). Probabilistic models, such as Markov chains and Bayesian networks, offer a more sophisticated approach, providing deeper insights into customer behavior and channel performance (Alexandrovskiy and Trundova 2022).

2.3 Importance of Market Attribution

Market attribution is essential for several reasons. First, it provides accountability and justification for marketing expenditures. As marketing is often viewed as a cost center, attribution models offer businesses a way to demonstrate the effectiveness of their campaigns and activities, thus justifying their investments (Oloyede 2022). Additionally, attribution models support decision-making by helping businesses determine where to allocate marketing budgets. Understanding which channels and tactics drive the desired outcomes allows for more strategic allocation and optimization (Leguina, Rumín, and Rumín 2020).

Attribution models also play a key role in measuring the return on investment (ROI) of marketing efforts. By assessing the financial impact of different marketing channels and campaigns, businesses can adjust their strategies to maximize profitability (Sriram et al. 2022b). Furthermore, these models provide valuable customer insights, such as brand awareness, engagement, and churn rate. By focusing on customer metrics instead of just business outcomes, companies gain a deeper understanding of customer behavior and preferences (Oloyede 2022).

2.3.1 Impact on the Business World

Market attribution influences various aspects of the business world. First, it aids in resource allocation. By identifying the most effective marketing channels, businesses can allocate their resources more efficiently, preventing overspending on underperforming channels and ensuring optimal use of marketing budgets (Danaher and Heerde 2018). Attribution models also contribute to strategic planning, as data-driven insights help businesses craft more targeted and effective marketing strategies based on channel performance (Buhalis and Volchek 2021).

Moreover, attribution models enable businesses to measure their marketing performance accurately, setting realistic goals and benchmarks for future campaigns (Jayawardane, Halgamuge, and Kayande 2016). Businesses that master attribution can gain a competitive advantage by improving their ROI and optimizing marketing strategies, leading to increased market share and better financial performance (Méndez-Suárez and Monfort 2021). The transparency and accountability provided by attribution models further help businesses justify their marketing budgets and gain support from other departments (Danaher and Heerde 2018).

2.3.2 Challenges and Considerations

While market attribution is valuable, its implementation comes with challenges. Data integrity and the complexity of the buyer's journey can hinder the effectiveness of attribution models. Marketers must ensure data accuracy and fully understand how to use attribution tools to derive meaningful insights (Oloyede 2022). Additionally, selecting the right attribution model is crucial, as different models provide different insights. Businesses need to choose models that align with their specific goals and the nature of their customer journeys (Buhalis and Volchek 2021).

Chapter 3

Methodology

3.1 Data Collection

The dataset employed in this research was procured from an anonymous source and is intended solely for academic and research purposes. It encompasses data collected over a five-year period, from 2019 to 2024, providing a comprehensive and longitudinal view of customer interactions across multiple digital platforms. This time span allows for an in-depth examination of evolving customer behaviors and engagement patterns, capturing a rich historical context for analysis. The below are the tables containing the features and discription of the dataset.

Field	**Definition**
mmm_timeseries_id	Unique identifier for a single MMM timeseries.
organisation_id	Unique, anonymous identifier for an eCommerce brand.
organisation_vertical	The top-level category of the highest selling products.
organisation_subvertical	The sub-category of the highest selling products.
organisation_marketing_sources	At least one of Google, Meta, and/or Tiktok.
organisation_primary_territory_name	The organisation's territory with the highest average daily orders.
territory_name	Values include multi-country "All Territories" and country-level roll-ups.
currency_code	Currency for monetary fields.
date_day	Observation date.
first_purchases	Number of web purchases for new customers, i.e., acquisitions.
first_purchases_units	Number of units purchased by new customers.
first_purchases_original_price	New customer total value of merchandise before discount.
first_purchases_gross_discount	New customer total discount value.

Table 3.1: Dataset Description (Part 1)

Field	Definition
all_purchases	Number of web purchases for all customers.
all_purchases_units	Number of units purchased by all customers.
all_purchases_original_price	Total value of merchandise before discount.
all_purchases_gross_discount	Total discount value.
google_paid_search_spend	Google spend on (non-branded) paid search.
google_shopping_spend	Google spend on shopping ads.
google_pmax_spend	Google spend on performance max campaigns.
google_display_spend	Google spend on display ads.
google_video_spend	Google spend on video ads.
meta_facebook_spend	Meta spend on Facebook ads.
meta_instagram_spend	Meta spend on Instagram ads.
meta_other_spend	Meta spend on ads from other platforms.
tiktok_spend	TikTok spend.
<platform>_<channel>_clicks	Ad clicks for each channel with spend.
<platform>_<channel>_impressions	Ad impressions for each channel with spend.
<channel>_clicks	Web traffic from "non-paid" channels.

Table 3.2: Dataset Description (Part 2)

The dataset holds significant value for marketing professionals as it sheds light on the origins of customer touchpoints across platforms such as Google, Meta, TikTok, and others. By analyzing these touchpoints, marketers can gain critical insights into customer acquisition channels and determine the effectiveness of their advertising efforts. This analysis enables a more informed allocation of marketing budgets, helping organizations to identify which platforms generate the highest returns on investment (ROI) and which are less impactful. Such data-driven decision-making empowers businesses to maximize their advertising efficiency and optimize resource utilization.

Beyond identifying effective platforms, the dataset facilitates advanced analyses such as sales forecasting and the detection of customer behavior patterns. It enables marketers to uncover trends and recurring patterns in customer interactions, which can provide actionable insights into future customer behaviors. This capability is particularly valuable for organizations seeking to anticipate demand, plan inventory, or refine their customer targeting strategies.

Additionally, by applying Marketing Mix Modeling (MMM) to the dataset, it is possible to integrate and analyze the influence of external factors that drive customer sales. These factors may include seasonality, public holidays, promotional events, economic conditions, and market trends. Such comprehensive modeling allows for a more nuanced understanding of the interplay between external variables and sales performance, equipping organizations with deeper strategic insights. This holistic approach enhances the ability to identify levers for growth, refine marketing strategies, and sustain competitive advantage in dynamic market environments.

3.2 Using Robyn for MMM

Robyn is an experimental, AI/ML-driven, open-source package for Marketing Mix Modeling (MMM) developed by Meta's Marketing Science team. The tool leverages automation through a variety of advanced techniques, including a multi-objective evolutionary algorithm for optimizing hyperparameters, time-series decomposition to account for trends and seasonality, Ridge regression for model fitting, and a gradient-based optimizer to determine budget allocation. Robyn is specifically designed for granular datasets containing numerous independent variables, making it particularly well-suited for digital and direct response advertisers who have access to rich data sources.

3.2.1 Why Was Robyn Developed?

Democratizing Modeling Knowledge: At the core of Robyn's development is the belief that transparency in measurement fosters trust. The aim is to empower businesses of all sizes by transforming marketing practices based on data and scientific rigor.

Inspiring Innovation in the Industry: Robyn strives to advance the marketing industry by pushing the boundaries of marketing science. The tool is built with a focus on collaboration, aiming to inspire others in the industry to innovate and contribute to the collective growth of marketing science.

Reducing Human Bias: The development of Robyn is also motivated by a vision for a future where AI/ML techniques are applied responsibly and in a privacy-friendly manner. By leveraging automation in modeling, Robyn helps reduce human bias, thereby enhancing the decision-making process and increasing the efficiency of marketing strategies.

Fostering a Strong Open Source Community: Robyn is grounded in the belief that open-source collaboration is vital for driving industry innovation. By contributing to the growth of an open-source marketing science community, Robyn seeks to strengthen bonds among practitioners and drive ongoing innovation in the field.

3.2.2 What insights can be gained using Robyn?

Understanding the contribution of each media channel to both online and offline sales is crucial for evaluating marketing effectiveness. Analyzing the return on investment (ROI) for each channel helps businesses assess the efficiency of their marketing spend and identify the most impactful platforms. Allocating the marketing budget effectively across channels to maximize key performance indicators (KPIs) ensures optimal use of resources, while deciding where to invest the next marketing dollar helps prioritize high-impact opportunities.

Determining the optimal spend for each major channel enables businesses to allocate their budgets efficiently, while assessing the impact of changes to the marketing plan helps predict sales outcomes. In cases where budget cuts are necessary, identifying which areas to reduce funding allows for strategic reallocation. Additionally, understanding how execution factors (e.g., buying objectives, frequency, creative quality, targeting) affect the performance of platforms like Facebook can improve channel-specific strategies.

Pricing decisions, such as whether to increase prices and by what amount, should be based on market analysis to avoid negative impacts on sales. Analyzing the impact of competitor advertising helps gauge external influences on brand performance. Finally, evaluating the incremental revenue generated by trade and promotional activities allows businesses to measure the effectiveness of these efforts in driving sales growth.

3.2.3 Robyn Input

The below defines the setup for a Robyn marketing mix model by configuring several key parameters, including the input dataset, dependent and independent variables, time frame, holiday effects, paid media variables, and adstock settings. The primary objective is to establish a comprehensive model that can evaluate and optimize the influence of marketing efforts on revenue, while also factoring in seasonal fluctuations, holiday-related impacts, and the lingering effects of past advertising activities.

- **data(dt_prophet_holidays):** This command loads a dataset containing holiday information, which is used in the Prophet model to account for the impact of holidays on the sales data.
- **dt_input:** The main dataset used in the model. It contains the marketing data (media spend, sales, etc.) that will be analyzed.
- **dt_holidays:** The holiday dataset, which is used by the Prophet model to adjust for the effect of holidays on sales and customer behavior.
- **date_var:** Specifies the date variable (e.g., "Week") in the dataset, which helps the model understand time-series structure and analyze the data by time period.
- **window_start & window_end:** These define the period of time the model should analyze, from `window_start` to `window_end`, setting the boundaries for the dataset.

- **dep_var:** The dependent variable (e.g., `FIRST_PURCHASES_ORIGINAL_PRICE`) that the model is trying to predict, usually the sales or revenue data.

- **dep_var_type:** Specifies whether the dependent variable represents "revenue" or "conversion." This helps the model understand the nature of the target variable.

- **prophet_vars:** The variables related to seasonal effects that the Prophet model will use, such as holidays and seasons, to adjust forecasts.

- **prophet_country:** Specifies the country (e.g., "UK") to adjust the seasonal and holiday patterns according to the specific country.

- **paid_media_spends:** Lists the media spend variables for different advertising platforms, which are used to evaluate how paid media campaigns impact the dependent variable.

- **paid_media_vars:** Lists the click variables for paid media channels, which are used to assess the impact of clicks on the dependent variable (e.g., purchases or revenue).

- **organic_vars:** Specifies any organic variables (e.g., unpaid traffic), although in this case, it is `NULL` meaning no organic variables are used in the model.

- **context_vars:** Defines external factors (e.g., `FIRST_PURCHASES_GROSS_DISCOUNT`) that influence the dependent variable, allowing the model to account for these contextual variables.

- **context_signs:** Specifies the expected relationship of the context variables with the dependent variable, in this case, "negative" (indicating that higher discounts may reduce revenue).

- **adstock:** Defines the decay model for how the impact of advertising spending decreases over time. `"Geometric"` means a fixed rate of decay is assumed for the effect of past media spend.

Chapter 4

Exploratory Data Analysis

4.1 Correlation Between First Purchases & All Purchases

The below correlation heatmap reveals significant relationships among various purchase metrics, highlighting both strong and weak associations. Strong positive correlations, such as between FIRST_PURCHASES_ORIGINAL_PRICE and FIRST_PURCHASES_GROSS_DISCOUNT (0.86), and ALL_PURCHASES_UNITS and FIRST_PURCHASES_UNITS (0.89), indicate consistent patterns. Conversely, weaker correlations, such as between FIRST_PURCHASES_UNITS and FIRST_PURCHASES_ORIGINAL_PRICE (0.25), suggest minimal interdependence.

4.1.1 Key Insights

- A strong link exists between initial purchases (`FIRST_PURCHASES`) and overall purchases (`ALL_PURCHASES`), with a correlation of 0.85, indicating aligned customer behaviors.
- Discounts (`GROSS_DISCOUNT`) are strongly correlated with original prices, showing their significant impact on purchase decisions.
- Purchase quantities (`UNITS`) exhibit moderate correlations with total purchases, reflecting their relevance in analyzing customer behavior.

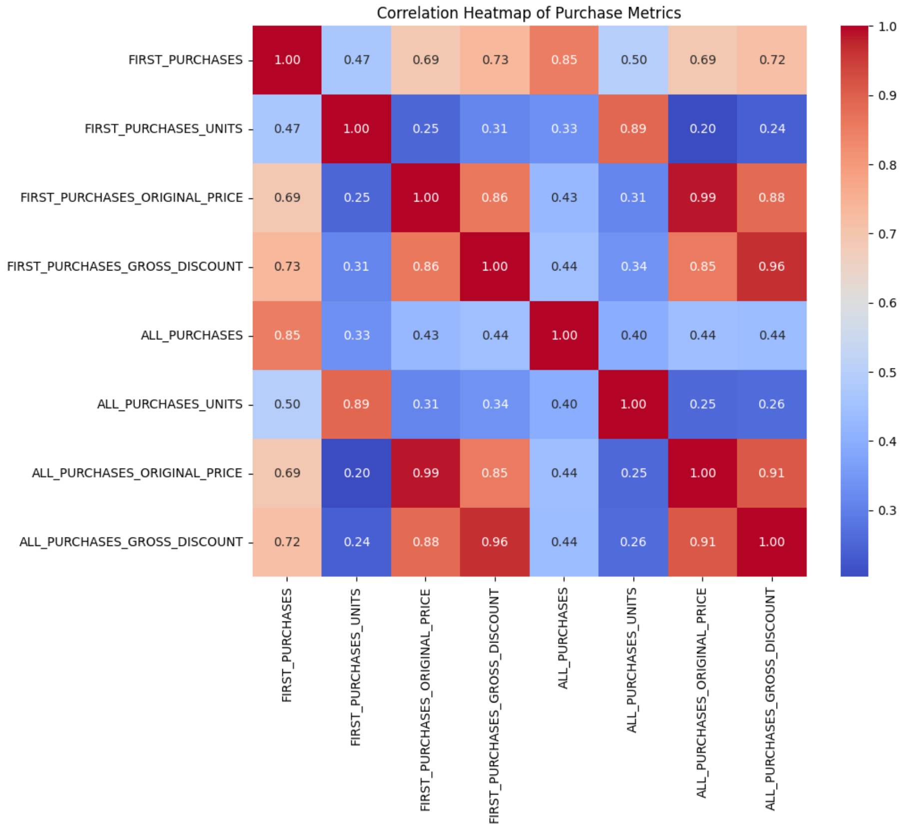

Figure 4.1: Correlation heatmap

4.1.2 Strategic Implications

- High correlations between discounts and spending suggest that discount-driven promotions can significantly boost sales.
- Moderate correlations with purchase quantities can help identify frequent or high-value buyers.
- Metrics with weak correlations require independent analysis for better forecasting and optimization.

These findings provide actionable insights for designing targeted strategies to enhance customer engagement and improve sales performance.

4.2 Ads Spent Platform

The line chart visualizes marketing spend across channels from mid-2021, revealing trends such as spending spikes, stable allocations, and shifting priorities. Key observations include significant spikes in Google Display Spend in late 2022 and early 2024, indicating targeted campaigns, and a steady increase in Meta Instagram Spend, suggesting growing reliance on the platform. Other Meta Spend remains stable, while Google Paid Search and Google Shopping show consistent, low investments.

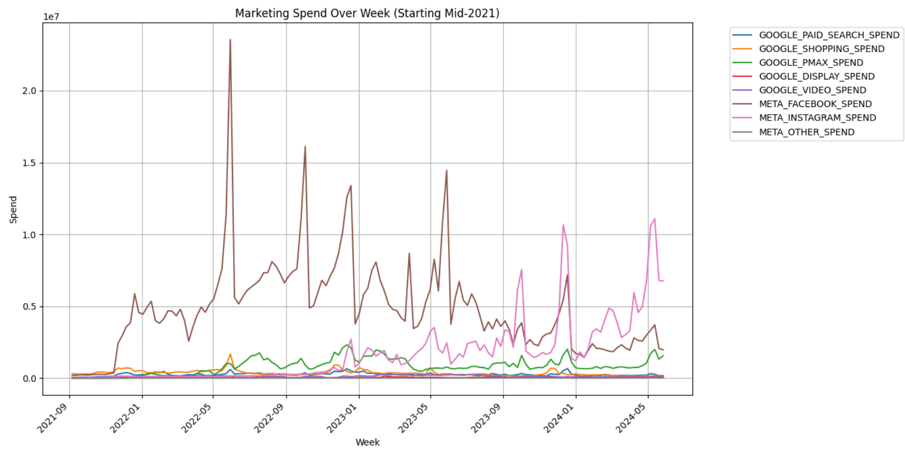

Figure 4.2: Line graph on ads spend

Seasonality is apparent, with spikes in Google Display and Instagram likely tied to major events, while other channels reflect steady, always-on campaigns. Google Display and Meta Instagram are prioritized with larger budgets, while Google Paid Search and Google Shopping maintain stable, smaller allocations.

This data highlights opportunities for budget optimization, particularly for high-investment channels, and suggests evaluating their ROI. The growth of Meta Instagram underscores the importance of visual platforms, while assessing lower-spend channels like Google Shopping is essential to ensure performance goals are met.

Chapter 5

Data Modelling & Pareto Output

5.1 Nevergrad

In Robyn, an open-source marketing mix modeling (MMM) tool developed by Meta, Nevergrad is a Python library used for black-box optimization. It helps optimize the parameters of Robyn's models by exploring complex, non-linear relationships between marketing inputs and outcomes. Nevergrad supports various optimization algorithms, such as Bayesian optimization, Genetic Algorithms, and Differential Evolution, which are essential for fine-tuning Robyn's models. These algorithms allow Robyn to find the best parameters without requiring explicit gradients, making it especially useful when dealing with complex datasets. Nevergrad, along with other Python libraries used in Robyn (such as pandas, NumPy, and scikit-learn), enables efficient and effective model optimization, ultimately enhancing the accuracy and performance of marketing mix models.

To create a Market Mix Model we need to first setup a python environment so as to perform statistical calculation for a robyn model. This step is crucial without which robyn libraries cannot work.

5.2 Hyper-parameters

In the hyperparameter section, critical parameters are defined to guide the Robyn model in effectively capturing the dynamics of media performance and its impact on the dependent variable. These hyperparameters govern essential aspects of advertising impact modeling, such as the decay of media effectiveness over time, the saturation of response curves, and the scaling of returns, ensuring that the model aligns with real-world advertising dynamics.

The **theta parameter**, also known as the adstock decay rate, encapsulates how the effectiveness of a media exposure diminishes over time. By specifying a range for each media channel, such as:

$$\text{GOOGLE\_PAID\_SEARCH\_SPEND\_thetas} = [0.1, 0.3],$$

the model is provided with flexibility to capture varying decay patterns. A lower theta value signifies a faster decay, indicating that the advertising impact is short-lived, whereas a higher theta value suggests a prolonged effect, reflecting a more sustained influence of media exposure.

Complementing this, the **alpha parameter** controls the curvature of the response function, representing the saturation effect of increased media spending. Defined as ranges, such as:

$$\text{GOOGLE\_PAID\_SEARCH\_SPEND\_alphas} = [0.5, 3],$$

alpha determines how returns diminish as spending intensifies. A lower alpha value reflects rapid diminishing returns, where incremental spending quickly loses effectiveness, while a higher alpha indicates more gradual diminishing returns, suggesting sustained efficiency of spending.

The **gamma parameter** further refines the response function by determining the inflection point at which returns begin to saturate. For instance:

$$\text{GOOGLE\_PAID\_SEARCH\_SPEND\_gammas} = [0.3, 1],$$

specifies that a lower gamma shifts the saturation curve leftward, denoting quicker saturation at lower levels of spending. Conversely, a higher gamma shifts the curve rightward, implying that higher spending thresholds are required before significant diminishing returns are observed.

These hyperparameters are assembled into a unified object and incorporated into the Robyn model's input structure using the `robyn_inputs` function. The ranges provided enable the model to explore diverse scenarios during optimization, allowing it to identify the parameter configurations that best explain the observed relationship between media spend and business outcomes, such as first purchases. Collectively, these hyperparameters play a pivotal role in ensuring the model reflects the nuanced and non-linear relationships characteristic of advertising dynamics, thereby enhancing the robustness and interpretability of the analysis.

These ranges are recommended based on platform type, for online platform alpha the range is [0.5 3] while for tv or radio its [0.3 1.5] and so on. This is because each platform type has effects differently on customers.

5.3 Result

5.3.1 Evaluation

Metric	Value
Adjusted R-squared (Adj R2)	86%
Normalized Root Mean Squared Error (NRMSE)	7.3%
Decomposition Residual Sum of Squares (Decomp.RSSD)	8.8%

Table 5.1: Model Performance Metrics

5.4 Model Performance Evaluation

The performance of the model is evaluated using several key metrics: Adjusted R-squared (Adj R^2), Normalized Root Mean Squared Error (NRMSE), and Decomposition Residual Sum of Squares (Decomp.RSSD). Each of these metrics provides valuable insight into different aspects of model performance. The interpretation of these metrics is as follows:

5.4.1 Adjusted R-squared (Adj R^2)

Adjusted R-squared is a statistical measure that indicates how well the model explains the variation in the dependent variable. Unlike the traditional R-squared, which can increase with the addition of more predictors, Adjusted R-squared accounts for the number of predictors and penalizes the inclusion of irrelevant variables. It provides a more accurate measure of goodness-of-fit, especially for models with multiple predictors.

An Adjusted R^2 value of 86% means that 86% of the variance in the dependent variable (e.g., sales, revenue, etc.) is explained by the model. This indicates that the model has a strong explanatory power, capturing a significant proportion of the variability in the data. However, the remaining 14% of the variance is unexplained. While a higher Adj R^2 generally indicates a better fit, it is important to consider other metrics to evaluate the model's generalizability, as a high R^2 could reflect overfitting.

5.4.2 Normalized Root Mean Squared Error (NRMSE)

The Normalized Root Mean Squared Error (NRMSE) is a metric that assesses the accuracy of the model's predictions. It is the square root of the mean squared error (RMSE), normalized by the range (or mean) of the observed data. This normalization enables comparisons of model performance across different datasets or models, accounting for the scale of the target variable.

$$\text{NRMSE} = \frac{\text{RMSE}}{\text{Range of the Target Variable}} \times 100$$

Where RMSE is the square root of the average squared differences between predicted and observed values.

The NRMSE value of 7.3% indicates that the model's average prediction error is 7.3% of the range of the target variable. A lower NRMSE indicates higher accuracy. In this case, a value of 7.3% suggests that the model's predictions are relatively accurate and that the model performs well in terms of predictive accuracy, considering the scale of the data.

5.4.3 Decomposition Residual Sum of Squares (Decomp.RSSD)

Decomposition Residual Sum of Squares (Decomp.RSSD) is a measure of unexplained variance or residual error after the total variation in the model's predictions has been decomposed into different components. It indicates the proportion of the total variance that is not accounted for by the model after considering factors such as media spend, lag effects, and other components.

A Decomp.RSSD value of 8.8% means that 8.8% of the variance in the data is unexplained after the model's decomposition. This is considered a small portion, suggesting that the model effectively explains the majority (91.2%) of the variance in the target variable. A lower Decomp.RSSD is desirable, as it indicates that the model has captured the primary drivers of the dependent variable. However, some unexplained variance remains, which may offer opportunities for further model refinement.

5.4.4 Summary of Model Performance

- **Adjusted $\mathbf{R^2}$ = 86%**: The model explains 86% of the variation in the target variable, suggesting a strong fit to the data.
- **NRMSE = 7.3%**: The model's predictions are accurate, with an average error of 7.3% relative to the data's range.
- **Decomp.RSSD = 8.8%**: After accounting for various components, 91.2% of the variance is explained by the model, with 8.8% unexplained.

Collectively, these metrics suggest that the model performs well: it captures a significant portion of the variance in the dependent variable, provides accurate predictions, and effectively decomposes the sources of variability. However, the residual unexplained variance (Decomp.RSSD) indicates that there may still be opportunities for improvement, potentially by incorporating additional explanatory factors or refining the model further.

5.4.5 Pareto Front Outputs

The Pareto front, a concept from multi-objective optimization, represents the set of optimal solutions where improving one objective necessitates compromising another. In marketing optimization, for example, it might reflect trade-offs between maximizing ROI and minimizing marketing costs. Each solution on the Pareto front is non-dominated, meaning no other solution is better across all objectives, making it an essential tool for identifying optimal trade-offs.

From the Pareto front, decision-makers gain insights into the trade-offs between competing objectives, enabling informed choices based on specific priorities or constraints. The front also serves as a benchmark for evaluating solution quality; solutions not on the front indicate room for improvement. Moreover, the shape of the Pareto front can reveal sensitivities, such as whether small changes in one objective result in significant impacts on others.

In practical applications, the Pareto front is widely used in fields like marketing, engineering, and supply chain management to provide a range of optimal solutions for complex decision-making. By analyzing the front, organizations can prioritize objectives effectively, ensuring that chosen strategies align with their goals while balancing competing demands. Below are the graphs generated by Pareto front output:

Actual VS Predicted

The below figure shows the comparison between predicted data and actual data. The orange line depicts the Actual while the blue dotted line is the Predicted.

This image shows that untill 2022 there have not been actual revenue, this may happen if the business was relatively new at that time or advertisements had little effect.

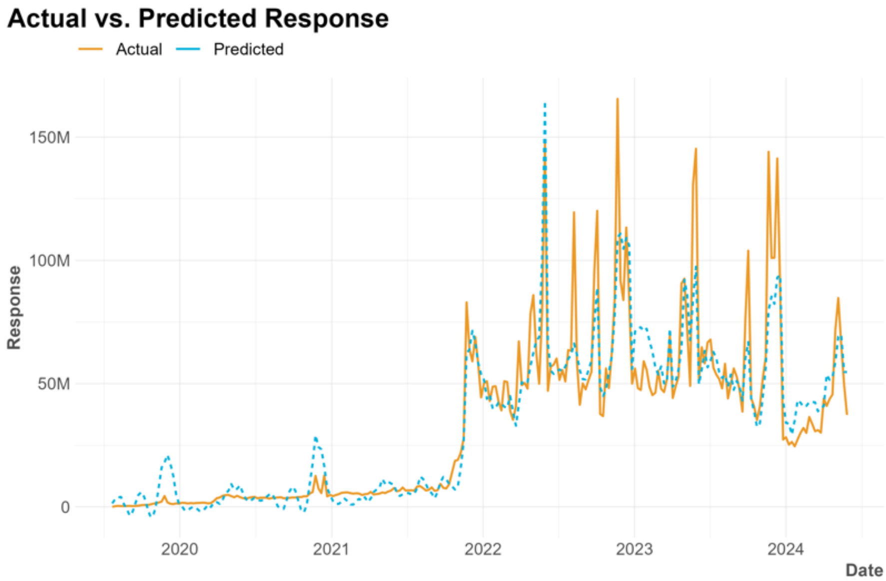

Figure 5.1: Actual VS Predicted

Although we have received an accuracy of **86%** we can see some areas where the model predicts higher than usual in the spikes seen in 2020 and 2021, this could be cause by an unknown factor that diminished the marketing effect. Apart from that there are similar patterns during the mid and end of the year between 2022 & 2023 and between 2023 & 2024 where although diminishing there maybe a trend during those specific periods.

Response Decomposition Waterfall

The waterfall model shows how much each platform has contributed to ROI over 100%.

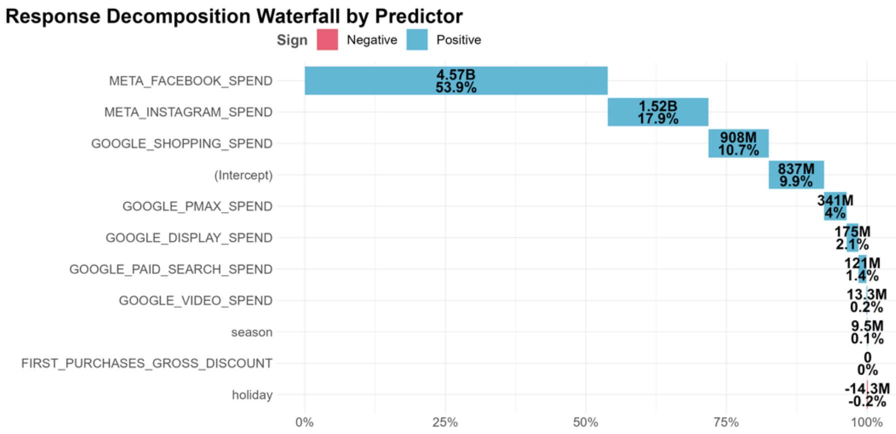

Figure 5.2: Response Decomposition Waterfall

Meta_facebook has contributed the highest of more than 50%, there is one factor that had a negative effect on ROI (holiday).

Share of Total Spend, Effect & ROAS

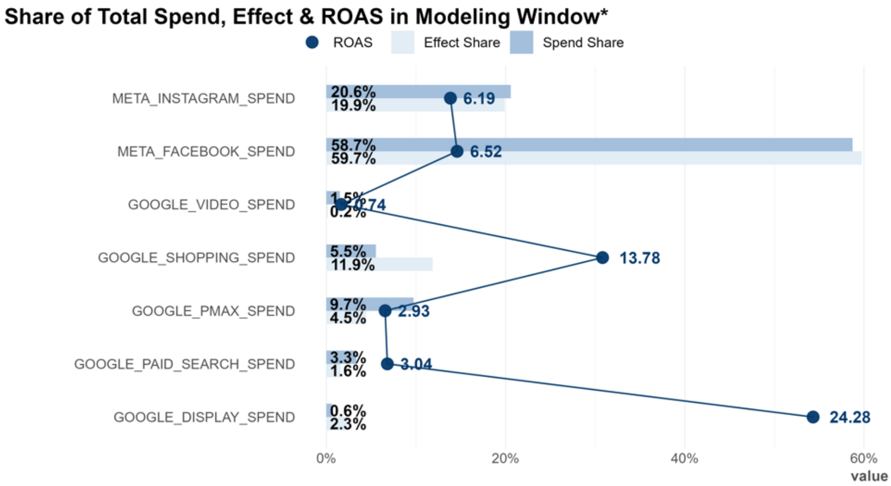

Figure 5.3: ROAS vs Spent vs Effect

The above figure shows composition between Total spend on each platform, Return on ad spend and Investment Effect. This figure tells how much you have spent on ads, how much revenue has been generated from that and how effective were the ads.

There are some interesting areas having extreme negative and positive effects that can be seen here, for instance ads spent on Meta_Facebook had a similar effect over customer impressions but customer may have not needed the product at that time due to which there was a lower ROI. While Google_shopping ads spend had less share spent, it had a higher impression of 5.4% more and returns even higher, this situation can be seen with google_display_spend with almost double ROI compared to google_shopping.

Carryover Vs Immediate Effect

There can be either a Carryover effect or Immediate effect on a customer. This means that supposedly if the customer has a good impression of the product he may want it at that time, that will give the customer an Immediate effect while carryover effect is, a customer may want to buy the product later and buys the product much later than when he had watched the ad.

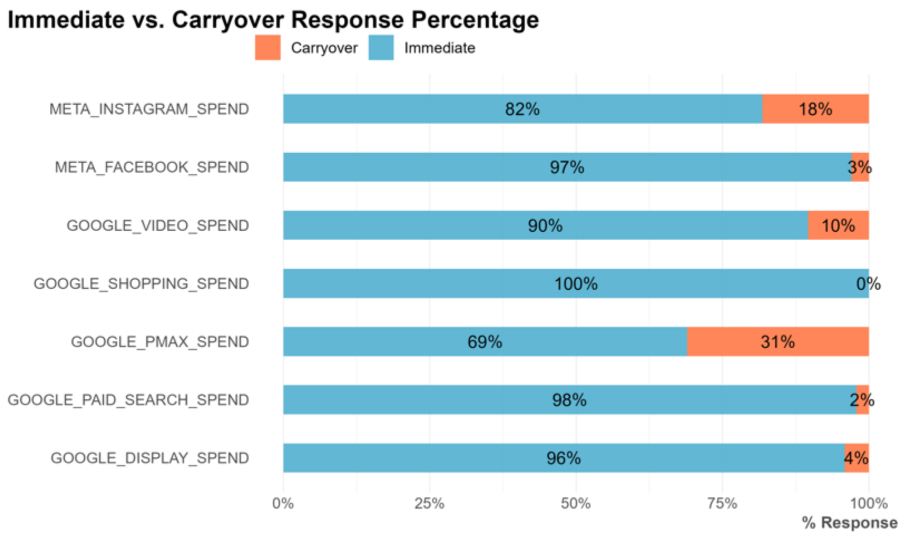

Figure 5.4: Actual VS Predicted

Most of the platforms had an immediate effect as compared to carryover effect on the customers, most of which have over 90% while only google_pmax had carryover of 31%.

Prophet Decomposition

There are various trend factors that drive customer sales some of which are specified in the below figure. While specifying robyn_input arguments one of the pre-existing datasets in robyn libraries had holidays and season for different countries.

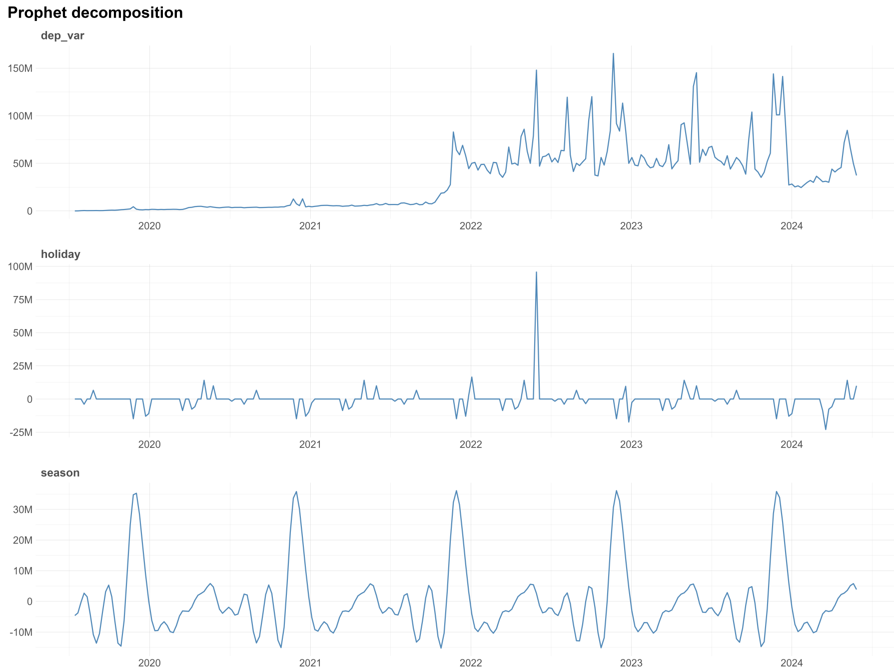

Figure 5.5: Prophet Decomposition

This image shows the break down of the predicted data from its other trend factors based on holiday and season. Seasonality had a constant trend patterns over the years with the highest spike closing to the end of the year. While holiday effect had constant pattern over the years but had an abnormal spike at mid of 2022, this may have triggered due to some unknown factor that is not known to us.

Chapter 6

Conclusion & Further Work

This research successfully demonstrates the application of Marketing Mix Modeling (MMM) using Robyn to predict ROI and assess the effectiveness of various marketing channels. By analyzing historical data across platforms like Meta, Google, and TikTok, the study provides actionable insights into customer acquisition trends and advertising efficiency. The results show that Meta Facebook contributed significantly to ROI, while other channels like Google Shopping exhibited high returns with comparatively lower investment. The inclusion of seasonal and holiday factors further enriches the predictive capabilities of the model.

Despite achieving a high Adjusted R^2 of 86% and a low Normalized Root Mean Squared Error (NRMSE) of 7.3%, the analysis reveals areas for improvement. For instance, unexplained variances and potential biases in data highlight the need for future research to incorporate additional variables and refine the model further. Moreover, the findings underline the importance of understanding both immediate and carryover advertising effects to optimize marketing budgets effectively. Future work could expand the scope of this study by exploring alternative attribution models, integrating real-time data, and investigating the influence of emerging marketing platforms. By addressing these aspects, businesses can achieve more precise and adaptable marketing strategies, ensuring sustained competitive advantage in dynamic markets.

Appendix:

To access the code please click on the github link: Predicting-ROI-On-Market-Attribution-Using-Market-Mix-Modelling

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