Towards data-driven marketing organization

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Author: Juha Rasi
Subject: Strategy and entrepreneurship
Supervisor: Mikko Rönkkö

JYVÄSKYLÄN YLIOPISTO

ABSTRACT

Author Juha Rasi	
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Abstract
This study delves into the challenges and solutions associated with implementing marketing-mix modeling (MMM) within organizations, especially under the complexities of restrictive privacy laws affecting current marketing effectiveness measurement approaches. Using a comprehensive mixed-method approach encompassing an interview-modeling-interview sequence, the research examines the challenges encountered in a prior MMM implementation attempt by a private Finnish healthcare company. This approach allowed for the extraction of valuable insights through initial interviews, the application of these insights within a practical MMM framework, and the subsequent validation of findings through follow-up interviews.

The study uncovers critical organizational challenges, such as the need for strong project commitment, adequate resource allocation, and clear goal setting, alongside technical challenges, including data availability and quality. The findings from this methodological approach offer pragmatic recommendations for effectively integrating MMM into organizational decision-making processes. These recommendations address human and technical dimensions, ensuring a comprehensive strategy for implementing complex analytical tools.

This study makes theoretical contributions by emphasizing the importance of organizational qualities, such as skilled personnel, data-driven culture, and well-defined processes, for successfully adopting advanced analytical methods like MMM. It also provides empirical validation of MMM's effectiveness in real-world marketing scenarios. By bridging the theoretical and practical realms, the research enhances understanding of MMM's potential in marketing data analysis and offers valuable insights for academia and practitioners. Filling a notable gap in academic literature, this research presents empirical evidence on the practical implementation of MMM, contributing substantially to academic research and practical applications in data analytics and marketing.

Keywords
Marketing-mix modeling, marketing measurement, data-driven organization

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Tiivistelmä – Abstract

Tämä tutkimus syventyy haasteisiin ja ratkaisuihin, jotka liittyvät markkinointimix mallinnuksen (MMM) käyttöönottoon organisaatioissa, erityisesti rajoittavien yksityisyydensuojalakien aikana, jotka vaikuttavat nykyisiin markkinoinnin tehokkuuden mittausmenetelmiin. Kattavan monimenetelmällisen lähestymistavan avulla tutkimus tarjoaa syvällisen tarkastelun haasteista, joita kohdattiin aikaisemmassa MMM:n käyttöönottoyrittämisessä yksityisessä suomalaisessa terveydenhuoltoyrityksessä. Tämä lähestymistapa mahdollisti näkemysten keräämisen ennen mallinnusta ja näiden näkemysten soveltamisen MMM:ssä ja mallinnuksen tulosten käsittelyn seurantahaastatteluissa.

Tutkimus paljastaa muutamia kriittisiä organisaation haasteita, kuten vahvan projektisitoutumisen tarpeen, riittävän resurssien allokoinnin ja selkeiden tavoitteiden asettamisen. Lisäksi tutkimuksessa löytyi teknisiä haasteita, jotka sisältävät mallinnukseen käytettävän datan määrän ja laadun. Löydökset, jotka on johdettu tästä menetelmällisestä lähestymistavasta, tarjoavat käytännöllisiä suosituksia MMM:n tehokkaaseen integrointiin organisaation päätöksentekoprosesseihin. Nämä suositukset käsittelevät sekä ihmisiä että teknisiä ulottuvuuksia, varmistaen kattavan strategian monimutkaisten analyysityökalujen käyttöönotolle.

Tutkimus tekee teoreettisia kontribuutioita korostamalla organisaation ominaisuuksien, kuten taitavien henkilöiden, datavetoisen kulttuurin ja hyvin määriteltyjen prosessien tärkeyttä edistyneiden analyyttisten menetelmien, kuten MMM:n, onnistuneessa integroinnissa. Se tarjoaa myös empiiristä validointia MMM:n tehokkuudesta todellisissa markkinointiskenaarioissa. Teoreettisen ja käytännöllisen maailman välisen kuilun ylittävänä, tutkimus laajentaa ymmärrystä MMM:n potentiaalista markkinointidatan analysoinnissa ja tarjoaa arvokkaita näkemyksiä sekä akateemisille tutkijoille että käytännön ammattilaisille. Tämä tutkimus esittää empiirisiä todisteita MMM:n käytännön toteuttamisesta, antaen tuloksia sekä akateemiseen tutkimukseen että käytännön sovelluksiin.

Asiasanat
Marketing-mix modeling, marketing measurement, data-driven organization

Säilytyspaikka
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LIST OF TABLES AND FIGURES

1 INTRODUCTION

1.1 Unlocking the power of data: the importance of analytics for organizations

As the relevancy of data and analytics in value creation has been substantiated by a wealth of empirical studies (Ghasemaghaei et al., 2018; Wedel & Kannan, 2016), organizations have increasingly committed themselves to adopting data-driven methodologies. However, despite the growing recognition of the transformative potential of data and analytics, a recent survey conducted in September 2022 by the CMO Survey (2022) unveils a compelling paradox within contemporary business landscapes. While the evidence indicates a notable shift towards data-informed decision-making, with approximately 50% of marketing decisions now being influenced by analytics—a significant surge from the 30% reported less than a decade ago—an underlying implication accompanies this transformation: there remains a perceptible margin for improvement. This thesis focuses on this interesting contrast between the importance of data and analytics and the need for organizational improvement.

Data and analytics can inform business decisions, improve products and services, and target advertising and other marketing efforts (Wedel & Kannan, 2016). They can also be used to develop new products and services or to create new business models (Chesbrough, 2010). These make data a valuable resource for a competitive edge, but the data itself holds no value (Branda et al., 2018). The actual value of data emerges when it is analyzed to extract actionable insights, which can then be used to make decisions that create value (Barton & Court, 2012), particularly in the fields and applications mentioned earlier.

The marketing field and marketers' access to marketing data have evolved significantly over the last three decades (Kannan & Li, 2017). In the past, traditional marketing channels such as television and radio commercials, print advertisements, and billboards were the primary means of reaching consumers, as digital platforms did not exist or were relatively rare among customers. These methods were often costly and required a substantial investment in creative and media buying without any way to measure the results accurately.

'Half the money I spend on advertising is wasted;
The trouble is I do not know which half.
— *John Wanamaker*

With the advent of digital technology, marketers have access to more data on how their campaigns perform. These channels include, but are not limited to, search engines, social media, email, and display advertising (Kannan & Li, 2017). Platforms offering advertising services on various channels include tools to analyze campaign data directly within their respective environments. While this feature increases accessibility, it can simultaneously introduce complications when viewed from a broader perspective. Each platform's data is restricted to its advertising activities, complicating the attribution process for marketing campaigns extending across multiple channels at both tactical and brand levels. This limitation, due to the access only to single-channel data, often results in a preference for 'last-click attribution.' This model prioritizes channels at the lower end of the sales funnel, leaving brand-oriented channels without attribution (Kannan et al., 2016).

Web analytics has long been touted as a tool that could provide marketers with a comprehensive understanding of sales from multiple advertising channels (Chaffey & Patron, 2012; Järvinen & Karjaluoto, 2015). Web analytics have been an effective tool in the past to monitor activity on a website, but it has limitations. To gain a comprehensive understanding of the customer journey across numerous websites, marketers can now use third-party cookies to develop attribution models. Studies have shown that customers usually require multiple touchpoints before making a purchase, highlighting the importance of attribution models (Frambach et al., 2007; Gensler et al., 2012). These models would enable marketers to attribute various touchpoints accordingly since different touchpoints have different effects on the likelihood of a purchase (H. Li & Kannan, 2014). Attributing channels according to their impact allows marketers to justify their marketing budget with data-based evidence, making it more understandable (Kannan et al., 2016; Wedel & Kannan, 2016).

In recent times, privacy regulations such as the General Data Protection Regulation (GDPR) in the European Union and the California Consumer Privacy Act (CCPA) in the United States have made it mandatory for users to give their consent for tracking before any personally identifiable data can be collected (Wolford, 2019). Some browsers like Firefox and platforms like IOS have made it easier for users to block unwanted tracking by automatically blocking third-party cookies and requiring each app to seek permission to collect data explicitly (Firefox, 2023; O'Flaherty, 2021). However, since organizations are required to obtain consent before collecting data, they may not be able to collect data from all their users. This can lead to discrepancies between results in channel-specific advertising tools, web analytics, and actual sales numbers. Consent requirement reduces the completeness of data, leading to fragmented or biased data that may cause inaccuracies in analysis and data-driven decision-making (Kakatkar & Spann, 2019).

In today's world, with all the challenges associated with current data collection, it is crucial to ask to what extent marketers genuinely rely on data-driven decision-making. If the data used in decision-making contains deviations at every stage, how can it be used to make reliable and profitable decisions in an uncertain business environment? To address these challenges, an emergent approach involves abandoning customer-specific tracking in favor of analytical methodologies that utilize statistical techniques.

One such method, marketing mix modeling (MMM), is not new and dates back to the 1960s. Originally, MMM was proposed as a solution to the challenges of measuring offline marketing campaigns. Though it has proven effective in assessing the impact of such campaigns, its calculations are complex and time-consuming (Wedel & Kannan, 2016).

While digital marketing platforms conveniently provide marketers with campaign analytics, statistical methods pose a challenge due to their complexity and need for customization. They also may not be as readily accessible to marketers. Implementing these models demands careful planning and specific organizational capabilities. Despite the technical requirements, numerous studies indicate that the primary issues with these technological tools are more organizational than technological (Davenport & Harris, 2017; Gonzalez & Melo, 2017; Hughes et al., 2017; Lavalle et al., 2012; Wedel & Kannan, 2016).

Because of that, this thesis will study organizational readiness to implement statistical analytics models that can be used to assess past success and predict the most prominent actions to take. Therefore, this thesis will explore the following research question: "**What are the challenges of implementing marketing mix modeling in an organization, and how might they be addressed?**".

Organizations are complex bundles of systems, structures, processes, people, and cultures that work together to achieve the organization's goals and objectives. To simplify the complexities, the MARKORG framework by Moorman & Day (2016) is used to assess the case organization. MARKORG framework (2016) explains these complex organizational constructs by dividing them into four elements: (1) capabilities of the marketing organization refer to the skills, knowledge, and expertise possessed by its members to perform marketing functions and adapt to changes in the market environment; (2) configuration of the marketing organization by defining the metrics, processes, and structure of the organization; (3) human capital meaning leaders and employees that shape the organization's strategy, processes and performance; (4) culture, that refers to the shared values, beliefs, attitudes, and behaviors that shape the organization and influence how it operates (Moorman & Day, 2016).

This thesis focuses on the analysis of a private healthcare company in Finland. In 2021, the company attempted to introduce MMM as a new tool in planning their marketing strategy. Unfortunately, the modeling did not meet the expected standards, so the marketing team could not fully integrate it into their practices. This thesis aims to explore the causes of the failure and offer solutions for the organization to implement the model as standard practice in marketing successfully.

1.2 Thesis structure and research method

In the initial phase of this thesis, a comprehensive review of the literature was conducted to explore analytical approaches, MMM, and organizational aspects structured according to the MARKORG framework. This review aimed to establish a theoretical foundation for understanding the existing knowledge in the field and to create a framework for the subsequent study phases.

After the literature review, the thesis describes a mixed-method approach incorporating qualitative and quantitative research. This methodology proceeds sequentially through three distinct phases, each building on the findings of the preceding phase. The first and final phases of the mixed-method approach consist of interviews, while the second phase focuses on modeling.

In the next phase, the study analyzes the results obtained from the qualitative interviews and the quantitative modeling. The qualitative data gathered through interviews provides insights and perspectives from the organization's representatives, while the quantitative modeling allows us to test the interview results in practice.

Finally, the study concludes with a discussion section, synthesizing and interpreting findings from previous phases. This section provides an opportunity to identify key findings, highlight challenges, and draw meaningful conclusions based on the comprehensive study.

Specific AI tools were employed to refine the process to ensure the clarity and accuracy of the thesis content. Initially, ChatGPT, a large language model (LLM), was utilized to enhance the structure of sections and paragraphs after the initial content draft. Furthermore, ChatGPT aided in translating interview quotes. Towards the conclusion of the process, Grammarly Go was employed to examine and refine the grammar of the thesis text. During the literature review, ResearchRabbit proved to be instrumental in identifying literature that correlates with sources already utilized. This tool integrates with Zotero, a reference management software, thus facilitating the effortless synchronization of current sources. ResearchRabbit excels in constructing visual maps that highlight the relationships between the literature currently in use and other potentially relevant articles, offering new directions for exploration and connecting existing research.

2 LITERATURE REVIEW

This literature review aims to provide a comprehensive overview of analytical approaches and MMM, its origins, methodologies, and limitations. To fully understand the challenges that organizations face when implementing MMM, this thesis takes an organizational view building on the framework of capabilities, culture, configuration, and human capital proposed by Moorman and Day (2016). By examining the literature through this lens, this thesis aims to shed light on the factors influencing the MMM's successful adoption and integration in organizations.

Ultimately, the literature review will serve as the foundation for investigating the complexities of implementing analytical tools, such as MMM, within organizations. It will provide a comprehensive understanding of the topic and offer valuable insights for practitioners and researchers.

2.1 Opportunities and applications of analytics

Before exploring MMM and the organizational attributes vital for its implementation, it is crucial to understand the different analytical approaches organizations commonly adopt. Analytical approaches can be broadly categorized into four distinct types: descriptive, diagnostics, predictive, and prescriptive, which support decision-making (Banerjee et al., 2013; Iacobucci et al., 2019; Wedel & Kannan, 2016). However, some researchers mention only three types, omitting diagnostics (Delen & Ram, 2018; Kiron et al., 2013). As visualized Figure 1 (Delen & Ram, 2018, p. 189), diagnostics is sometimes considered to be relatively similar with its outcomes and usage as descriptive analytics and, due to that, mentioned simply as descriptive analytics. However, to ensure clarity and comprehensiveness in the analytical framework employed in this thesis, the classification of the four types of analytics will be adopted: descriptive, diagnostics, predictive, and prescriptive. This approach allows for a more precise and holistic understanding of the various analytical dimensions and their implications for decision-making.

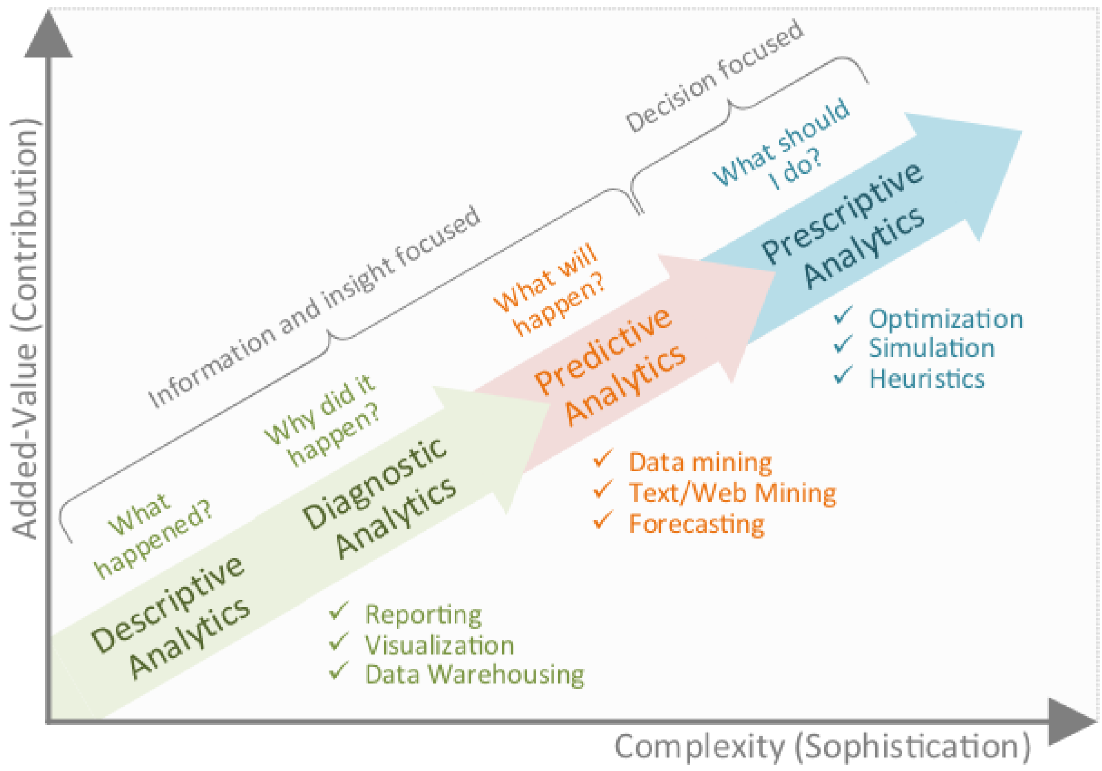

Figure 1 Types of analytics and their purpose (Delen & Ram, 2018, p. 189)

Descriptive analytics is a type of data analysis focusing on examining past data to provide insights into historical trends and events (Cech et al., 2018). The fundamental purpose of this analytical approach is to describe a phenomenon through various measures that can capture its essential dimensions and alert businesses to what has transpired or is likely to occur (Banerjee et al., 2013; Saura, 2021). Descriptive analytics is often the initial step for any organization seeking to integrate data-driven facts into its decision-making process. Owing to the simplicity of descriptive analytics, the prerequisites typically include possession of relevant data, access to fundamental data analysis tools, and managerial support (Davenport & Harris, 2017, Chapter 6).

Businesses can obtain a comprehensive understanding of past trends and patterns by analyzing data and identifying key metrics, such as sales figures, customer demographics, or website traffic (Sivarajah et al., 2017). This enables organizations to accurately define the current business status, making developments, patterns, and exceptions evident. This analysis can produce standard reports, ad hoc reports, or alerts, which assist organizations in making informed decisions based on past performance (Sivarajah et al., 2017).

Diagnostic analytics is an analytical approach that aims to uncover the underlying reasons or causes behind observed events or trends (Delen & Ram, 2018). By examining historical data and identifying patterns or relationships between variables, diagnostic analytics helps decision-makers understand why specific outcomes occurred (Banerjee et al., 2013; Delen & Ram, 2018).

Diagnostics often involves data exploration, visualization, and statistical analysis techniques to gain insights into the factors contributing to the observed phenomena (Banerjee et al., 2013). As a natural progression from descriptive analytics, diagnostic analytics relies on tools and techniques such as visualization, drill-down, and data mining to identify and reveal the fundamental causes of a given issue (Banerjee et al., 2013; Delen & Zolbanin, 2018; Sivarajah et al., 2017).

For instance, consider a scenario where a company experiences an unexpected decline in sales for a particular quarter. Diagnostic analytics could be employed to investigate the underlying causes of this downturn. This process would involve examining a range of data points, including customer purchasing patterns, prevailing market trends, competitive activities, and broader external factors like economic conditions. Analyzing these aspects makes it possible to pinpoint which factors have most significantly contributed to the decrease in sales. For example, through diagnostic analytics, the company may discover that the decline in sales was due to an increase in competitive activity, revealing that a rival company had launched a new product with features that outperformed its own. Alternatively, it might be found that a significant proportion of negative customer feedback was related to slow delivery times, indicating a potential issue in the supply chain that needs to be addressed. Such insights can inform strategic decisions to counteract negative trends, improve performance, and avert similar situations. Diagnostic analytics thus plays a vital role in problem-solving and decision-making within an organization.

Predictive analytics is founded on creating statistical models that recognize patterns in historical data to forecast future events (Waller & Fawcett, 2013). By utilizing statistical or data mining techniques, this field empowers businesses to identify future imperatives and predict potential outcomes (Waller & Fawcett, 2013). The forecasting nature of predictive analytics necessitates more specialized quantitative and domain knowledge in addition to available high-quality data (Waller & Fawcett, 2013). In addition to internal data sources, the organization must evaluate potential external data sources that may be crucial for creating a robust predictive model. This could enable predictive analytics to generate more accurate forecasts, assuming all other factors remain somewhat constant or controllable based on the historical data used in the analysis (Waller & Fawcett, 2013).

The widespread adoption of predictive data analysis across various industries and organizations attests to its proven effectiveness (Davenport & Harris, 2017). A practical example of predictive analytics in action is its use to forecast product sales for the upcoming period, which allows companies to optimize product or service availability, thereby enabling more efficient resource management. For instance, accurate sales forecasts can prevent overproduction or underproduction, reducing excess warehousing costs associated with unsold goods. It can also help manage staff resources better by aligning staffing needs with anticipated sales volumes. If a sales surge is predicted, additional staff can be scheduled in advance to handle increased demand, and conversely, during slower periods, staffing can be reduced to minimize labor costs.

Prescriptive analytics represents an advanced form of data analysis that extends beyond the scope of descriptive diagnostics and predictive analytics by offering specific recommendations to optimize organizational processes and attain strategic goals (Banerjee et al., 2013). This analytical method links decision options with anticipated outcomes, employing sophisticated tools such as optimization, simulation, and decision analysis (Banerjee et al., 2013; Sivarajah et al., 2017). By streamlining operations and minimizing costs, organizations can improve service quality and address customer needs more effectively (Sivarajah et al., 2017).

For instance, a company may face two seemingly equivalent strategic paths. At first glance, neither option appears to have a distinct advantage. In such scenarios, prescriptive analytics can be utilized to simulate the potential outcomes of each strategy, thereby providing quantifiable data to aid decision-makers. This approach empowers decision-makers with substantive data, enabling them to make more informed choices between distinct strategies.

Table 1 summarizes the different types of analytical approaches. Each of these analytical methods requires different levels of expertise, tools, and increasingly varied and higher-quality data from the organization. Therefore, some organizations have challenges in advancing to more specialized types of analytics. Many organizations transition through descriptive and diagnostical analytics towards more demanding analytical techniques instead of starting from predictive or prescriptive approaches (Davenport & Harris, 2017, Chapter 6).

Table 1 Types of analytical approaches (Banerjee et al., 2013)

Descriptive analytics	What happened?
Diagnostics analytics	Why did it happen?
Predictive analytics	What is likely to happen?
Prescriptive analytics	What should be done about it?

2.2 Marketing mix modeling

In today's competitive business landscape, organizations continually strive to optimize their marketing efforts and maximize return on investment (ROI). To achieve this, it is crucial to understand and quantify the impact of marketing activities on sales performance and other key performance indicators (KPIs). This section introduces MMM, a statistical model that uses historical data to quantify the relationship between marketing inputs and their corresponding outputs, such as sales (Chan & Perry, 2017; A. Kumar et al., 2020; Wedel & Kannan, 2016).

2.2.1 A brief history of the method and its benefits for organizations

The development of MMM can be traced back to the 1960s when marketing scholars and professionals identified the necessity of quantifying the impact of marketing activities on business performance (Chan & Perry, 2017; Wedel & Kannan, 2016). MMM emerged as a response to the demand for a systematic and data-driven approach to evaluate the efficiency of diverse marketing efforts and optimize resource allocation at a time when marketing data was more scarce (Wedel & Kannan, 2016).

Over the past few decades, MMM has evolved and adapted to keep pace with the rapidly changing marketing landscape, accommodating new marketing channels, customer behaviors, and analytical methodologies. Several factors have contributed to its growing popularity. Firstly, the exponential growth of digital marketing channels, such as social media, search engine marketing, and online display advertising, has resulted in an abundance of data available for analysis (Wedel & Kannan, 2016). This wealth of information has allowed organizations to assess the effectiveness of their marketing endeavors with greater granularity and precision. Secondly, big data and advanced analytics tools have facilitated the processing and analysis of large, intricate datasets (Saura, 2021). As a result, businesses can now derive more accurate and actionable insights from their data (Ghasemaghaei et al., 2018), improving the feasibility and effectiveness of MMM. Thirdly, organizations increasingly recognize the value of using empirical evidence to guide their marketing decisions (Ghasemaghaei et al., 2018; Saura, 2021). MMM offers a structured, quantitative approach to gauge the impact of marketing actions, enabling businesses to make informed decisions based on historical performance and projected outcomes (A. Kumar et al., 2020). Fourthly, MMM's capacity to estimate attribution amid privacy concerns and the challenges of measuring offline channels has contributed to its growing prominence (Wedel & Kannan, 2016). The rise in public awareness and regulations surrounding data privacy, such as GDPR, has led many users to decline consent for tracking their online activities (YouGov, 2021). The absence of comprehensive data can make it challenging for advertisers to depend exclusively on user-level data for decision-making. Nevertheless, MMM offers a practical alternative, as it enables the estimation of marketing impact without relying on individual user data (Chan & Perry, 2017). By aggregating data at a higher level, MMM addresses privacy concerns associated with user-level data analysis and continues to provide valuable insights into the effectiveness of various marketing initiatives (Chan & Perry, 2017; Jin et al., 2017).

2.2.2 Core concepts and methodologies of marketing mix modeling

Building upon the historical context and growing prominence of MMM, this section will now explore essential factors that should be considered. These factors include adstock, decay effects, diminishing returns, and seasonality. Additionally, this part will discuss common statistical approaches like regression and Bayesian models and analyze potential outcomes of the modeling process.

2.2.2.1 Influential factors in marketing mix modeling

MMM utilizes historical data to model the past relationships between marketing elements and the desired outcome, such as sales, by estimating a historical model with sales as the dependent variable and various factors such as marketing activities, seasonality, price, weather, market competition, and other influences as independent variables (Chan & Perry, 2017; A. Kumar et al., 2020; Wedel & Kannan, 2016). This approach enables the prediction of the impact of future marketing activities on the desired outcome.

To fully understand the dynamics of MMM, it is essential to consider the role of adstock, its decay effect, and diminishing returns on the impact of advertising campaigns. The theory of adstock, or advertising carry-over, suggests that the effects of advertising are not immediate and that the impact of a given ad campaign will continue to be felt even after the campaign has ended (Köhler et al., 2017; V. Kumar et al., 2013). In essence, each advertising exposure builds up a "stock" of brand awareness or consideration that can be drawn upon later (Gijsenberg et al., 2011). However, the effect of adstock is not constant over time. Instead, adstock decays, which is the rate at which the results of the advertising campaign diminish over time and eventually disappear in the absence of advertising (Broadbent, 1984, as cited in Gijsenberg et al., 2011).

The decay rate can be used to estimate the lifetime value of an advertising campaign. It can be helpful for media planning, as it can help to optimize the timing, frequency, and budget allocation of advertising campaigns to maximize return on investment (A. Kumar et al., 2020). It is important to note that the decay effect is often assumed to be similar across all channels, but in reality, different channels behave differently. Therefore, each channel should have its channel-specific decay rate (H. Li & Kannan, 2014). For example, the decay rate for television advertising is likely different from the decay rate of search engine advertising. An example of the decaying effect of marketing as adstock and the delayed effect of lag is shown in Figure 2.

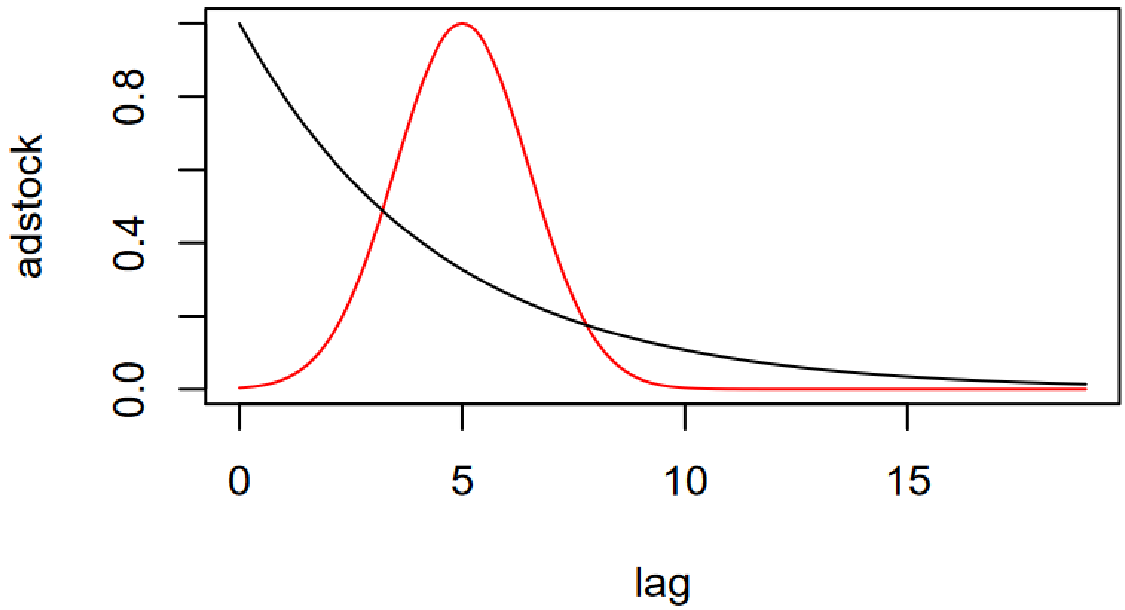

Figure 2 Examples of immediate and delayed adstocks (Jin et al., 2017, p. 4)

The law of diminishing returns is an economic principle that explains the diminishing marginal utility that a consumer gets from each additional unit of a product consumed (Brue, 1993). In the context of marketing, it means that as more resources are invested in advertising, there will be a point where the resulting output will eventually increase at a declining rate (Ambler & Roberts, 2008). This is because the audience can only be exposed to a limited number of ads before desensitization. Therefore, optimizing budget allocation and maximizing returns on investment in marketing activities is essential to ensure that the advertising efforts are effective and efficient (Ambler & Roberts, 2008; Ryals et al., 2007). By doing so, businesses can ensure that they get the most out of their budget and achieve their marketing goals in the most cost-effective way possible.

To achieve the best results, companies need to determine the optimal amount of marketing spend. Instead of linearly increasing the channels and campaign budget, the budget should be distributed among channels and campaigns by focusing on those more likely to produce higher returns (Ambler & Roberts, 2008). Due to the diminished returns, it is more beneficial to save the budget for later instead of going beyond the point of maximized ROI (Ambler & Roberts, 2008).

2.2.2.2 Statistical approaches to marketing mix modeling

MMM is a powerful data-driven approach that enables businesses to evaluate the effectiveness of various marketing strategies and make informed decisions based on historical performance and projected outcomes (Cain, 2010; A. Kumar et al., 2020; Wedel & Kannan, 2016). In the past, these results have been achieved using various statistical approaches such as regression-based models, Bayesian models, econometric models, and time-series analysis (Cain, 2010, Chapter 4; Chan & Perry, 2017; Gatignon, 1993; Jin et al., 2017). The most common approach to MMM has been using regression (Chan & Perry, 2017). However, the Bayesian approach has recently become popular for MMM because it allows the model to deal with uncertainty in the model inputs and parameters (Jin et al., 2017). It is worth noting that these approaches can overlap, such as the Bayesian regression model used in this thesis.

The mentioned approaches differ in their utilization of MMM, yet they all strive to achieve one or more of the following potential results listed by Kumar et al.:

1. evaluating the past influence or effect of marketing actions
2. predicting the future impact that various marketing mix components can have on sales.
3. projecting the consequences of future strategies (2020).

The first area of focus is evaluating the past influence or effect of marketing actions. This provides insights into how different marketing strategies contribute to sales, allowing organizations to identify effective tactics and allocate resources efficiently. Assessing the impact of brand-related marketing efforts can be daunting for businesses with prolonged purchase cycles. The longer purchase cycles may require using adstock with smaller decay, which can lead to an accumulation of the marketing effect beyond reasonable numbers.

Shifting to the second point, historical data comes into play to predict the future impact various marketing mix components can have on sales. The MMM assumes all other factors remain constant. This means the model presumes conditions will continue as they have in the past unless instructed otherwise. Understanding the effects of diverse marketing actions, businesses can evaluate the value of their current marketing mix and make informed adjustments, such as reallocating resources between marketing channels, to achieve an optimal ROI.

Lastly, the third point focuses on projecting the consequences of future strategies. MMM can be employed to estimate the effect of strategic changes on sales. This functionality enables organizations to assess the feasibility of new marketing initiatives and make data-driven decisions. Ultimately, it helps optimize marketing efforts, maximize ROI, and foster growth.

The Bayesian approach utilized in this thesis, which is a statistical methodology grounded in the concept of probability, provides a way to incorporate prior knowledge and information into the model. Prior knowledge here refers to the initial assumptions or beliefs before new data is considered (McElreath, 2020, Chapter 2). This approach is helpful because it allows us to use what is already known when making predictions or testing hypotheses. For example, when tossing a coin, we know there is a 50% chance of getting heads because the coin has two sides. It also generates posterior distributions for the parameters, allowing for more informed decision-making and uncertainty quantification (McElreath, 2020, pp. 65–66). Posterior distributions are essentially the revised probabilities of our hypotheses after considering new data. In other words, they allow us to update our prior beliefs based on the evidence provided by the new data. In addition, Bayesian models can easily incorporate complex relationships between variables and handle missing or incomplete data (McElreath, 2020, Chapter 15), which is often the case with actual marketing data. These features make the Bayesian approach well-suited for marketing mix modeling, where there are often multiple sources of uncertainty and complexity in the relationships between marketing mix inputs and sales outcomes.

2.2.3 Weaknesses of marketing mix modeling

As discussed, MMM can be a valuable tool for organizations seeking to understand the impact of their marketing investments on sales performance. However, several inherent limitations must be acknowledged and considered when interpreting the results derived from MMM. This sub-section discusses some of these limitations, focusing on issues such as causality versus correlation, data limitations, attribution challenges, lack of granularity, and limited adaptability to fast-changing environments.

One fundamental limitation of MMM is the challenge of distinguishing between causality and correlation (Chan & Perry, 2017). While MMM estimates the correlations between marketing activities and sales outcomes, it is important not to assume that these relationships are causal automatically. Correlations may indicate a relationship between variables but do not guarantee causality. If confounding variables or external factors are not adequately accounted for, MMM might produce misleading conclusions, leading organizations to misinterpret the effectiveness of their marketing strategies (Rossi, 2014; Wedel & Kannan, 2016). This could, in action, mean that if two or more channels are frequently used similarly, for example, during marketing campaigns or have similar rolling budgets, they might cause equal sales. However, one channel could be responsible for nine of every ten sales. This phenomenon is known as multicollinearity, where two or more predictor variables are strongly associated (McElreath, 2020, Chapter 6.1). In this case, the marketing channels were used in a similar approach and, therefore, are strongly associated, making it hard to distinguish between each channel. Interpreting the results without considering the level of causality can lead to an incomplete or skewed understanding of the impact of individual marketing initiatives on sales performance. To overcome this limitation, organizations are encouraged to employ supplementary marketing analytics techniques to refine attribution and gain a more accurate picture of marketing effectiveness (Google, 2022).

Another concern with MMM is data limitations. The reliability and accuracy of MMM outputs are highly dependent on the quality and completeness of the input data (Chan & Perry, 2017). In cases where historical data used in the modeling process is limited, outdated, or inaccurate, the resulting insights may be unreliable or misleading (Ghasemaghaei et al., 2018). For many organizations, a prime example of historical data that may not accurately predict future trends is the data from the COVID-19 period. This unprecedented event altered customer behavior and temporarily compelled businesses to adapt their operating models, creating an anomaly in the data patterns (X. Li et al., 2022). Thus, organizations must ensure access to relevant, comprehensive, and accurate data to minimize the risk of drawing incorrect conclusions from their MMM analyses.

Furthermore, MMM generally operates at an aggregate level (Chan & Perry, 2017; Wedel & Kannan, 2016). This means that MMM analyses are not conducted on individual units, such as single transactions or customers, but rather on combined or grouped data. For example, it could look at total sales generated by different marketing channels over a specific period rather than focusing on each sale. By working on this aggregate level, MMM provides insights into the effectiveness of various marketing activities and their impact on broad business metrics. To address this limitation, organizations could consider employing other analytics tools and techniques besides MMM to analyze marketing performance at a more granular level and tailor their strategies accordingly.

By recognizing and addressing these limitations, organizations can ensure that they use MMM effectively and in conjunction with other marketing analytics tools to gain a comprehensive understanding of the effectiveness of their marketing efforts and make informed decisions on marketing resource allocation.

2.2.4 Summary of marketing mix modeling

This section discussed MMM, a data-driven approach for evaluating the effectiveness of various marketing strategies and making informed decisions. MMM originated in the 1960s and has evolved alongside the growth of digital marketing channels, advanced analytics tools, and the increasing recognition of empirical evidence in guiding marketing decisions. MMM uses historical data to model the relationships between marketing activities and sales performance. It involves three main steps: evaluating past marketing actions, predicting the future impact of marketing mix components on sales, and projecting the consequences of future strategies.

Adstock, decay effect, and diminishing returns play pivotal roles in understanding the impact of advertising campaigns and refining them to enhance the model's accuracy. Selecting appropriate values for each of these variables can significantly affect the outcome of the analysis.

While MMM presents an intriguing approach, it has inherent limitations. These include distinguishing causality from correlation, dealing with data limitations, addressing attribution challenges, handling the lack of granularity, and adapting to rapidly changing environments. To mitigate these limitations, organizations should consider implementing complementary marketing analytics techniques. Using MMM with these additional tools can help organizations leverage their marketing data and knowledge more fully.

2.3 Marketing organization

Although MMM is a valuable tool for understanding the connection between marketing inputs and outputs, it is not enough to fully grasp the factors contributing to a marketing organization's success. As mentioned earlier, the challenges in implementing new technologies often lie in organizational domains rather than technological ones. These complexities include change management, user resistance, project planning, and the project's intricacy, as Hughes et al. outlined (2017). These organizational challenges will be explored later in this section using the structure from the MARKORG framework (Moorman & Day, 2016).

The MARKORG framework extends a comprehensive view of the critical elements vital to the success of a marketing organization (Moorman & Day, 2016). It recognizes that organizations are complex systems composed of multiple components and that success in marketing requires a holistic approach that considers all these elements and their relationships. Interestingly, these elements resonate with what Davenport and Harris (2017) cite as the keys to fostering an analytics-driven competitive advantage, encompassing organizational structure, human resources, and technology (Davenport & Harris, 2017, p. 161). Consequently, the MARKORG model emerges as a foundational paradigm for marketing organizations aspiring to embed analytical and data-driven decision-making into their strategies to elevate performance.

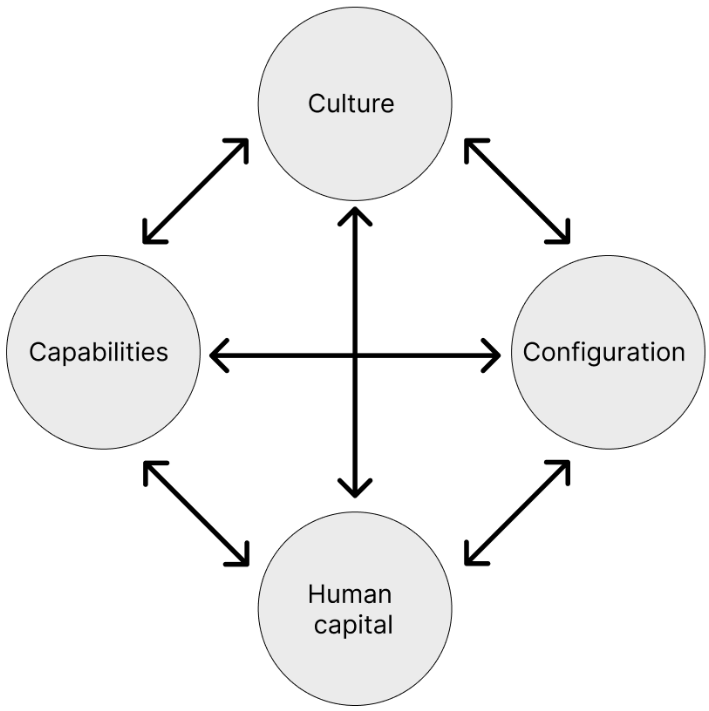

Figure 3 Four elements of marketing organization (MARKORG) as seen in Moorman & Day, 2016, p. 11

The four components of the MARKORG framework (Figure 3) are capabilities, configuration, human capital, and culture. The framework was created based on marketing and management journals from 1990 to 2015 (Moorman & Day, 2016). Capabilities represent an organization's skills and resources to perform its activities, including analytical capabilities and data processing skills. Configuration refers to an organization's systems, processes, and technology to support data-driven decision-making. Culture refers to the shared values, beliefs, attitudes, and behaviors that shape the organization and influence how it operates. Human capital encompasses the people within an organization, including managers and employees, who bring the necessary skills, knowledge, and expertise to support data-driven decision-making (Moorman & Day, 2016). The definitions used in the Moorman & Day (2016) are listed in the Table 2.

Table 2 Definitions of organizational components of the MARKGORG model

Capabilities	"marketing capabilities, which are the complex bundles of firm-level skills and knowledge that carry out marketing tasks and firm adaptation to marketplace changes." (Moorman & Day, 2016)
Configuration	"marketing configuration comprises the organizational structures, metrics, and incentives/control systems that shape marketing activities." (Moorman & Day, 2016, p. 6)
Culture	"the pattern of shared values and beliefs that help individuals understand organizational functioning and that provide norms for behavior" (Deshpandé and Webster 1989 as cited in Moorman & Day, 2016, p. 24)
Human capital	"marketing leaders and employees are the human capital that creates, implements, and evaluates a firm's strategy." (Moorman & Day, 2016, p. 6)

The remainder of this section will utilize these four components of the model as perspectives to evaluate their potential contributions to organizations striving to become data-driven.

2.3.1 Capabilities

The concept of capabilities in strategic management originated in the 1980s, notably influenced by Wernerfelt's work (Wernerfelt, 1984). Within this resource-based view, a firm's resources encompass both tangible assets and intangible capabilities. These elements are often cultivated slowly, becoming unique to the organization. The primary task of management within this framework is to ascertain the optimal ways to develop, leverage, and enhance these resources to secure a competitive advantage (Mikalef et al., 2018; Moorman & Day, 2016).

In marketing, this broad understanding of capabilities takes on specialized forms. The MARKORG framework emphasizes that a marketing organization's capabilities encompass the skills, knowledge, and expertise that enable the organization to plan, execute, and evaluate marketing activities effectively (Moorman & Day, 2016). According to Moorman and Day (2016), marketing capabilities can include various types, such as marketing sensing and knowledge management capabilities, relational capabilities, strategic marketing planning and implementation, and functional capabilities related to the marketing mix.

This thesis will precisely zoom in on an organization's analytical capabilities, which are fundamental to various abilities previously highlighted, including marketing sensing, knowledge management, marketing planning, and choosing the best marketing mix. Analytical capabilities encompass the competence to process, dissect, and reconfigure data, which allows for identifying patterns, extracting invaluable insights, and enhancing decision-making processes (Mikalef et al., 2018; Wu et al., 2020).

In the contemporary business landscape, the pertinence of these capabilities is becoming increasingly apparent. With the surge in data availability and volume, organizations globally are rapidly adopting data-driven approaches, a shift propelled by the expanding realm of analytics (V. Kumar et al., 2013; Wedel & Kannan, 2016). The reason for this shift is apparent: analyzing data is crucial to making well-informed, data-driven decisions, which can lead to improved performance outcomes (Hanssens & Pauwels, 2016; Johnson et al., 2021; V. Kumar et al., 2013).

This rapidly evolving field has led to a diverse range of analytics classifications. Whether web analytics (Chaffey & Patron, 2012), big data analytics (A. Kumar et al., 2020), or business analytics (Rikhardsson & Yigitbasioglu, 2018), the choice hinges on the data source, nature, and the specific application in view. Anchoring its primary focus on MMM implementation, this thesis will prioritize marketing analytics. As defined by Wedel and Kannan, this domain revolves around "the methods for measuring, analyzing, predicting, and managing marketing performance to maximize effectiveness and return on investment (ROI)." (p. 108).

2.3.1.1 Marketing Analytics

In modern marketing, the role of analytical capabilities cannot be understated. Central to the effective allocation of resources and amplification of marketing channels, they offer marketers unparalleled advantages on multiple fronts (Wedel & Kannan, 2016). Regarding advertising, analytical capabilities can strategically target specific audience groups with tailored messages (Branda et al., 2018; Hossain et al., 2023). This allows marketers to create ads that resonate deeply with their intended recipients. Furthermore, discerning the highest-performing channels will enable businesses to allocate resources strategically. This targeted approach ensures that efforts are directed towards avenues yielding the highest returns, enhancing efficiency and return on investment (Hanssens & Pauwels, 2016). Strategically, analytics can grant a comprehensive understanding of the market landscape. Companies can effectively identify potential opportunities and threats by closely monitoring market trends, analyzing competitors' strategies, and monitoring internal performance metrics (Wedel & Kannan, 2016). This vital data informs strategic planning, guiding decisions on market positioning and product or service differentiation (Wedel & Kannan, 2016). Companies are empowered to forecast market shifts by leveraging tools like predictive analytics and scenario planning (A. Kumar et al., 2020). By doing so, they can adapt strategies in advance, ensuring agility in a constantly evolving marketplace. These analytics applications go beyond traditional trial-and-error methods, enabling companies to quantify the success of their marketing efforts and refine their strategies based on concrete evidence (Wedel & Kannan, 2016).

2.3.1.2 Development of analytical capabilities

The cultivation of analytical capabilities requires diverse considerations and commitments from an organization. As highlighted previously, organizations typically progress from basic analytics to more advanced techniques like predictive and prescriptive analytics (Davenport & Harris, 2017). This transition entails consideration of technical facets — like data collection mechanisms, storage options, and analytical software — and organizational aspects, such as employee expertise, cultural shifts, and established processes (Davenport & Harris, 2017; Wedel & Kannan, 2016).

For data collection, decisions revolve around the systems chosen to collect data. This might involve tools like Google Analytics for web traffic data or CRM platforms like Salesforce that capture detailed customer interactions and preferences. When it comes to data storage, organizations decide whether to opt for traditional data warehouses or modern cloud-based storage solutions, ensuring data is readily accessible for analysis. The analytical tools chosen may vary based on the complexity of the analysis. While Excel may suffice for rudimentary analysis, intricate evaluations might necessitate specialized tools or coding languages like Python or R (Davenport & Harris, 2017; Wedel & Kannan, 2016).

On the organizational front, employee expertise is pivotal (Wedel & Kannan, 2016). The depth of an organization's analytical proficiency is often mirrored in its employees' skills. Building these skills might require internal training initiatives (Ghasemaghaei et al., 2018) or recruiting experts from outside the organization (Moorman & Day, 2016), which can be challenging due to the high demand of analytics professionals (Wedel & Kannan, 2016). As the field of analytics is ever-evolving, fostering a culture of continuous learning becomes imperative for organizations aiming to enhance their analytical prowess (Chatterjee et al., 2021). Furthermore, the broader organizational culture plays a significant role. By making data broadly accessible, organizations can embed data-driven decision-making into their operational culture (Wedel & Kannan, 2016). This promotes a culture of inquiry and encourages deeper data exploration, leading to richer insights (Chatterjee et al., 2021). Organizational processes are paramount, particularly those that guarantee data quality and traceability (Kwon et al., 2014). Implementing strict measures in these areas enhances confidence in the insights derived from the data.

2.3.2 Configuration

The configurations part of the MARKORG framework outlines the key elements of an organization's structure and how it operates. This includes the organization's structure, processes, and metrics, shaping its functions (Moorman & Day, 2016). These configurations help organizations measure performance, establish effective processes, and build a structured, efficient decision-making system.

They play an important role in ensuring the organization can reach its goals and are crucial for its success.

2.3.2.1 Structure

As Robbins and Judge (2022, Chapter 15) explain, a company's structure encompasses its reporting relationships, lines of authority, and allocation of responsibilities. This structure is crucial for coordinating work and breaking it down into smaller, manageable units, as Olson et al. (2005) note. Essentially, the structure serves as a roadmap for the company, outlining how information is shared, and decisions are made.

A common approach to structuring an organization is assembling modular operating units based on their roles and responsibilities (Lee et al., 2015). This helps to ensure that each department can focus on its specific area of expertise (Robbins & Judge, 2022, Chapter 15). The goal of this division is to reduce complexity and ensure tasks that are similar or related to the same objectives are grouped within the same sections of the organization (Lee et al., 2015). When tasks are allocated in this manner, each department of the organization can cultivate a specialization, which Lee et al. (2015) define as “the degree to which jobs in the organization require narrowly defined skills or expertise” (p. 77). In the context of a marketing organization, specialization could mean the division of brand and tactical marketing to their sub-units within the marketing organization. This enables organizations to have more specialized employees rather than generalists. Olson et al. (2005) observed that specialists are better equipped to navigate the challenges of fluctuating market conditions, ultimately enhancing the efficiency of organizations. This is because their roles are more clearly defined, reducing the requirement to focus on a broad range of skills in a rapidly changing environment.

In relation to the distribution of employees specialized in analytics, Grossman and Siegel (2014) identify three prevalent approaches to integrating an analytics function within an organization. The first approach is having employees with analytical capabilities in a specific analytics department. This approach can help the organization achieve the benefits of analytics with fewer analytical personnel (Wedel & Kannan, 2016). Additionally, analytical employees can benefit from knowledge sharing within their designated department. However, the downside of having an analytics department is that analytical personnel may be located too far from the business units and may not be familiar with the needs and specialties of each unit.

The second approach is to embed analytical employees within each business unit. While this approach may require more analytical personnel to serve all departments, the analysts are more familiar with their respective departments' needs and specialties. However, when all analysts are spread across different organizational departments, knowledge sharing can become more challenging, reducing the knowledge-sharing potential of the employees (Wedel & Kannan, 2016).

The third and last approach Grossman and Siegel (2014) suggest is a hybrid model. In this model, some analytical employees are located in centralized units, while other functional units have their designated analytics personnel. This can help an organization develop a knowledge unit from which analysts in specific business units can draw knowledge (Wedel & Kannan, 2016).

While these structural approaches primarily focus on employees with specialized analytical roles, it is pertinent to recall, as previously discussed, that contemporary marketing necessitates a baseline level of analytical insight for all marketers. This implies that each marketer should possess a fundamental skill set to interpret data and make informed decisions based on insights derived from analytical tools.

2.3.2.2 Processes

Organizational processes serve as a fundamental blueprint outlining the functional operations of an organization (Robbins & Judge, 2022, Chapter 15). These processes can be conceptualized as formal guides, providing employees with structured directions for completing their daily tasks (Lee et al., 2015; Robbins & Judge, 2022, Chapter 15). These processes encompass various activities, from routine operations to complex decision-making. Establishing clear, repeatable protocols ensures consistency, efficiency, and effectiveness in executing tasks. Moreover, well-defined processes facilitate coordination and communication within the organization, enabling teams to work synergistically towards common objectives. In essence, these processes are not just administrative tools but crucial elements that underpin the organization's operational integrity and strategic alignment (Robbins & Judge, 2022, Chapter 15).

A practical illustration of these organizational processes is the continual understanding of market and customer dynamics, which involves a series of steps beginning with data collection. This process encapsulates gathering relevant data from diverse sources such as web analytics or customer relation management system (CMS) and its analysis to extract meaningful insights. Such processes are crucial in marketing departments, where understanding consumer behavior and market trends directly influences strategic decisions (Wedel & Kannan, 2016).

The concept of formalization in these processes is essential. Formalization refers to the extent to which processes are standardized, documented, and integrated into the organizational framework (Robbins & Judge, 2022, Chapter 15). This formalization ensures that tasks are executed consistently and efficiently. For example, in marketing, a formalized process for campaign planning, from inception to execution, reduces inefficiencies and enhances the effectiveness of marketing efforts.

As Olson et al. (2005) highlights, process efficiency is significantly impacted by the organization's structure. Specialization, where the organization is divided into units with focused responsibilities, tends to enhance efficiency within these units. This is primarily because specialized units develop expertise and streamlined workflows for their specific tasks, leading to more efficient operations. This efficiency contrasts with the potential inefficiencies in units with a broader range of responsibilities, which may lack the same level of focus and expertise.

However, while specialization promotes efficiency and productivity, excessively narrowing job scopes can lead to negative consequences. Over-specialization can result in human diseconomies, such as boredom, stress, and fatigue. These factors can adversely affect productivity, quality of work, and job satisfaction and could even increase absenteeism and turnover rates (Robbins & Judge, 2022, Chapter 15). As a result, some experts suggest that broadening job responsibilities might enhance productivity by providing employees with opportunities for learning and a varied workday (Robbins & Judge, 2022, Chapter 15). This highlights the necessity of balancing specialization and generalization in organizational processes, ensuring that while efficiency and expertise are maximized, employee well-being and adaptability are not compromised.

2.3.2.3 Metrics

Decisions regarding organizational configurations, such as structure and processes, are crucial, but it is equally important to establish measures for assessing an organization's performance. Organizations need a set of relevant metrics or targets linked to various activities to evaluate performance. By choosing the right metrics, organizations can better understand their progress toward goals and the impact of their actions. In a marketing organization, key metrics often relate to marketing outcomes, such as Return on Investment (ROI), Customer Acquisition Cost (CAC), and Customer Lifetime Value (CLV), among others (V. Kumar et al., 2013; Wedel & Kannan, 2016). However, metrics concerning the organization, like job satisfaction and decision-making efficiency (Robbins & Judge, 2022, Chapters 3, 6), can also significantly influence the marketing organization's success. Enhanced organizational efficiency could lead to more effective creation and implementation of marketing strategies.

Furthermore, metrics offer an objective method for assessing and comparing the performance of different marketing activities. This helps organizations optimize their marketing strategies and achieve better results (Hanssens & Pauwels, 2016). For organizations aspiring to be data-driven, well-chosen metrics are indispensable, setting clear benchmarks for any analytical processes (Anderson, 2015, Chapter 6). Anderson (2015, Chapter 6) suggests that an effective metric should be both simple and standardized. This means selected metrics should be easy to explain to others and maintain consistency across the organization, thus preventing any ambiguity.

Effective data management becomes crucial to support these metrics. This involves collecting and systematically storing relevant data that can be analyzed in relation to these metrics. Effective data management is an indispensable component of a successful modern organization, as businesses nowadays hold large amounts of data on all aspects of their business (Sivarajah et al., 2017; Wiese, 2015, Chapter 1). This data forms the foundation for various operational activities and strategic decisions, particularly in organizations relying on data-driven approaches such as predictive statistical models (Sivarajah et al., 2017; Wiese, 2015, Chapter 1). Effective data management involves developing and implementing data collection, storage, cleaning, and maintenance protocols (Wiese, 2015, Chapter 1). It ensures the integrity and reliability of data, improving its accessibility and usability and significantly enhancing the organization's efficiency and productivity in utilizing these metrics.

2.3.3 Culture

Culture is the last of the four components in the MARKORG model. Culture refers to the shared values, beliefs, attitudes, and behaviors that shape the organization and influence how it operates (Moorman & Day, 2016; Warrick, 2017). In the MARKORG model context, culture is an integral cornerstone that profoundly impacts the organization's operations and decision-making processes. The underlying fabric binds the organization's members together, fostering a shared understanding guiding their actions and interactions (Moorman & Day, 2016; Robbins & Judge, 2022, Chapter 16).

In the context of data-driven culture, the value of culture is in improved performance caused by more accurate decisions based on insights gained from data analysis (Chatterjee et al., 2021; Kiron et al., 2012). Kiron et al. characterize data-driven culture as “a pattern of behavior and practices by a group of people who believe that having, understanding, and using certain kinds of data and information plays a crucial role in the success of their organizations” (2013, p. 18). This is in contrast to some other cultural approaches, such as customer-oriented culture, which can be defined as a focus on the customer’s needs and expectations to maximize business profits (Appiah-Adu & Singh, 1998), or market-oriented culture, which can be explained somewhat similarly but also considers how competitors actions and market trends affect the overall market (Gainer & Padanyi, 2005). However, these approaches are not mutually exclusive. Still, some nuances make a difference between the different cultural approaches in how the organization acts regarding patterns of beliefs, behaviors, and practices. For example, one could argue that a data-driven culture emphasizes collecting data to support decision-making and answer the needs and expectations of a customer. In contrast, customer or market-oriented cultures might not emphasize the actual data to support decisions on how to meet the customers’ needs and expectations.

The reason for any organization to desire to become data-driven is to improve decision-making and performance (Kiron et al., 2013). Research indicates that enhancing an organization's data-driven culture can leverage its analytical capabilities, improving overall performance and providing a competitive advantage (Kiron et al., 2012; Vidgen et al., 2017). Furthermore, van Rijmenam et al. (2019) found that data-driven organizations tend to be more agile than their counterparts. This agility, stemming from a robust data-driven culture, allows organizations to swiftly identify and react to potential threats and navigate through unprecedented events (Van Rijmenam et al., 2019). Relying on data for decision-making processes can lead to more accurate and insightful conclusions, enhancing strategic foresight and operational efficiency (Kiron et al., 2012; Vidgen et al., 2017).

2.3.4 Human capital

As mentioned, when integrating technology and data into organizations, many assume the most significant challenge lies in the technological domain. However, Chaffey and Patron (2012) highlight that the more substantial obstacles often pertain to human factors – specifically, the roles and dynamics of people, structures, and organizational processes. This perspective, echoed by Gonzalez and Melo (2017) and Wedel and Kannan (2016), underscores the pivotal impact of individual roles and responsibilities on an organization's effective utilization of data in marketing. To thoroughly explore these dynamics, this section is systematically divided into two critical subsections: one focusing on employees and the other on managers. Such a bifurcation enables a more detailed and nuanced examination of both groups' distinct yet interconnected contributions to the organization's overarching functionality in the context of data-driven marketing.

2.3.4.1 Managers

The role of managers in implementing new initiatives is crucial to an organization's success. Research by Branda et al. (2018), along with insights from Davenport and Harris's book, (2017) demonstrates that managerial support is critical for the successful adoption and integration of organizational changes. This backing from management significantly enhances the likelihood that new initiatives, such as data-driven culture, will be embraced and effectively implemented across the organization. With their unique organizational perspective, managers are pivotal in identifying and leveraging innovative opportunities and tools for growth while safeguarding against inefficiencies that might deplete resources from more compelling opportunities (Moorman & Day, 2016).

Building on the fundamental role of managers in initiating and supporting organizational changes, their influence is particularly profound in steering an organization toward a data-driven culture. Managers act as catalysts in this transformation, promoting the adoption of data analytics and fostering an environment where data-driven decision-making becomes the norm (Ghasemaghaei et al., 2018; Wedel & Kannan, 2016).

For instance, managers can exemplify the importance of data-driven decision-making by consistently requesting that suggestions and proposals be substantiated with data and analysis. This practice highlights the practical benefits and value of data-driven insights and sets a standard for the team, encouraging them to incorporate similar practices in their work. In addition to leading by example, managers can support this culture shift by organizing training sessions and workshops. As noted by Waller and Fawcett (2013), these educational initiatives are instrumental in enhancing team members' data literacy, equipping them with the necessary skills to understand and utilize data in their roles effectively.

Another key aspect is creating a supportive environment that encourages experimentation and learning (Gonzalez & Melo, 2017). Managers can foster a culture where employees feel comfortable using data to explore new ideas, even if it means encountering occasional failures. This approach builds confidence in using data and stimulates innovation within the organization (Wu et al., 2020).

2.3.4.2 Employees

Compared to managers, employees play different types of roles in organizations. While managers are responsible for strategy development and oversight, employees are tasked with the operational execution of these strategies. The efficacy of their contribution is influenced by a range of factors, including their individual experience, skillset, and the level of support and guidance they receive from management. This distinction is particularly crucial in data-driven environments, where the success of initiatives often hinges on the practical application of strategies by skilled employees.

Organizations typically have two approaches to acquiring the talent necessary for making data-driven decisions: hiring new employees with the requisite skills or training existing staff. However, as noted by Ghasemaghaei et al. (2018) and Wedel & Kannan (2016), there is a notable challenge in hiring employees with the necessary blend of domain expertise and analytical skills. This challenge is intensified by an increasing demand for analytical capabilities, which has led to a scarcity of readily available talent (Branda et al., 2018; Davenport & Harris, 2017). Wedel and Kannan (2016) note an educational gap, particularly in marketing analytics. Marketing students often lack deep analytical training, whereas students from more quantitative disciplines like mathematics or econometrics might not have sufficient marketing knowledge. As a result, many organizations find themselves needing to invest in training their existing workforce to bridge this analytics skill gap. This process can be more time-consuming than hiring, but it is necessary for building a competent data-driven team (Branda et al., 2018).

Transitioning to a data-driven culture extends beyond merely acquiring new skills; it necessitates a profound cultural shift throughout the organization. This shift entails creating an environment where data is not just readily accessible but also forms the cornerstone of all decision-making processes (Wedel & Kannan, 2016). It demands a move away from intuition-based decisions to those grounded in data-driven insights. To achieve this, organizational culture must embrace continual learning, openness to change, and a commitment to using data effectively (V. Kumar et al., 2013). Schein (2016, Chapter 17) echoes this sentiment, highlighting the importance of commitment to learning and openness to change as crucial attributes for a thriving organizational culture. Thus, the ability of an organization to learn and adapt to a changing environment becomes a pivotal attribute that its employees should embody, underpinning the successful transition to a data-centric operational culture.

However, cultural change often encounters resistance (Dent & Goldberg, 1999; Grama & Todericiu, 2016). Employees may be wary of new processes that challenge their established ways of working. Concerns about job security or fear of the unknown can also contribute to resistance (Grama & Todericiu, 2016). To ease this cultural change within organizations, Schein (2016, Chapter 16) emphasizes the importance of defining specific behavioral goals rather than vaguely aiming for "culture change." He posits that the assimilation of new cultural elements occurs gradually through consistently practicing successful and fulfilling behaviors. Schein notes that a shift in the fundamental beliefs of a culture often requires individuals to unlearn their previous convictions, a process that can be emotionally challenging. He acknowledges the inherent anxiety linked with acquiring new knowledge and behaviors, underscoring that, while necessary, transformative change is seldom a straightforward or effortless journey. This perspective highlights the complexity of cultural transformation and the need for deliberate, focused efforts in guiding and supporting individuals through the process. Erwin and Garman (2010) noted that to mitigate resistance, it is essential to have clear and consistent communication about the benefits of the change. This includes not just business benefits but also personal growth opportunities for employees. Involving employees in the transition process, seeking input, and addressing their concerns can help alleviate resistance. It is essential that employees see the transition as a positive evolution of the organization that also supports their personal and professional development.

2.4 Literature review summary

As learned in this section, organizations are complex bundles of systems, structures, processes, people, and cultures that work together to achieve the organization's goals and objectives. This literature review aimed to understand common analytical approaches, MMM, and organizations to understand how organizations work and build the foundation to conduct analytics to help make decisions.

Besides building an understanding of the organizations, one of the main points of inspection of this literature review was understanding different approaches to analyzing data. Delen and Ram (2018) illustrated (Figure 1) in their study that there are four different types of analyses: descriptive, diagnostical, predictive, and prescriptive. While the complexity increases, the questions that can be answered move from the past toward predicting what will happen and even testing how different decisions might affect the outcome. Their work demonstrates that complexity can bring higher added value from the analyses. The complexity of MMM is closely related to the higher value. While the simple methods of extracting attribution of different marketing actions can often be gained by using last-click attribution from web analytics, the last-click attribution model does not give any credit for the steps that might have happened before (Frambach et al., 2007; Gensler et al., 2012; Kannan et al., 2016). Therefore, MMM's complexity can potentially deliver higher added value as described in Figure 1.

If anything, the MMM can be described as a complex analysis tool. It draws signal strength of the marketing effect from historical data to model what happened, what will happen, and what could happen. These signals can be small and, therefore, hard to comprehend without extensive calculations.

However, the value can be high as the modeling practice can produce results that can help the marketing team make more justifiable decisions (Wedel & Kannan, 2016).

The path to achieving a higher level of added value from analytics demands efforts in elevating the underlying organizations attributes to support a higher level of analytical complexity. Davenport and Harris (2017, Chapter 6) listed insights into performance drives, performance management, process redesign, leadership and executive commitment, fact-based culture, and securing the correct skill for the organization to improve its analytical capabilities. These elements are discussed in the literature review through the lens of the Moorman and Day (2016) MARKORG framework, which focuses on the qualities of the marketing organization. As shown in Figure 3, all these organizational attributes are interconnected to each other. The idea behind these connections is that each of these pillars supports each other. Specific culture led to certain approaches to working. At the same time, the capabilities of the people can again affect the culture and approaches to problem-solving can then again change the culture and processes. The optimal decision between focusing on these pillars depends on business strategy and goals (Olson et al., 2005), but as described, each is equally important in developing analytical capabilities. After all, the promise of the added value from the more complex analyses is built on top of the foundation of solid organizational attributes that support the analytical people, culture, processes, and capabilities.

However, the literature review did not discuss a critical topic regarding the research question. Why do IT projects fail? It was mentioned earlier that the challenges regarding implementing technological tools are organizational rather than technological (Davenport & Harris, 2017; Gonzalez & Melo, 2017; Hughes et al., 2017; Lavalle et al., 2012; Wedel & Kannan, 2016). Shepherd et al. define project failure as “Project failure occurs when a project's activities cease due to unsatisfactory or insufficient progress” (2009, p. 589). Hughes et al. (2017) list a range of reasons for project failures, spanning across various organizational themes, hence the decision to address this topic towards the end of the literature review. One common theme identified is the array of management issues related to project planning, such as establishing a business case, conducting evaluations, goal setting, resource allocation, and project support. These elements are critical as they lay the groundwork for project success, and their mismanagement can lead to project failure.

Moreover, Hughes et al. (2017) found that in some instances, projects failed because they were too large or complex for the organization undertaking them. This ties back to the discussion on organizational capabilities, highlighting the importance of assessing an organization's capacity to handle complex analyses and projects. The organization's ability to manage the scale and complexity of a project is vital for successful implementation, and failure to do so can be a significant contributing factor to project failure.

Additionally, Hughes et al. (2017) noted that in some cases of project failure, there had been insufficient effort to understand the reasons behind these failures. Learning from past failures is critical in enhancing an organization's capability to complete future projects successfully. This observation underscores the rationale for the mixed-method approach used in this thesis, where the initial phase includes research into why the initial attempt to implement MMM was unsuccessful. By understanding the specific reasons behind the failure of the previous MMM implementation, the study aims to provide insights that can guide more successful future implementations in the case organization and, more broadly, similar organizational contexts.

3 DATA AND METHODOLOGY

This section explains the methodological approach utilized in the thesis. It begins with an introduction to the case organization and the associated industry. Subsequently, the research methods employed for the study are introduced, followed by an outline of the research design. The section concludes with an account of the data used in the quantitative portion of the study.

3.1 Case organization

The case organization in this research is one of the leading private healthcare firms operating in Finland and Sweden. The organization's main operations segments are occupational healthcare, general healthcare, and specialist healthcare, which consist of different services such as dental, pediatrics, gynecology, and psychology services.

The case organization has placed a strong emphasis on digitalizing healthcare. This includes introducing innovative methods for connecting patients with specialists through digital platforms, enabling service delivery independent of location. Given the firm's significant focus on digital tools and development, it presents an ideal setting for examining the implementation of MMM. This approach could significantly transform the organization's marketing functions, particularly planning and budgeting. Furthermore, the organization has previously attempted to outsource the MMM solution without success. This history provides a valuable context for exploring the reasons behind the project's failure and identifying potential approaches to rectify these shortcomings in future implementations.

The company's business-to-consumer (B2C) marketing function is divided into two specialized units, which actively work on dental healthcare-related marketing and sales. Given the complexities of the extended purchase cycle, this decision was made to improve efficiency and better allocate resources. The first unit is responsible for branding and increasing the company's visibility. Its primary objective is to generate awareness amongst potential customers at the top of the sales funnel. This is essential for creating a solid brand presence and increasing the number of leads entering the funnel.

The second unit, the digital sales team, converts prospects into customers. This is achieved by focusing on the bottom of the sales funnel and utilizing various digital marketing tools and tactics, such as email marketing, social media, and retargeting. The purchase cycle is often lengthy, so prospects require careful nurturing on their journey toward conversions. Therefore, having a dedicated team with a deep understanding of the customer journey is essential for success.

The marketing organization consists of four hierarchical levels. At the top level, a director oversees the overall marketing and sales of the private customer segment. This director sets the overall strategy for the marketing function, ensuring that it aligns with the company's broader goals and objectives.

The second level of the organizational structure comprises directors responsible for either marketing or sales functions. These directors work collaboratively with each other and the top-level director to establish the strategic direction for private customer marketing and sales activities. Multiple teams are dedicated to a specific marketing or sales area within each function. These teams may have distinct focuses, such as directly increasing sales or enhancing marketing strategies by refining existing tools. The team-oriented structure enables specialized attention to different aspects of marketing and sales, allowing for targeted efforts and specialized expertise within the organization.

Each team is led by a marketing or sales manager, who guides its focus and ensures its activities align with the broader organizational objectives. Finally, multiple marketing specialists are responsible for creating and executing campaigns at a tactical level. They work closely with the managers and directors to ensure that their activities support the overall strategy and direction of the marketing function.

3.2 Research method and design

This thesis applies a mixed-method research design using qualitative and quantitative methods to answer research questions. Mixed methods are appropriate research methods when the researched topic requires an explorative understanding of the problem in qualitative research to construct quantitative elements to answer the correct problems. The benefits of using a mixed method approach to answer research questions are that using both qualitative and quantitative methods helps to overcome the weaknesses of the other research type by providing different kinds of results. While interviewing would only reveal the interviewee's views on the topic, supporting that knowledge with other research methods can help the researcher understand the topic objectively (McKim, 2017; Saunders et al., 2019, p. 181).

According to Saunders et al. (2019, pp. 183–184), the balance of qualitative and quantitative research methods may vary in a study, so one methodology can have a dominant role. In contrast, depending on the desired results, the other has a more supportive role in the study. Due to the research design of this study, which will have two rounds of interviews, the balance of methods will be more towards qualitative methods as the study aims to understand organizations' challenges with the new processes.

The research design of this thesis adheres to a sequential exploratory research approach, partitioned into three distinct sections. An exploratory research design typically entails qualitative research as a precursor to quantitative research—qualitative research functions to delve into and enhance understanding of the problem prior to undertaking a quantitative study. Notably, the design of this study integrates additional qualitative elements after the quantitative study. Including these additional qualitative aspects at the culmination of the study facilitates a comparison of the situation and processes both before and after conducting marketing mix modeling experimentation (Saunders et al., 2019, pp. 182–183).

Following the design presented, the first part is a qualitative study that consists of semi-structured interviews of marketing managers and specialists who oversee and plan dental healthcare marketing. The first phase of interviews aims to understand the challenges and problems present during the initial attempt to implement MMM as part of the marketing planning process. This part will help answer why modeling was not integrated into the marketing decision-making.

Insights gleaned from the initial segment of the study will serve as a foundation for an attempt to formulate a prototype of a marketing mix model. This model aims to surmount the shortcomings identified in the prior modeling endeavor. The model's input will encompass marketing expenditure across diverse channels over previous years, aggregated into weekly increments. The output will propose an allocation of spending across each platform to maximize sales.

In the concluding section of the study, another round of semi-structured interviews will be conducted with marketing managers responsible for planning and budgeting marketing initiatives. These discussions will focus on the implications of the newly developed model, their previous challenges with marketing mix modeling, as revealed in the initial interviews, and whether the marketing mix modeling executed in this study has addressed those challenges. A primary concern will be determining whether the model's suggested actions contribute substantial value to the planning and budgeting processes in marketing.

3.3 Qualitative research

This section outlines the methodology for collecting and analyzing the qualitative data utilized in this study. The qualitative research was undertaken in an exploratory manner to comprehend the organization's challenges in its previous attempts at implementing MMM. These insights form the basis for the quantitative modeling part of the thesis. Additionally, the interviews serve a dual purpose by identifying issues and assessing the credibility and applicability of the model's results. Integrating these two research approaches provides a more nuanced understanding of the complexities of implementing MMM within the organizational context.

3.3.1 Qualitative data collection and the interview process

Two rounds of interviews were conducted for the qualitative section of the thesis. Research interviews can be divided into unstructured, semi-structured, or structured. Unstructured or semi-structured interviews are good when the researcher aims to conduct exploratory research on a topic because they allow the interviewer to freely change the interview flow based on the interviewer's intuition of the interviewing situation. In a semi-structured interview, the interviewer uses a set of pre-prepared questions as a roadmap for the conversation. This approach provides a structured framework for the interview while allowing for some flexibility in the flow of the discussion. The interviewer is free to change the order of the questions, delve deeper into any topics that arise during the discussion, and adjust the line of inquiry based on the interviewee's responses. The semi-structured format allows for a more natural and dynamic exchange of information, as opposed to a strictly structured interview where the interviewer is limited to a predetermined set of questions. This type of interview is particularly useful in gathering qualitative data, as it allows the interviewer to respond to the nuances and complexities of the interviewee's responses (Saunders et al., 2019, Chapter 10).

The first round took place early in the process to investigate the factors that caused the unsuccessful implementation of MMM. The second round followed simulations conducted on marketing data using the lightweightMMM library. This round aimed to deepen the understanding of the organization's functioning and gather impressions on the simulation results.

The first interview phase of this thesis started in December 2022 and was finalized at the beginning of February 2023. All four interviewed marketing organization members were in the organization and at least partially involved in the earlier attempt to include MMM in the marketing planning process. The second interview phase was done in May and included three interviewees from the first round and one new interviewee who was not present during the first attempt to implement MMM. The new interviewees did not participate in MMM's initial implementation attempt but were chosen for interviews based on their role in the organization. A list of interviews and interviewees' roles are presented in Table 3.

Table 3 List of interviews

Interviewee	Title	Duration	Date
Person A (pilot interview)	Sales manager	29:25	13.12.2022
Person B	Marketing Coordinator	32:03	03.01.2023
Person C	Director	43:10	17.1.2023
Person D	Sales manager	21:25	8.2.2023
Person A	Sales manager	57:26	19.5.2023
Person B	Marketing Coordinator	56:13	19.5.2023
Person C	Director	42:23	22.5.2023
Person E	Digital sales specialist	39:31	17.5.2023

The thesis was a research contract for the case organization, so the interviewees were contacted using internal channels. Interviewees gained a high-level list of themes (appendix 1) to be discussed in the interview to prepare interviewees with the interview themes. Interviewees did not have to do any further preparation for the interviews. Interviews were conducted via Teams, which allowed the interviewer and interviewees to be more flexible with the scheduling and enabled the easy recording of the interviews.

The one-to-one interviews were guided by a set of pre-defined questions that guided the semi-structured interview. This ensured that the interview process could move fluidly through the questions and options for diving deeper into specific topics and uncovering new areas of interest. The semi-structured interview style allowed the interview to proceed conversationally. Some of the questions were not asked in some interviews, as they were answered naturally during the earlier questions.

The interviews started with a warm-up question about the interviewees' responsibilities within the organization. This established a more concrete base for the viewpoint of the follow-up questions during the interview. The interviews then moved to organizational questions that aimed to understand the current structure and processes of the case organization. After establishing the organization's current state, the interview proceeded to the third part, which consisted of MMM-related questions. The part began with the exploration of the past modeling process to uncover what kind of problems the organization faced with the previous attempt. The final part ended with questions that aimed to understand how interviewees describe MMM and what kind of results they expect from the model.

The pilot interview had an exploratory nature early in the thesis process, and its underlying task was to help steer the theoretical framework of the thesis and to gain an initial understanding of the organization and events during the first modeling process. The structure of the pilot interview consisted of three more significant questions that guided the flow of the interview:

- What is the structure of the marketing organization?
- What were the problems with the last attempt to do marketing mix modeling?
- What kind of results should the model give for it to be useful?

The pilot interview helped narrow this thesis's focus to organizational aspects of the MARKORG model. In addition, the interview structure was incremented by new questions concerning the process of creating marketing campaigns from the idea to action and the interviewees' idea of what the goal of MMM is (Appendix 1). This follows the Gioia approach, where interviews help to transform the direction of the follow-up interviews (Gioia et al., 2013).

Following each interview, I did an initial analysis based on the participants' most notable and immediate thoughts. Subsequently, the audio recordings from the interviews were submitted to Words online transcription tool, which generated preliminary transcriptions that were then corrected by hand. Transcriptions from the first round of interviews resulted in 31 pages across four interviews. In contrast, the second round produced 62 pages of transcripts from four interviews.

3.3.2 Interview data analysis

This thesis adopts an exploratory design, and the analysis of interviews was conducted iteratively during the data collection phase. This approach is consistent with the interdependent and iterative relationship between data collection and data analysis in qualitative research, where data analysis informs and is informed by data collection strategies (Saunders et al., 2019, p. 640). The Gioia method was employed for the analysis. In the method outlined by Gioia (2013), content analysis is performed by initially categorizing the most basic concepts found in the data into broader, coherent themes and subsequently organizing these themes into overarching dimensions to develop new theoretical models and frameworks. However, the methodology applied in this thesis differs from Gioia's approach in that it does not aim to create new models or frameworks. Instead, the interview process directed the research toward pre-existing marketing organization theories integrated into this thesis.

In the first round of the coding process, printed interview transcripts were used to identify and highlight significant passages, which were then transferred to an Excel spreadsheet for later analysis. During this preliminary phase, the interviews were segmented according to the questions addressed by the interviewees. When a single transcript segment contained answers to multiple questions, all relevant questions were highlighted and appropriately marked. This initial coding stage also emphasized parts of the transcript deemed noteworthy, either because they correlated with the four elements of the MARKORG model or due to their connection to technical challenges or aspirations articulated by the interviewee.

During the second coding phase, the interviews were revisited, and the highlighted passages were systematically transferred to an Excel spreadsheet and categorized according to their thematic relevance. When a passage aligned with multiple categories, additional color-coded cells were employed to establish connections between these relevant categories, ensuring a comprehensive and accurate representation of the data. The resulting data structure is illustrated in Figure 4.

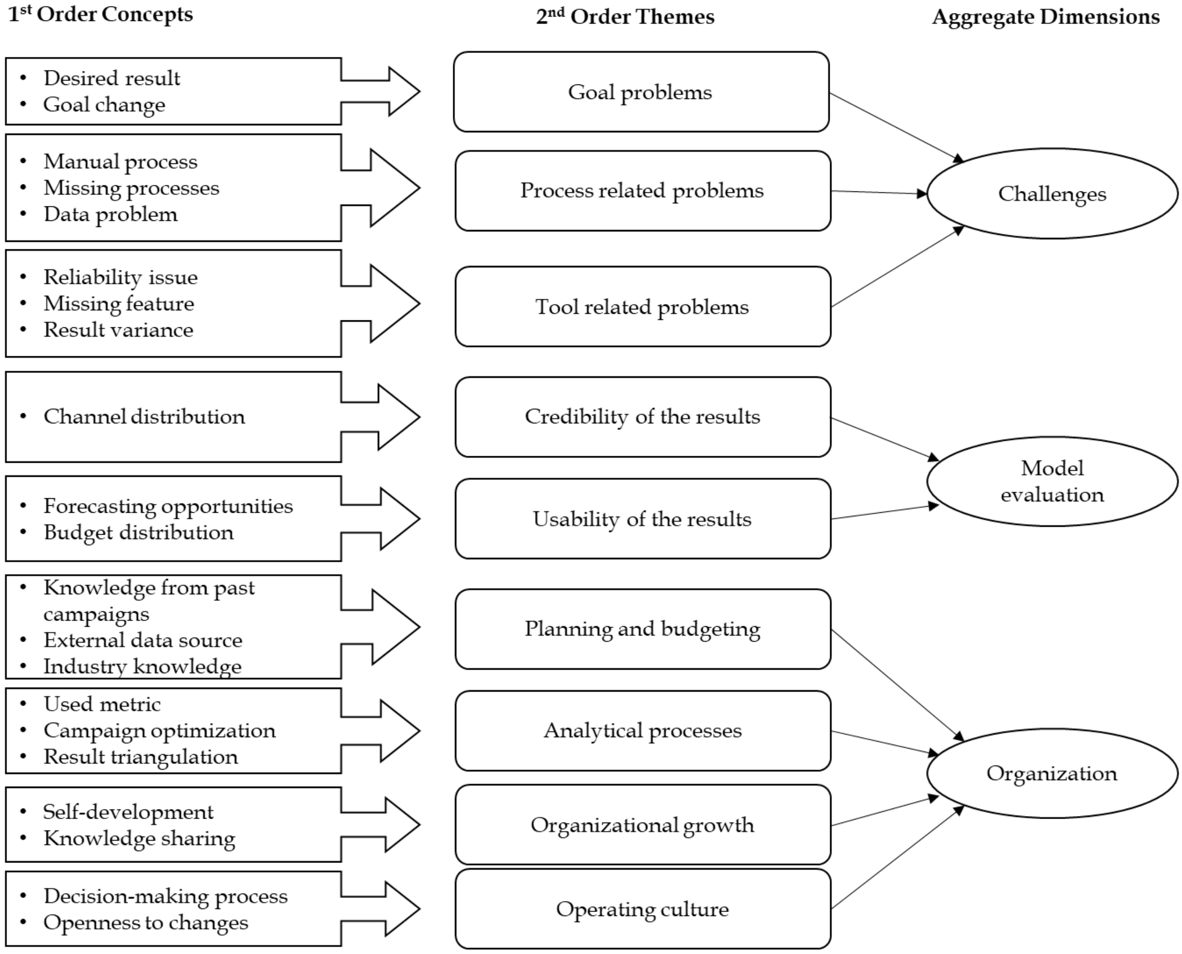

Figure 4 Interview data structure

3.4 Quantitative research

This section details the data acquisition process for the thesis's modeling component and introduces the specific model used. The modeling portion of the thesis was conducted to test whether the challenges faced by the case company during the initial implementation could be overcome. Additionally, the research aimed to identify potential areas for further evaluation that the case company should consider when implementing MMM. This examination is instrumental in understanding the opportunities and obstacles associated with effectively utilizing MMM within the organization.

3.4.1 Data for marketing mix modeling

In order to conduct a reliable and accurate MMM, it is generally necessary to gather data spanning multiple channels and several years with a sufficiently high level of expenditure. However, the organization in question has opted to conduct a smaller-scale MMM focusing exclusively on dental services. While the organization has engaged in dental-specific marketing on various platforms since 2011, it has only recently expanded to new channels. Unfortunately, data from multiple platforms was not stored in the organization's database and was lost due to the platforms' data retention policies, resulting in less than two years of complete marketing data being available starting from March 2021.

The dependent variable for this modeling process is defined as new dental appointments, or "sales," which are viewed as initiating a patient's dental care path. The booking data was located in the internal database. The database for booking data had a wide variety of columns that provided additional information on the patients and whether the booking happened, was canceled, or was moved. However, only some columns were relevant to counting the number of care path starting bookings. Columns queried were patient ID, creation date, booking start time, and row indicating whether the booking was made or canceled. The query was done starting from the end of 2020, which is earlier than available marketing data, and ending in early 2023 to balance the initial higher number of "new" bookings due to the start of the calculation. The query resulted in 965 807 rows of data.

The independent variables for the model include marketing channel data and Finnish holidays. As mentioned earlier, the marketing data was only available from March 2021. The marketing data was queried using SQL from the database. The marketing data in the database consisted of information from three different channels. The database for marketing data included daily data on digital marketing platforms for all the different fields in which the case organization operates, and the first task was to query only rows corresponding to dental marketing. The whole digital dental marketing dataset consisted of 7 134 rows of data. The marketing data in the database was augmented with extra columns created based on the naming structure of the campaigns. However, the automated process had not been able to fill in all the information for all rows due to the different naming structures in some cases. Due to that, the empty rows were filled during the data cleaning process. While MMM can model marketing actions that are not digital, the dental care industry did not have any recorded offline marketing campaigns during the period in which the organization had data for the digital platforms. Therefore, the modeling was conducted solely based on digital platform data.

The Finnish holiday data was obtained using Python from the Bank of Finland's open data API. The inclusion of holiday data in the model is based on evidence indicating that dental appointments tend to be lower during holiday periods. Therefore, if the week contains fewer than five normal working days, it is likely that dental bookings will be lower. The holiday data was collected for the period spanning from the beginning of 2021 to the end of 2023, which resulted in 1 095 rows of daily data.

After all, data was fetched from the databases and the API and cleaned using Pythons Pandas library. Pandas' library allows the user to input data into data frames and perform operations such as joining multiple data frames together, dropping rows or columns, and filtering data.

First, the marketing data was divided into channel-based data frames to fill the empty columns, such as the brand or tactical column, based on the campaign's name or other indicators in the other columns. After every row had a brand or tactical identifier, the channels' marketing rows were divided into brand and tactical data frames. The idea behind the division was to handle different types of marketing spending differently so that, for example, brand marketing campaigns should have a different kind of marketing effect than tactical marketing.

After each channel's marketing was divided into branded and tactical, the various campaigns run on the same days were grouped, resulting in a single row for each day, and other columns besides the date and spend were dropped. At that point, the visualizations revealed that some channels, such as Google Ads, did not have any brand-related marketing, making its effect insignificant. In these cases, brand marketing spending was combined with tactical marketing spend.

The booking data was queried from the database without any aggregation or selection beside the relevant columns. For the process of modeling sales, the only relevant booking is the one that starts the dental care path. Marketing would not influence the follow-up bookings booked on the spot for the customer. The challenge with determining whether a booking is a new or a follow-up is that there is no static measurement of what constitutes the end of the care path. To simplify the creation of bookings per day data, it was decided that each patient's care path would be completed within 60 days of the booked date.

It is important to note that the appointment timing is determined based on when the patient makes the booking rather than the date of the dental visit, where the 60 days were calculated. This distinction is crucial because the model's objective is to forecast sales that can be directly attributed to marketing initiatives. Therefore, if a patient schedules a dental appointment for the following month, it is inferred that the marketing efforts influenced the actual booking rather than the scheduled date of the dental visit. This approach also excludes follow-up bookings more efficiently than if 60 days were counted from the booking date.

While cleaning the data, it was revealed that some rows had an earlier start time than the row creation date. The analysis revealed that some rows were created days after the actual visit. It seems that most of the rows created after the visit were done within three days of the actual visit. However, some rows were created much later, so it is unclear why this was the case. It is suspected that these rows were created to make a note of the past. In any case, these rows only accounted for 0.01% (105 rows) of all rows and were therefore not deemed significant for the results. As a result, they were removed for the sake of clarity. After the defined follow-up bookings were removed, the dataset had 475 260 rows. In the end, booking data was aggregated into daily bookings based on the booking date.

After all, the data frames were cleaned and cut from beginning to end based on the dates of the shortest data frame, digital marketing. Besides that, the marketing data was available from March of 2021. Due to the changes in the goals of the marketing function, there was no marketing spending on dental from the beginning of 2023. This resulted in every dataset being set to begin from 19.3.2021, even if they had data from the preceding time and ended on 31.12.2022.

As a last matter, the daily data was aggregated to weekly data as it was the default setting for the modeling framework. The beginning date for data was changed to 22.3.2021 only to include full weeks in the final dataset. The final dataset for the modeling consisted of weekly columns, bookings per week, each channel's brand and tactical spending, and the number of holidays. A full list of different types of data and their source is presented in Table 4.

Table 4 Sources of modeling data

Data	**Source**
Booking	Internal database
Marketing	Internal database
Extra features (holidays)	Bank of Finland’s open API

3.4.2 Modeling

The MMM simulations were conducted to assess the feasibility of MMM in the context of the case organization. These simulations utilized the marketing data of the case company to evaluate whether the model could produce reliable results and accurately attribute the impact of various marketing channels. The aim was to determine if the model could provide plausible insights into the effectiveness of different marketing strategies and their associated channels. By performing these simulations, the study aimed to gauge the suitability and potential of MMM as an analytical tool within the context of the case organization.

Simulations were done using Google's open-source marketing mix model called LightweightMMM. The LightweightMMM is a Bayesian MMM library built with Python. The library offers users a simple and efficient approach to training MMMs and obtaining channel attribution insights. In addition, the library has an array of advanced features, such as geo-level modeling, media allocation optimization, and graph visualization tools that can deliver insights visually (Duque et al., 2022).

Among the available options in lightweightMMM, three types of adstocks can be used: carryover, adstock, and hill adstock. These approaches involve distinct mathematical formulas that assign varying weights to lag and decay effects within the model. The adstock is an integral part of the MMM because it helps to determine the lag and length of the marketing impact in the model. Without adstock, the model would treat marketing actions as simple on/off events, thereby failing to account for the lasting impact these actions can have on customers. A more detailed description of different adstocks in the package is explained next in the text, while the mathematical description of the chosen model is shown in section 4.2.1.

The carryover model considers the influence of past marketing activities on the current period. Essentially, it applies a decay rate to the effect of marketing and factors in diminishing returns based on the amount spent on each marketing channel. Differing from the carryover model, the adstock model incorporates a recursive function. This means it acknowledges past marketing actions, factors in current marketing activity, and a portion of the past's adstocked marketing activity. The amount of adstock carried over is determined by the decay rate, and like the carryover model, the adstock model also includes parameters for diminished returns. The third and last option in the package is hill adstock. The Hill adstock model introduces an additional layer of complexity by using a hill function instead of a power law. A hill function is a type of sigmoid function that starts slowly, accelerates in the middle, and then decelerates. This characteristic allows more flexibility in modeling the diminishing returns of media investments. The carryover advertising calculation in the hill adstock model is similar to the adstock model, as it, too, uses a recursive function (Duque et al., 2022).

4 RESULTS

This section introduces the results derived from the combination of expert interviews and MMM in answering the research question: "What are the challenges of implementing marketing mix modeling in an organization, and how might they be addressed?" The study's findings are not confined to elucidating the challenges within the organization itself but extend to uncovering specific difficulties associated with MMM. By integrating the qualitative insights obtained from in-depth interviews with case company experts and the quantitative results obtained through robust modeling techniques, this section crafts a cohesive and comprehensive response to the research question posed. The subsequent sections will systematically detail the findings, weaving together the narrative insights and empirical evidence to offer a detailed understanding of the challenges and potential pathways to address them in the context of MMM implementation.

4.1 Case company's earlier challenges with the marketing mix modeling

The findings from the first-round interviews align with previous literature on the causes of failures in IT projects. It is commonly observed that the challenges faced in projects are often associated with organizational factors rather than technical solutions (Davenport & Harris, 2017; Gonzalez & Melo, 2017; Lavalle et al., 2012; Wedel & Kannan, 2016). This tendency is understandable, given that in the case of MMM, the entire process and outcomes heavily rely on the organization's understanding of the business and the data available for modeling.

The interviewees emphasized a significant challenge related to the manual work involved in various steps of the process. Specifically, naming the campaigns emerged as a crucial step to ensure the partner company's understanding of the relationship and type of each campaign conducted by the case organization. For instance, the previous modeling necessitated a specific naming style for each campaign and ad group, resulting in a need for everyone in the organization to adjust their working processes accordingly to accommodate the new naming procedure. Interviewee B expressed this issue, stating,

> **"The data input relied too much on manual work. Whenever new personnel came in, campaigns were marked in different ways, and all of them had to be reviewed every few months."**

Additionally, interviewee A pointed out that the internal resources were not on par with what would have been required to make the model more successful. According to interviewee A, the key reason the case organization stopped using the model was that they lacked the resources to keep the project going. Furthermore, the initial attempt was seen as somewhat proof of concept or test that could inform them on what they would need internally from the marketing team and what kind of assistance they would need from the rest of the organization to make the model function as expected,

> **"I also know that partly it was [the reason for cancelling the project] because of the fact that we also had some internal issues here, perhaps some challenges with its implementation, that would have also required, in order for it to start functioning, it would have required much more resources internally from us than what we were prepared for or what was also feasible in terms of time. A contributing factor to us stopping was also that we wanted to kind of start it from a clean slate, so when we tested it and we kind of noticed those problem areas, then sort of to start fresh, trying to do it better from the ground up, and also so that we know what kind of resources we need and what it requires, for example, from people outside our team and what kind of actions"**

One of the problem areas that interviewee A pointed out in the last quote was related to the input data used in the modeling. While the transfer of data from digital platforms was managed effectively, with automated systems ensuring a smooth flow of information directly into the partner company's database for modeling purposes, significant challenges arose in the context of offline channel data. Specifically, difficulties were encountered in transferring data related to expenditures on outdoor billboards, television, and radio advertising. These challenges are associated with the flow of information within the case organization. For example, interviewee B said,

> **"The data from online platforms automatically transferred to the model, but accessing the results and costs of offline campaigns was difficult. We first had to internally obtain a report on how much money was spent and within what timeframe. Obtaining results from offline media was truly challenging."**

Insufficient resource allocation may have caused a change in the modeling goal during the project. Initially, the goal was to model the effect of marketing on all sales, but later, it was changed to include only digital sales channels. Interviewee C explained,

> **"The main reason was that the goal changed, and what was modeled was digital sales, which is only a part of our revenue. Many other factors also affect it, in addition to marketing investments. When the model did not have explanatory factors such as booking rate or capacity, the results were all over the place."**

This change in focus poses challenges considering the functioning of the model and the fact that digital sales were not the primary sales channel for the case organization. Consequently, the model lacked the essential information required for accurate attribution. Following the interview with interviewee C, interviewee A confirmed that the booking data used for modeling was collected from web analytics because it was readily available. However, utilizing web analytics instead of the actual booking data from the enterprise resource planning system presented challenges. Web analytics gathers data from the front end of the website, making the numbers susceptible to significant variations due to user actions such as page reloading and potential browser blockers that impede web analytics. This introduces potential discrepancies and limitations when relying solely on web analytics for modeling purposes.

Perhaps due to these input challenges, all participants in the initial round of interviews identified the unreliability of the results as the primary obstacle from the previous modeling effort. This unreliability was characterized by outcomes that seemed inconsistent with the interviewees' professional experiences as marketers. The inconsistency emerged as a significant concern, revealing a disconnect between what the model predicted and what the marketing professionals perceived as realistic or feasible based on their understanding of the market dynamics and consumer behavior.

The divergence between the modeled outcomes and their real-world expectations raised questions about the model's credibility and the validity of its underlying assumptions. These discrepancies increased doubts about the model's applicability in shaping strategic decisions, undermining its potential utility in guiding marketing efforts. Interviewee D encapsulated this sentiment by stating,

> **"I do not have such precise information, but I have a general understanding that the modeling did not produce realistic results, such credible results. It was never completed in a way that the model would have been perfect or good enough."**

Interviewee A continued,

> **"Yes, it felt unreliable, if I may say so. But I also know that partly it was because internally we had some problems with its implementation, that it would have required much more resources from us internally than what we had allocated or was feasible to invest in it at the time. That is partly the reason why we eventually stopped."**

This was followed by Interviewee C, who expressed further concerns regarding the fluctuation in the results, stating,

> **"It was stopped because it did not meet the goal set for us. The goal was to better allocate our advertising euros. We never got sensible results from it. It is not credible that one euro spent on search advertising would bring us €13,000 in sales. And then the results varied from month to month. Sometimes it was thirteen thousand euros, sometimes 13 euros. So, our common sense tells us that there can not be such a large variance"**

These comments reflected particularly high swings in the modeled outcomes, creating an additional layer of uncertainty. Even at the lowest estimations, the results appeared considerably high, deviating from what might be considered reasonable or justifiable based on the market understanding.

Interviewee C's observations highlighted the possible over-optimism or bias inherent in the model, reflecting a potential weakness in its ability to capture the nuances of marketing dynamics accurately. The presence of significant variance and excessively large predictions raised doubts among the users regarding the reliability of the results. Unfortunately, for some unknown reason or simply due to an unreliable model, they had no means to verify whether the fluctuating results were genuinely accurate. Interviewee C's sentiment was captured in the following expression:

> **"It was like a black box. It was not clear why the results were fluctuating so much."**

This metaphor emphasizes the opaque nature of the modeling process and underscores the need for greater transparency and validation in MMM. Similarly, interviewee B stressed the lack of trust in the model, stating,

> **"It should have been such that you look at a number and can trust it, but in that model, I just could not trust that number because I did not know how much it told the truth."**

Trust plays a vital role in any modeling process, as without trust in the model's accuracy, individuals are less likely to follow the suggested steps, rendering the modeling process worthless. In addition to the required variables, the lack of other explanatory variables could have contributed to the inaccuracy of the results in the context of MMM. Since MMM aims to model sales and the impact of marketing activities on them, it may require additional variables beyond marketing spending. Interviewee C highlighted this point, stating,

> **"Many other factors also affect [the model's] accuracy, in addition to marketing investments. When the model did not have explanatory factors, such as booking rate or capacity, the results were all over the place."**

Moreover, interviewee A emphasized the importance of considering supply-related factors, stating,

> **"The model did not take supply into account at all, but we would have wanted the system to also recognize that there may not be more available times."**

Indeed, the supply-related challenges in service-oriented industries, such as healthcare, are especially critical. Customers in these industries often have a strong desire for prompt service delivery. Unlike physical products that can be scaled in production to meet demand, service businesses face the inherent difficulty of scaling their workforce rapidly, which is often impractical or unfeasible in the long run.

Furthermore, the location of the service facility plays a significant role in meeting demand. Services need to be located near customers to ensure convenience and accessibility. This adds another layer of complexity to the modeling process, as modeled demand from customers not located near the available service locations cannot be adequately addressed.

In conclusion, the modeling process for the case company was ultimately deemed unfeasible due to various challenges, such as a lack of resources and commitment, changing goals, and data-related issues that likely led to unreliable results. Despite initial aspirations to optimize advertising budget allocation, these challenges and limitations prevented attaining desired outcomes. Consequently, the decision was made to discard the modeling process as it failed to fulfill its intended purpose for the case company.

4.2 Marketing mix modeling

Given the challenges encountered by the case organization during their initial modeling attempt, this thesis aimed to address the issues identified in the first phase of interviews. The objective was to develop a new model capable of producing actionable results for the organization's future use. Further interviews were conducted to evaluate the credibility of this new model and determine whether it met the necessary criteria, especially since the old model was no longer available for comparison. These additional interviews explicitly focused on the outcomes of the new modeling. Employees and managers of the case organization were interviewed to gather their opinions on the results and visualizations, assessing whether the new model met theoretical expectations and conformed to practical requirements.

4.2.1 Model structure

The MMM in this thesis is a Bayesian regression model with five media channels and holidays as independent variables and bookings as dependent variables. The following equation describes how the model is built.

$$\underbrace{kpi_t}_{Bookings} = \alpha + \underbrace{\mu t^{\kappa}}_{Trend} + \underbrace{\underbrace{\sum_{d=1}^{2}\left(\gamma_{1,d}\cos\frac{2\pi dt}{365} + \gamma_{1,d}\sin\frac{2\pi dt}{365}\right)}_{Seasonality\ (daily\ observations)} + \delta_{t \bmod 7}}_{Seasonality\ (weekly\ observations)} + \underbrace{\sum_{m=1}^{M}\beta_m\left(\frac{1}{1+\left(\frac{\chi_{t,m}^{*}}{Km}\right)^{-Sm}}\right)}_{Media\ channels} + \underbrace{\sum_{i=1}^{N}\lambda_i Z_{it}}_{Other\ factors}$$

First, the key performance indicator (KPI) for a given time 't' is computed as an outcome of various factors such as baseline sales (α), trend, seasonality, media channel advertising, and other miscellaneous factors, for instance, holidays, price discounts, or weather conditions.

In the model, the constant α, often referred to as the baseline, embodies the average value of the KPI when all other variables are set to zero. It represents the underlying level of the KPI without any external influences or factors. Essentially, α encapsulates the KPI measurement's starting point or reference value or, in everyday terms, “what would happen if we stopped all advertising?”

The trend component in the model captures the systematic or gradual changes observed in the KPI over time, revealing its long-term behavior. It identifies and analyzes consistent upward or downward shifts in the KPI, enabling the distinction between sustained growth and decline of the KPI around the defined time, for example, a year.

The seasonality term in the equation captures recurring patterns and fluctuations that occur periodically in the KPI. A Fourier series models these variations, utilizing both sine and cosine functions. The Fourier series considers the daily observations by considering a year with 365 days. By incorporating sine and cosine functions, it effectively captures the cyclic nature of the data. To further account for seasonality at the weekly level, the model employs the delta function in conjunction with the modulus (mod) operation of 7 corresponding seven days of a week. By applying the mod operation with a divisor of 7, the model accurately represents the seasonality with weekly observations, providing a comprehensive understanding of the KPI's behavior. By utilizing the Fourier series for daily observations and incorporating the delta function with the mod operation for weekly seasonality, the equation effectively captures the various temporal fluctuations and recurring patterns that influence the KPI, enabling a more comprehensive analysis of its behavior.

The media channels part of the equation introduces the non-linear effect of their impact on the KPI by utilizing the Hill function. The utilization of the Hill function in the model acknowledges the non-linear impact of media channels on KPIs, such as bookings or sales. This function is crucial in understanding that the relationship between marketing spend and outcomes is not always linear. As time progresses, the efficacy of marketing spend tends to diminish, a phenomenon that the Hill function effectively encapsulates within the model. This non-linear approach enables a more accurate representation of the relationship between media channels and the KPI, considering the diminishing impact of marketing activities over time. Factors such as market saturation, audience fatigue, or changes in consumer behavior contribute to this effect. With parameters like the saturation level (Km) and the slope (Sm), the Hill function captures the diminishing effect of marketing spend on the KPI, providing a realistic view of the complex dynamics between media channels and observed outcomes. By recognizing the non-linear nature of these relationships, the model offers valuable insights into the optimal allocation of marketing resources, helping to identify the point of diminishing returns and guiding informed decisions about the most effective use of media channels.

The equation also incorporates various miscellaneous factors that can influence the KPI. These factors include elements like holidays, price discounts, or weather conditions, each potentially impacting the value of the KPI. Each factor is assigned a coefficient lambda (λ), which signifies their respective weight or importance in the equation. The products of these factors and their coefficients are aggregated, effectively representing the cumulative influence of these miscellaneous elements on the KPI. This inclusion ensures that the equation comprehensively evaluates the KPI, considering the primary variables and the additional features contributing to its overall behavior and fluctuations. An example of such a factor is the number of banking days, which is particularly significant in determining the available weekly bookings in healthcare services. This comprehensive approach allows for a more nuanced understanding and prediction of KPI trends and outcomes.

4.2.2 Model optimization

In evaluating the optimization of models, it is crucial to recognize the common goals and outcomes related to the modeling process. Traditionally, MMMs have been used to gauge the impact of less tangible marketing activities, such as offline advertising through television or newspapers (Jin et al., 2017; Wedel & Kannan, 2016). These models determine the effect that each marketing channel has on a chosen metric, commonly sales. They also align future marketing strategies with previous successes, guiding the best use of available resources to meet specific targets. The seasonality component within MMMs can furnish invaluable insights into optimal campaign timing, aiding in the strategic synchronization with market trends and consumer behavior. Furthermore, MMMs can serve as a potent instrument for assessing the potency of various marketing techniques, including budget alterations or promotional discounts. The data within these models heavily influence the results achieved, emphasizing the need for accurate and relevant information to derive meaningful outcomes.

Initially, the modeling process involved aggregating the data to a weekly level. However, due to the limited number of weeks available in the final dataset (93 weeks), an alternative approach was explored by experimenting with the daily version of the data. This was made possible through the lightweight-MMM library, which offered the possibility of using daily data for modeling purposes (Duque et al., 2022).

The daily and weekly models were assessed using two statistical measurements, R-squared (R^2) and Mean Absolute Percentage Error (MAPE), to gauge the forecasting accuracy of the test data. R^2 ranges from 0 to 1, with 0 indicating that the model explains none of the variability of the response data around its mean and 1 signifying that the model explains all the variability (Cameron & Windmeijer, 1997). A higher R^2 is generally preferable, but it is essential to note its limitations as a single inspection point. A high R^2 does not necessarily translate to an effective model, as its value can increase by including insignificant independent variables or through overfitting (Gelman et al., 2019).

MAPE, on the other hand, is calculated by taking the absolute difference between the actual and predicted values, dividing this by the actual value, and then averaging these percentages across all observations (Montaño et al., 2013). In essence, MAPE measures the error distance in the model's predictions. However, MAPE is not without its limitations. Its calculation becomes undefined with zeros, and it may exhibit bias towards overestimation, as overestimations can result in higher percentage errors than underestimations (Montaño et al., 2013). These complexities underscore the need for careful interpretation and contextual understanding when relying on R^2 and MAPE as indicators of model accuracy.

The outcomes derived from these two modeling approaches exhibited notable differences. In the daily model, the effects of various channels demonstrated a more balanced distribution in terms of their mean values and standard deviation. Additionally, the daily model yielded better R^2 values, indicating a stronger relationship between the independent and dependent variables. However, it is important to note that the MAPE values, representing the accuracy of predictions, were significantly worse in the daily model than in the weekly model. Considering the importance of metrics for model evaluation, the MAPE value was deemed more crucial for assessing prediction accuracy, as it directly measures the deviation between predicted values and actual outcomes. Conversely, R^2 reflects the fit of the model and its ability to explain the variance in the dependent variable. Therefore, the weekly model was selected as the preferred approach, prioritizing the accuracy of predictions over the model's fit.

As previously discussed, the booking dataset generated bookings for both 60-day and 90-day care paths. This approach aimed to assess and compare the variations in results that emerged from employing different care path durations. By generating bookings for these distinct time frames, it became possible to evaluate the differential impact and outcomes of the modeling process.

The implementation of the 60-day and 90-day care paths had a noticeable impact on the results of the models. These care paths refer to the method used in processing customer booking data. In the 60-day care path, all of a customer's visits within 60 days following the initial visit are counted as a single care path. Similarly, in the 90-day care path, all dental visits within a 90-day window are treated as a single care path. This approach is designed to eliminate bookings that may have been influenced by dental professionals' guidance of the customer through care rather than marketing efforts. By treating such related bookings as part of a single care path, the analysis aims to isolate the impact of marketing on customers' booking behaviors.

Implementation of the 90-day care path led to a slight increase in the effect of marketing overall, except for tactical marketing on the AdForm channel compared to the 60-day care path dataset. However, the impact was more significant when interpreting the half-max effective concentration and lag weight variables. These variables indicate the speed at which the effectiveness of each marketing channel decreases and the time delay before marketing activities start to have an effect. It is important to note that the changes in these effects were inconsistent across all channels and varied in magnitude. Furthermore, the model's accuracy on the training data was inferior when using the 90-day care path compared to the 60-day care path. As a result, the final modeling was based on the 60-day care path dataset.

After recognizing the significant variations in daily bookings between weeks with different numbers of banking days, the data was enhanced by incorporating Finnish holiday information. The inclusion of holidays positively impacted the model's performance, leading to improved accuracy in predicting booking outcomes, as indicated by the MAPE metric.

The enhancements reduced MAPE for both the training and test datasets, highlighting the increased precision in predicting bookings. Moreover, incorporating holidays also improved the R^2 values for both datasets. Although including holidays did not significantly affect the results, it still demonstrated notable improvements in the model's performance. The addition of a simple variable like holidays contributed to enhancing the accuracy and fit of the model.

In conclusion, the modeling process involved careful considerations at various stages, from selecting the appropriate adstock model to exploring different approaches for data modeling and choosing relevant variables to enhance the accuracy and fit of the model. One crucial aspect was selecting the adstock model, which involved weighing the advantages and characteristics of different options such as carryover, adstock, and hill adstock. This decision influenced how past marketing activities were considered, incorporating decay rates, diminishing returns, and how the model captured marketing effects over time.

The data modeling process also required careful exploration and experimentation with different approaches. This involved aggregating the data at different time intervals, such as weekly or daily, and evaluating the impact of these choices on model performance and the interpretation of results. The selection of the appropriate time interval was crucial to balance the granularity of data and the available sample size.

Furthermore, the modeling process entailed identifying and including relevant variables to improve the accuracy and fit of the model. This involved considering media channels, advertising spending, and other influential variables that could significantly impact the desired outcome. These variables' careful selection and incorporation contributed to a more comprehensive and informative model.

Overall, the modeling process required thorough attention to various steps, including choosing the adstock model, data modeling approaches, and relevant variable selection. These considerations aimed to optimize the accuracy and fit of the model and ultimately enhance its effectiveness in predicting and understanding the dynamics of the marketing campaign.

Each model provides a unique set of parameters summarizing the statistical results, reflecting their different behaviors. After testing each model with the available data, it was determined that the hill adstock model yielded the best results among the three models based on the R^2 and MAPE values. Additionally, the visualization of the diminishing returns was the most straightforward to interpret due to the model's ability to calculate the spending curve related to KPIs.

4.3 Cumulative posterior results of the modeling

This section analyzes the cumulative posterior results of the Bayesian marketing mix modeling using Hill adstock. Interpreting these results is pivotal in understanding various marketing channels' incremental impact and efficiency.

Presented in Table 5, these findings offer a comprehensive perspective on the contribution of different marketing elements to bookings. A thorough examination of these results will reveal nuanced differences between channels, providing essential data-driven insights. These insights are invaluable for informing future marketing strategies, particularly optimizing campaign timing and channel spend distribution.

Table 5 Marketing mix modeling cumulative posterior results.

Variable	Mean	Std	Median	5.0%	95.0%	n_eff
Time and trend coefficient						
coef holidays (Z)	-0.02	0.01	-0.02	-0.04	-0.00	1105.37
coef_trend (μ)	-0.01	0.02	-0.01	-0.04	0.01	329.98
expo_trend	0.69	0.17	0.64	0.50	0.95	808.43
Sigma (Σ)	0.26	0.02	0.26	0.22	0.30	967.53
Intercept (α)	0.59	0.21	0.61	0.23	0.92	513.55
Coefficient media (β)						
Google Ads	0.59	0.43	0.51	0.00	1.09	692.72
AdForm brand	0.27	0.27	0.18	0.00	0.65	750.76
Adform tactical	0.16	0.18	0.10	0.00	0.39	625.40
Meta brand	0.23	0.15	0.21	0.00	0.44	627.64
Meta Tactical	0.37	0.25	0.34	0.00	0.66	579.65
Seasonality (γ)						
seasonality[0,0]	-0.05	0.07	-0.05	-0.16	0.05	524.26
seasonality[0,1]	0.06	0.06	0.06	-0.03	0.17	609.40
seasonality[1,0]	-0.03	0.05	-0.03	-0.11	0.05	765.80
seasonality[1,1]	0.08	0.05	0.08	-0.00	0.16	559.21
Half max effective concentration (K)						
Google Ads	1.13	1.09	0.77	0.00	2.68	1107.94
AdForm brand	1.08	1.15	0.70	0.00	2.55	1072.62
AdForm tactical	1.24	1.18	0.87	0.01	2.81	1588.76
Meta brand	0.86	0.96	0.53	0.00	2.13	1444.98
Meta tactical	1.58	1.35	1.22	0.01	3.39	855.38
Lag weight (χ)						
Google Ads	0.65	0.25	0.69	0.29	1.00	958.77
AdForm brand	0.73	0.23	0.79	0.38	1.00	1149.60
Adform tactical	0.76	0.22	0.82	0.41	1.00	848.21
Meta brand	0.72	0.21	0.77	0.40	1.00	1592.79
Meta Tactical	0.40	0.28	0.33	0.02	0.87	324.66
Slope (S)						
Google Ads	0.67	0.83	0.38	0.00	1.73	727.09
AdForm brand	0.69	0.86	0.37	0.00	1.74	984.59
Adform tactical	0.97	0.97	0.66	0.00	2.30	1163.17
Meta brand	0.74	0.86	0.44	0.00	1.87	1467.36
Meta Tactical	1.00	0.85	0.76	0.00	2.08	826.56

The coefficient media of the results indicate that media channels specially used for tactical purposes, such as Google Ads and Meta, tend to impact bookings significantly. In contrast, activities with similar goals but on the channel that achieves those goals by other means, such as banners from AdForm, have a lower impact on the bookings. Considering the underlying business, the results seem logical because the case company operates in private healthcare in Finland, where public healthcare can treat many customers who do not have an immediate need for dental healthcare. The customer base for private dental healthcare could be interested in immediate care.

Although tactical marketing channels, such as Google Ads and Meta, have demonstrated substantial impacts on bookings, it is noteworthy that brand-related channels also significantly contribute to these results. When comparing the stability of AdForm and Meta as brand-related channels, it becomes apparent that Meta exhibits less variability. The standard deviation for AdForm surpasses its mean, indicating considerable fluctuations in its effectiveness.

Moreover, it is essential to note that all channels exhibit relatively high standard deviations. This could be attributed to the irregular spending across these channels, which includes instances of zero expenditure during certain weeks in the data. Consequently, all media channels present credible intervals that encompass zero. This substantial uncertainty surrounding the effectiveness of these channels may also reflect the variations mentioned earlier in spending. The fluctuations suggest that the effectiveness of these media channels should be assessed cautiously, given the intrinsic uncertainty present in the marketing landscape.

Incorporating holiday data appears to have an anticipated effect on the model's predictions. The mean value of the holiday variable is -0.02, and the credible interval is exclusively negative. This evidence points to a potential decrease in bookings during holidays, which is understandable considering that services are not mostly offered during holidays. However, the upper bound of the credible interval reaches 0.00, which introduces uncertainty. It implies that holidays may not significantly affect the number of bookings in certain instances.

The intercept represents the baseline for the model's dependent variable, bookings. The median value of intercept is 0.59, meaning relatively high baseline bookings. The sigma value of the model represents the estimated standard deviation of the model’s error with a median value of 0.26. This value provides an understanding of the variability in the model's predictions and the degree of accuracy expected from the model's estimations.

The performance metrics of the model demonstrate effective convergence, as indicated by the r_hat values. Predominantly, these values are 1.00, with a singular deviation at 1.01 noted for the Meta tactical channel—the conventional cut-off value for r_hat often stands at 1.1 (Vats & Knudson, 2021). However, recent studies have prompted a reassessment of this threshold. Vats & Knudson (2021), in particular, suggest a more stringent cut-off point at 1.01 to ensure higher reliability in the r_hat value. Considering this benchmark, the r_hat values in the model, with only one channel exceeding the 1.0 mark, can be deemed satisfactory.

The key parameters related to Hill-adstock used in the model are half-max effective concentration, lag weight, and slope. The half-max effective concentration signifies the level of advertising expenditure required to attain half of the maximum possible effect. Lower values indicate greater effectiveness, necessitating less spending to reach half the maximum effect. In the case of Google Ads, for instance, a mean value of 1.13 suggests a relatively efficient performance. The disparity between Meta Brand 0.86 and Meta Tactical 1.58 raises a question regarding the underlying data. However, the single value does not necessarily mean that one approach is worse than the other because the disparity could mean that the other approach has a higher maximum capacity.

The lag weight represents the duration of marketing influence on consumer behavior, with higher values indicating a more prolonged effect—the mean values in the table range between 0.40 for Meta Tactical and 0.76 for AdForm Tactical. Interestingly, tactical advertising has the lowest and most prolonged effect, whereas preconceived notions would have expected brand-related advertising to have a higher lag weight. On the other hand, two-brand-focused advertising channels have a higher lag weight than tactical advertising channels. Google Ads channel has both brand and tactical types of advertising in a single column because brand-related advertising was relatively non-existent in the channel's advertising spend.

The elements in the model that represent seasonal changes show interesting patterns throughout the year. In this case, the yearly period starts from the end of March because the data used in the modeling starts from the end of March instead of the start of the year. The coefficients for the cosine and sine components of the first (seasonality[0, 0] and seasonality[0, 1]) and second (seasonality[1, 0] and seasonality[1, 1]) harmonics offer essential insights into these cyclic patterns. Notably, a negative cosine coefficient for the first harmonic (mean = -0.05) suggests a decrease in the KPI at the beginning of each yearly period, which is, in this case, during the summer. In contrast, the corresponding positive sine coefficient (mean = 0.06) indicates an increase in the KPI around the middle of the yearly period, indicating more bookings during the winter. Similarly, for the second harmonic, which represents cycles repeating twice a year, the negative cosine coefficient (mean = -0.03) indicates a KPI decrease at the beginning of each half-year period, and the positive sine coefficient (mean = 0.08) suggests an increase around the middle of these periods. These observations, while affected by the magnitude of the coefficients and the associated uncertainty, provide valuable insights into the annual cyclic behavior of the bookings, which can be used for strategic planning of the campaigns.

4.3.1 Model visualizations

Given the inherent complexity of large tabular data sets, results from the modeling process were visualized using the tools provided by lightweightmmm.

The visualizations presented in this section focus on the model's performance with training and test data and, notably, on the model's key outcome: the contribution of various marketing channels to total sales. These visualizations significantly enhance the ability to interpret and understand the data, transforming complex information into more accessible insights.

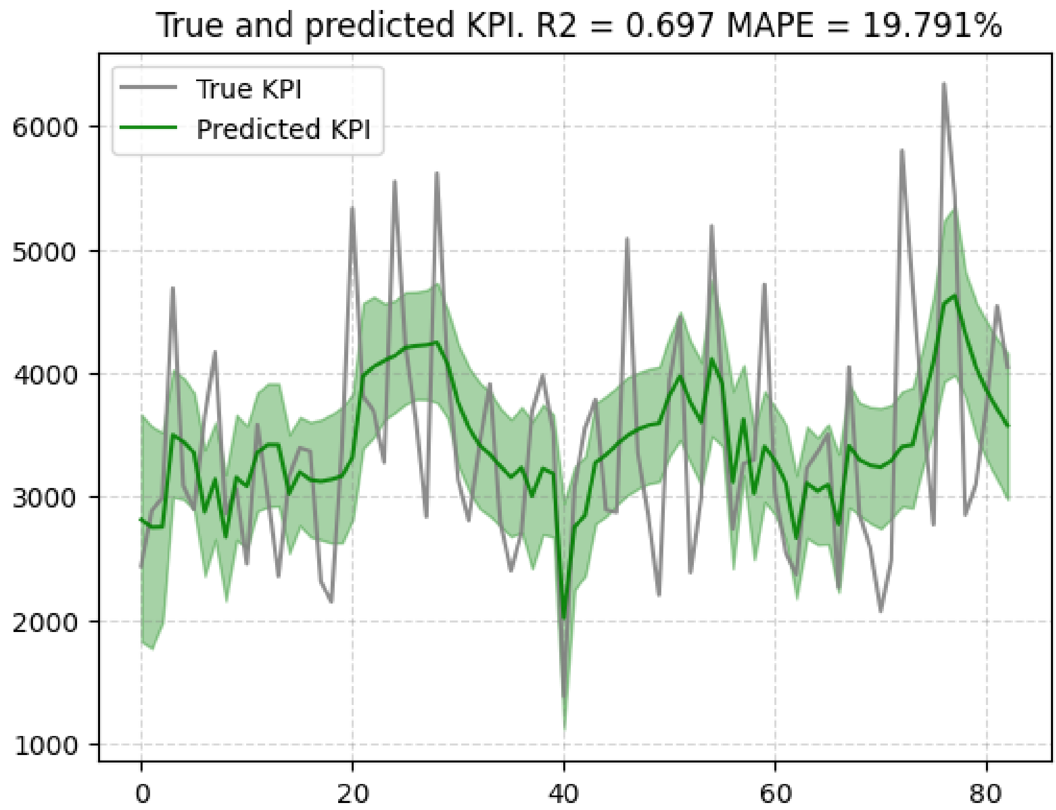

Figure 5 Models prediction compared to true key performance indicators (KPI) on weekly aggregated training data.

Figure 5 visually represents the model's capacity to forecast the number of bookings based on the training data. With an R^2 value of 0.697, this model can explain approximately 70% of the variation observed in the actual KPIs. The remaining unexplained variance can primarily be attributed to significant booking fluctuations. These oscillations lead to peaks and troughs in the KPI values that the model does not adequately capture, resulting in a tendency for the model to predict relatively steady, week-to-week booking figures rather than reflect the true variability in the data.

Regarding the model's MAPE of 19.791%, this value indicates an average deviation of around 19.8% between the model's predictions and the actual data. Generally, a MAPE below 20% is deemed acceptable in various business scenarios, indicating a reasonable accuracy level of the model's predictions (Montaño et al., 2013). However, the MAPE value close to this threshold emphasizes the model's difficulty in dealing with high fluctuations in bookings. This point should be considered when interpreting the results and considering potential improvements to the model.

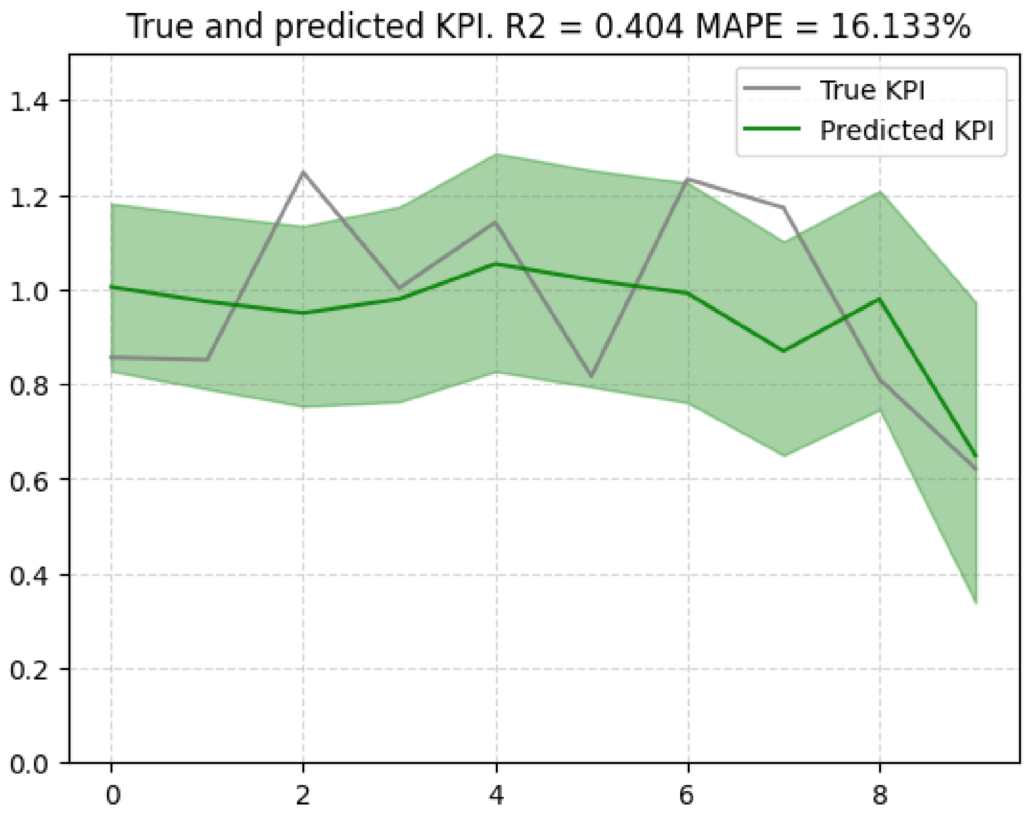

Figure 6 Models prediction on the test data that represents the last ten weeks of the data.

Figure 6 illustrates the model's predictive performance when applied to the test dataset. The R^2 value is 0.404, suggesting that the model accounts for about 40% of the variability in the actual KPIs within the test data. This lower R^2 value, compared to the training data, indicates that the model might not generalize as effectively to unseen data, potentially due to overfitting or patterns in the test data not captured during training, which might be caused by the generally low number of weeks in the training data.

Nevertheless, the model's MAPE on the test data is 16.133%, lower than the threshold of 20% and lower than the MAPE observed on the training data. This could be attributed to the more pronounced weekly spikes in bookings observed in the training data compared to the test data. It is important to note the inherent limitation of MAPE: errors larger than expected can disproportionately inflate the percentage value, leading to a higher MAPE (Montaño et al., 2013). This is particularly evident when actual values are significantly higher than forecasted values. This value implies that, on average, the model's predictions deviate from the actual data by approximately 16.1%. Despite the lower R^2 value, the reduction in MAPE suggests an improved accuracy of the model's forecasts on the test data relative to its performance on the training data. This indicates that the model may be more adept at predicting average booking levels rather than capturing the full range of fluctuations in booking numbers. Consequently, while the model may not fully reflect the variance in the data, its ability to predict general booking trends is relatively sound, as demonstrated by the lower MAPE.

4.3.2 Interviewees perceptions

During the second phase of interviews, the interviewees were presented with the results from the modeling process. This presentation sought to determine how well the model's predictions matched the interviewees' professional knowledge and experience. It aimed to see if the results seemed believable and consistent with what the experts knew to be true in their field.

The interviewees were generally hopeful and excited about the results from the MMM. They were optimistic about how these findings could be applied to the various elements of the marketing mix. The experts were particularly enthusiastic about the potential to use this information in their future strategies, recognizing modeling as a valuable tool for making decisions, fostering new ideas, and exploring innovative ways to approach the different marketing components.

The perceived usefulness of the model varied among the interviewees, depending on their roles and responsibilities. Those in higher-level positions focused on the strategic layer of the marketing mix found the model more beneficial than those concerned with operational work. This distinction aligns with the nature of MMM, as it provides insights geared towards long-term planning and the broader aspects of marketing rather than immediate and operational decisions.

When the interviewees were shown Figures 5 and 6, they were asked to assess the usefulness of these graphs for their work. Interviewee A responded,

> **"Yes, if we think about it, we always want to predict the future to some extent. Specifically, we would like to know during which time periods it is beneficial for us to take certain actions and how much time should be allocated to them during those periods."**

Interviewee B underscored the usefulness of having additional information to time advertising initiatives, stating,

> **"Well, of course, if one does continuous advertising, if it is possible to do such continuous advertising, then somehow timing it and knowing when there is the most potential? When there is like less potential."**

These perspectives on the model's usability were crucial, especially given that when asked about how campaign timing is determined, both interviewees indicated that it is mainly based on the timing of past campaigns. Over time, they have developed a "gut feeling" or "intuition" about what has worked and expect similar results in the future. Interviewee A elaborated,

> **"It is like gaining experience in that sense, understanding what actions we have taken in the past and what results they have yielded. Over time, there is a development of a gut feeling or intuition that often guides decision-making as well."**

Notably, even the modeling process requires a comprehensive understanding of the business to ensure accurate calibration, including selecting appropriate priors for the model. Therefore, the modeling could potentially assist in identifying optimal times for the campaigns.

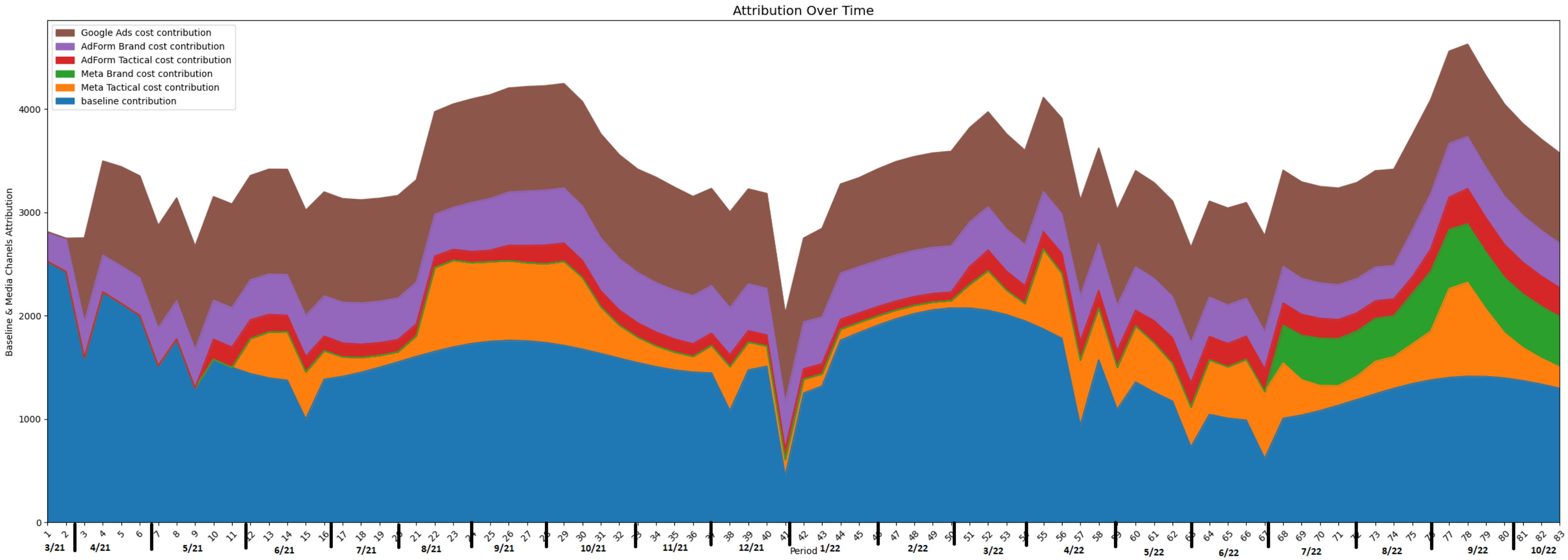

Figure 7 Attribution of each channel to the total bookings based on the modeling

When the interviewees were shown Figure 7 and asked whether the results seemed reliable from contribution perspectives, interviewee A said,

> **"This indeed supports the decision-making process regarding our continuous Google advertising. It provides evidence that it is a sensible approach, as it has consistently shown positive results. Therefore, it seems reasonable to continue investing in it on an ongoing basis."**

The contribution of Google Ads was on quite a high level during the modeling period as the channel is used continuously, even outside the actual campaigns, to generate bookings. Similarly, brand marketing is often ongoing to some extent. Still, the real contribution of brand-related marketing is hard to measure with standard last-click style attribution models because brand advertising is not usually the ad that prompts the booking. Due to that, interviewee B remarked,

> **"I am really positively surprised as well. Especially considering the impact of the brand-oriented approach, since there is very little direct data coming from AdForm. It is encouraging to see that it aligns well with the modeling and is indeed meaningful."**

A further noted the increase based on the budgeting and results,

> **"And also, the brand-oriented approach had its impact towards the end of the year, although it was clearly evident that, in terms of budget allocation, it did not represent a significantly large portion compared to our tactical efforts. However, it has increased the overall conversion rate, thus enhancing the overall effectiveness. It is really good to see that its influence is visible."**

However, the graph visualizes the decrease of the baseline sales during the modeling period towards the end, which interviewee C pointed out,

> **"The baseline seems to be decreasing and Meta and other tactical channels are driving a big impact. But the overall level of the bookings seems to be rising"**

Interviewee C further emphasized the worry over the decrease in the baseline by saying,

> **"I am worried that the baseline is dropping. Are we teaching our customers that it is not worth coming here unless there is a sale?"**

Overall, the fluctuations in the baseline were of keen interest to the interviewees and sparked discussions about the usability of such visualizations. For instance, Interviewee A remarked on the potential benefits of long-term monitoring, stating,

> **If we could do such monitoring over a longer period, then we would see, for example, if there is any period when it is not worth doing anything because there comes a situation where no matter what we do, the demand, as it were, decreases.**

This comment underscored the importance of organizations storing their data. It highlighted the need for internal data analysis capabilities, especially considering that specific marketing platforms might delete historical data, thus limiting retrospective analyses and insights.

4.4 Addressing the Organizational Challenges of Implementing Marketing Mix Modeling

4.4.1 Campaign planning and budgeting

The initial premise of this thesis posited that the entire organization contributes to the successful implementation of MMM. However, through a combination of interviews and literature review, it became evident that managers, particularly those overseeing marketing teams, have a pivotal role in adopting and utilizing organizational tools and process changes. These managers are uniquely positioned to implement and benefit from MMM within the organization. Their influence and decision-making power are critical in integrating MMM into the organization's marketing strategies, maximizing its potential benefits. This finding highlights the importance of managerial engagement and leadership in MMM's successful deployment and effectiveness.

During the interviews with members of the organization, it emerged from both top-down and bottom-up perspectives that within the digital sales organization, channel-specific budgeting is predominantly managed at the sales manager level. This point was particularly emphasized by Interviewee C, who stated,

> **"Of course, in this case, it is important to consider that my role is to provide information about the goals and approximate budget availability. Then later I review the plan and provide comments. As for other aspects and specific details, I may not have much information, but [sales managers] would be better equipped to provide insights in those areas."**

Echoing this sentiment, Interviewee B expressed uncertainty about the intricacies of budgeting but acknowledged its management by remarking,

> **“I am not quite sure where or from whom the budget comes from, which A nicely manages and tracks in Excel, providing approximate allocations for different channels like social media, display ads, and other digital channels based on the available budget and potential utilization."**

Sales Manager A confirmed this arrangement during an interview, asserting,

> **"For example, when my team handles all the paid media-related tasks, I usually take care of budgeting and determine how it should be allocated among different channels."**

Furthermore, it is not just internal past experiences that guide these decisions. External research, particularly regarding customer behavior, is an indispensable reference point for budget allocation. As illustrated by Interviewee A's observations,

> **"When planning campaigns, past campaign results and a demand forecasting report are utilized to inform decision-making."**

> **"We acquire a lot of information produced by research agencies about customers' behavior in different media. For example, what channels are used by families with children?"**

Hence, having a tool to estimate the appropriate budget ranges could prove useful for sales directors when planning the overall budget for a campaign. However, the most significant benefits would likely be realized when used at the sales manager level, as they are closest to the employees who are responsible for creating and analyzing channel-specific actions.

A recurring theme in budgeting pertains to the influence of historical campaign data, especially if the new campaign mirrors past efforts. Interviewee A explained this in this practice, noting,

> **"If we have some specific campaigns that repeat, we plan the next one in a certain way and when we conclude the previous one, we start to consider, Okay, when we do this next time, these and these things must be taken into account. Then we consider, Okay, when we have used this much budget and our CPA (cost per acquisition) has been this much in some channels, then at that point, a decision could be made not to include this channel at least for now, and this one was good that we could put a little more money into it.'"**

Corroborating this perspective, Interviewee B elaborated on the role of past campaign outcomes in shaping future strategies by saying,

> **"When planning campaigns, past campaign results and a demand forecasting report are utilized to inform decision-making."**

This reliance on historical data, particularly regarding budgeting, is not restricted to a few individuals. Interviewee D emphasized the broader organizational approach, commenting,

> **"In budgeting, we have had to rely heavily on assumptions about the effectiveness of marketing based on past campaigns."**

While sales managers predominantly oversee and guide campaigns, it is not an exclusive practice. Sometimes, individual team members assume full responsibility for campaigns, including dictating budgetary directions. Providing an insightful anecdote, Interviewee B recounted their experience with a relatively more minor initiative:

> **“If I take, for example, another such smaller campaign, it was that children's allergy webinar. In a way, I was responsible for its advertising. So it went a bit differently. Or rather, differently in the sense that I did receive a ready-made budget,**

but then. Where it was advertised, I had a lot more freedom there. Insofar that I got to choose or suggest which channels I wanted... The process was a bit shorter there, and I could have more influence myself. "

It is pivotal to understand that empowering employees with tools like MMM in such scenarios could be transformative. Tools like MMM could equip them with the knowledge to use data-driven decision-making to allocate budgets for specific campaigns. Elaborating on the budgeting specifics for the aforementioned campaign, Interviewee B reflected,

"Now, of course, there were fewer channels in use, and quickly I noticed that social media advertising was performing extremely well. I experimented with a few other options, but their conversion rate was significantly lower. So, I paused those and allocated even more of the budget to social media, continuously optimizing and allocating resources to channels based on the results that were achieved."

This strategy aligns with the sales organization's general practice, adopting a responsibility-centered approach to analyses. When assigned distinct advertising channels, employees immerse themselves deeply, scrutinizing the efficacy and alignment of ads specific to their designated channels. This approach and its broader implications for the sales organization will be elaborated upon in the following section.

4.4.2 Analytical processes

The analytical processes within the case company concentrate on the marketing campaigns on the responsibility level. For example, an employee responsible for a specific channel analyses that channel's performance during the campaign and improves its operational performance by choosing the best-performing ads and target groups. Interviewee E provided further insight,

"For example, I have been building a campaign in Meta, so I study in more detail how, let us say, a certain ad has performed, but we do not do a big analysis of the whole campaign. We just look at how our own actions have affected things."

Interviewee B elaborated on the dynamic nature of this analysis, highlighting how continuous recalibration is integral to optimizing campaign outcomes,

"During the campaign, we, of course, have some preconceptions. For example, if we have the previous campaign, we can look at the current stage of the campaign, how many appointments we had received then, and are we ahead or behind? And then, of course, if it feels like some campaign is underperforming, then we go a little more in-depth to look at that campaign. Can we try some new target groups or new ad variations?"

This philosophy of segmented responsibility in campaign analytics finds resonance across the organization, as Interviewee A corroborates,

"But now, as an example, if it is E's responsibility to see how social media performs and kind of makes related optimization actions in such a way that, if necessary, he turns off ads or reallocates the budget to some other activity. Then again,

when B is responsible for the display, B does the same with display advertising. That is, he might turn off certain ads if they seem to be performing poorly."

Simultaneously, sales managers assess the outcomes of the entire campaign. In addition to determining the budgets for each channel, they assume responsibility for the campaign's overall success. This involves evaluating and analyzing performance at the campaign level, as described by Interviewee E.

"So the results of the campaign, when the campaign is ongoing, are recorded in this Excel file, where we track them. Then, after the campaign, A and other sales manager will analyze how it has performed as a whole and then compile a PowerPoint presentation based on that."

Most of the case company's marketing campaign evaluations are based on web analytics, specifically employing a last-click attribution model. However, the case company has tested other readily available multi-touch attribution models. As interviewee D stated during the interview,

"I know that team A has experimented somewhat with different attribution models, but generally very little. We constantly look at those last-click conversions."

This approach is, of course, a lot simpler than the modeling approach tested in this thesis and has ever-growing tracking challenges, which is one of the reasons for this study. During the interviews, many interviewees mentioned that the case organization had done statistical analyses based on the regression models to determine if the results seen from the advertising platform were incremental. For example, interviewee A mentions that,

"For example, we have done something like this with keyword advertising, where we actually conducted our own ROMI (Return on Marketing Investment) modeling a couple of years ago. We carried out a test in such a way that for a certain part of the day, the ads were not active, and for another part, they were. We then performed a regression analysis from that to determine what the actual effect of this was."

Interviewee D mentioned ROMI modeling as an ongoing practice:

"For example, when we use ROMI modeling, it has the advantage over traditional modeling in that it allows us to include cross-effects and then calculate their impacts. So, if we start with email and other forms of advertising at the same time, what would be the effect of that?"

Further inquiries reveal that the analysis referenced was conducted earlier when one of the current sales managers was employed as a marketing analyst. During the interviews, the interviewees noted that recent campaign analyses are a collaborative effort involving the entire team. This collaborative approach results in a more extensive, in-depth, and breadth analysis. Individual employees are responsible for examining single marketing channels, while sales managers take on the task of analyzing entire campaigns, a point that was elaborated upon earlier.

4.4.3 Organizational growth

Continuous learning and self-development are not only regarded as critical attributes for organizational success. Still, they are also deeply ingrained in the culture of the case organization, where learning is seen as a vital component of job success. This was clearly articulated by Interviewee A, who stated,

> **"In a way, we also encourage that, and for instance, what I try to do with my team is to always emphasize the importance of actually taking time for one's own education and seeking and finding, so to say, new ideas."**

Furthermore, Interviewee A elaborated on the necessity of staying up-to-date with the latest developments to maintain a high quality of work, saying,

> **"We indeed have it so that we want our overall quality of work to be such high that we have to keep track of everything that happens. If something occurs or if there are changes in the agenda or something else, then we need to be pretty much on the crest of the wave, so to speak, all the time."**

This perspective sheds light on the organization's dynamic approach to adapting and evolving, ensuring that employees remain well-informed and responsive to changes and new information in their field.

The insights shared by Interviewee B further reinforced the emphasis on and encouragement of learning within the organization. They observed that their organization has a deeply ingrained understanding and attitude that views learning as necessary and valuable. This perspective is fundamental to the organization's culture, where continuous improvement and knowledge acquisition are seen as essential components of professional development and organizational success.

> **"In our organization, there is an understanding and attitude that learning is necessary and valuable."**

Interviewee B also noted,

> **“Learning is encouraged, and there are ample opportunities for it.”**

These statements highlight the organization’s proactive stance in providing resources and opportunities for learning. It suggests an environment where employees are motivated to learn and supported with the necessary tools and opportunities. This approach fosters a culture of lifelong learning, which is instrumental in driving innovation, adapting to changing market demands, and maintaining a competitive edge. The observations of both Interviewees A and B paint a picture of an organization that highly values continuous learning and self-development.

On the other hand, the allocation of time for learning within the organization appeared to lack a structured and formalized approach across different teams. This aspect was pointed out by Interviewee C, who observed,

"Learning is not very structured. D's team spent a couple of hours per month on learning, while A's team created guides and presentations on different marketing tools."

This statement indicates a variance in how learning is approached and prioritized among different teams within the organization, with some teams dedicating specific hours to learning. In contrast, others create practical resources like guides to teach about new tools to others. Interviewee D confirmed the unstructured practices by saying,

"It probably depends on the team, as each team may have its own practices. At least last year, in my team, we allocated a certain amount of time each month to develop our skills. We studied marketing tutorial videos on various topics. I am not sure how things are currently done in other teams, but personally, I try to make an effort to learn something new and develop my own work a little bit each month."

While some teams seem to have a more formalized approach to learning, others rely on personal initiative, pointing to the pivotal role of managers in influencing employees' performance and their approach to time management for learning and development.

Interviewee A pointed out the challenges of allocating time for learning amidst a busy schedule,

"But then whether it really happens, whether they do it, and whether they take the time for it, is another matter. Perhaps the situation is such that since we are constantly quite busy, the execution of tasks is easily prioritized, rather than contemplating or finding new methods."

This observation suggests that despite recognizing the importance of learning, practical challenges such as workload and task prioritization often impede the actual implementation of learning activities.

Interviewee E further confirmed the unstructured nature of learning within the organization, emphasizing the need for individual initiative.

"Well, perhaps it is something done on your own initiative, in that there is not specifically any work time allocated for personal skill development. However, from the company's side, there are indeed materials, for instance, such as CXL, a training platform, where there is everything related to marketing. Really good material. It is indeed offered by the company."

The case organization actively fosters a culture of knowledge sharing among its members, significantly enhancing collective learning and skill development. Sharing insights and experiences with colleagues is pivotal in disseminating information and identifying best practices within the organization. Interviewee A captured the essence of this idea by saying,

"Well, yes, what we actually do is share knowledge. So when someone has done something new, they also tell others what they have done, and, in a way, we are also searching for best practices through this. So, sharing knowledge and educating others are also things we try to do."

Interviewee B confirmed this collaborative learning practice, noting,

"One of us becomes familiar with and learns about a particular tool, and then shares what they have learned with others."

These statements reinforce the idea that individual learning experiences are not isolated but shared across the team, contributing to the collective expertise. Such a practice of knowledge sharing can be seen as a highly effective method for enhancing the skills and capabilities of the entire organization. Prior research has shown that knowledge sharing not only accelerates the learning process but also fosters a supportive environment where employees are encouraged to explore, learn, and contribute to the broader knowledge base of the organization. This approach can lead to more innovative solutions, better decision-making, and a more agile and informed workforce, which are crucial for the organization's growth and success in a dynamic business environment (Gonzalez & Melo, 2017).

5 DISCUSSION AND CONCLUSIONS

Section 5 synthesizes the research findings drawn from both qualitative and quantitative methodologies, focusing on the MMM and various organizational aspects. It offers conclusions derived from the data, features a comprehensive discussion, outlines the managerial implications and limitations, and provides recommendations for future research.

5.1 Purpose and research question

The study attempted to understand the problems of implementing MMM as a new approach to measure marketing performance analytically. While modern marketing has been highly focused on analytics due to the possibilities of digital marketing platforms, the MMM differs from the easily explainable results obtained from the platforms. The study used a mixed-method approach to mix interviews from the five interviewees working in the case company and statistical modeling using Google’s open-source library lightweightmmm. First, to recap the research question:

What are the challenges of implementing marketing mix modeling in an organization, and how might they be addressed?

The research question has two parts. The first part aims to understand the reason for the failure of the case company's initial attempt to integrate MMM into its organizational processes. The second part of the research question explores potential solutions for the failure of the case company's initial attempt to integrate MMM into its organizational processes.

As revealed through interviews, the failure of the first attempt was attributed to a combination of limited resources and commitment, shifting goals, and data-related issues that likely resulted in unreliable outcomes. This aligns with findings from the literature review, which suggests that challenges in IT projects are often linked more with organizational factors than with technical solutions (Davenport & Harris, 2017; Gonzalez & Melo, 2017; Lavalle et al., 2012; Wedel & Kannan, 2016). However, in this specific case, it became evident that while particular data-related challenges originated from organizational processes, a portion of these challenges also stemmed from technical aspects of the implementation. These challenges will be discussed in the following subsections, which will separately address technical and modeling-related challenges, as well as organizational challenges, along with their respective solutions. This approach ensures a comprehensive analysis of each category, allowing for a detailed understanding of the issues and the identification of effective solutions to address them.

5.1.1 Technical challenges and solutions to marketing mix modeling

Data quality is highly relevant for any modeling, especially for the MMM. Small skews or sampling errors in the modeled data can cause unexpected results (Wedel & Kannan, 2016). Perhaps the case organization's initial decisions to use offline and digital marketing spending to model what was essentially just digital bookings caused the initial stage of the failed modeling attempt to produce unbelievable results because a fair share of the case organizations' bookings still happen through other channels. Then, after the goal was narrowed further to only model digital advertising and digital bookings, the problem with counting the bookings was that it did not consider measurability errors from web analytics or whether the booking was new or follow-up. During both of these steps in the initial MMM attempt, the underlying data had either sampling or skews towards one way or another.

The modeling done in this thesis attempted to remedy this by using booking data obtained from the internal booking database, which contains all bookings. However, there was no possibility to filter bookings, only to include new bookings. This was remedied by using a static 60-day care path decision to gain an accurate count of the number of bookings. While imperfect, this approach was assumed to result in a more precise dependent variable for the modeling. The interviews did not mention much about the independent variables used other than that the campaigns were named following certain conditions that allowed the company operating MMM to allocate marketing channel spending accordingly. Because of this, the marketing channel spend data transformations could not benefit from the prior knowledge. Even without prior knowledge of the marketing channel data processing, the results from the modeling were convincing. Statistical evaluations revealed that the MAPE remained below 20% for both the training and test data, which is a favorable outcome. Interestingly, the training data displayed a higher MAPE despite the model being trained explicitly on it. This could be attributed to the more pronounced weekly spikes in bookings observed in the training data compared to the test data. It is important to note the inherent limitation of MAPE: errors larger than expected can disproportionately inflate the percentage value, leading to a higher MAPE. This is particularly evident when actual values are significantly higher than forecasted values. Nonetheless, the model maintained a MAPE below the 20% threshold for both datasets, aligning with the standards set by Montaño et al. (2013), who indicate that MAPE values under 20% are considered good in business contexts. On the R^2 values, which indicate how much of the model's variability the model is able to predict (Cameron & Windmeijer, 1997), the model performed well against the training data. However, on the unseen data, the value dropped drastically. This means the model could not accurately predict the number of bookings at this stage. This drop could be due to the low number of training data points. The model accounts for seasonality, and it had only one training period that time of the year that it was attempting to predict because the whole data set used in the modeling was smaller than two years. The model's accuracy would most likely improve with more data, which could alleviate doubts about the MMM's trustfulness.

Future refinements to the modeling process should consider including additional independent variables beyond just holidays. One such variable could be the impact of significant sales events like Black Friday, during which marketing expenses typically surge due to widespread discount advertising. These events can significantly influence consumer behavior and spending patterns, making them a considerable factor for MMM. Additionally, incorporating variables like price increases or inflation rates could provide deeper insights. These factors directly affect purchasing power and behavior over time and are likely to impact customer bookings and engagements substantially. Including these variables would enhance the model's comprehensiveness and accuracy in predicting customer responses under various market conditions.

5.1.2 Organizational challenges and solutions to marketing mix modeling

The organizational reasons for the failure of initial implementations derived from the interviewees were attributed to limited resources, commitment, and shifting goals. While these factors might have been the immediate causes, addressing the underlying organizational issues could offer solutions to these challenges. By enhancing the organization's underlying capabilities, culture, and processes, it could address and rectify these issues.

The lack of resources and commitment is a known reason for failure of projects (Hughes et al., 2017; Tabesh et al., 2019; Verner et al., 2008). Regrettably, these issues were not explored in depth during the interviews, which may have provided further insight. Interviewee A mentioned that the case organization did not have the required internal resources to work on the project. This could indicate that the implementation process might not have been perceived as sufficiently valuable or essential, especially compared to other ongoing projects or daily operational tasks. Branda et al. (2018) and Davenport & Harris (2017) mention that managerial support is critical for the success of any initiative. Without this support, the resources to solve problems in the project become hard, if not impossible.

A contributing factor to the resource drain and diminished commitment during the first attempt may have been the MMM's failure to meet its predefined goals of predicting marketing attribution. When the initial attempt did not achieve the expected standards, subsequent efforts to adjust and improve the data further strained resources. According to the interviewees, the model still failed to yield reliable results despite these additional investments.

Hughes et al. (2017) highlight a gap in the literature regarding whether project management and planning failures are attributable to an organization's skills and expertise or to the nature of project management itself. In the case of the organization studied the lack of in-house capabilities for MMM led to the cooperation with a consultancy on MMM implementation. However, the consultancy may not have possessed the necessary expertise to handle the organization's specific data, potentially leading to the issues encountered with the modeled data.

Wedel & Kannan (2016) emphasize the expertise of an organization's employees is crucial in advancing its analytical capabilities. If the individuals involved in the project had a deeper understanding of the organization's data, they might have been more successful in selecting appropriate data for modeling. On the other hand, in large organizations, the challenge of possessing comprehensive knowledge is significant. This underscores the importance of effective communication across different functions within the organization and the responsibility of managers to appoint individuals with the right skill sets for the project. These factors are essential for bridging gaps in expertise and ensuring the success of complex projects like MMM.

The case organization places a high value on learning despite the lack of a structured approach, with much reliance on the initiative of team managers. The significance of active learning is widely recognized in various scholarly works. For instance, Ghasemaghaei et al. (2018) underscore its importance in enhancing an organization's analytical capabilities. Similarly, learning is pivotal in cultural transformation, as Schein (2016) and Wedel and Kannan (2016) indicated, particularly in shifting towards a culture that embraces data-driven decision-making. This emphasis on learning, even in an unstructured format, highlights its critical role in developing technical skills and fostering an organizational environment conducive to continuous improvement and adaptation to new paradigms.

The expertise required for statistical analyses appeared to be highly centralized in the case organization. Interviewees indicated that specific statistical tasks, like regression analyses, were previously conducted. However, these analyses ceased when the employee responsible for them moved to a different role. This situation underscores the importance of disseminating analytical skills more broadly across the organization rather than relying on a select few individuals. By fostering a broader base of statistical expertise, the organization can mitigate the risk of losing valuable capabilities if employees with specialized skills change positions or leave altogether. This approach not only ensures continuity in analytical tasks but also enhances the overall resilience and adaptability of the organization in the face of personnel changes.

5.2 Theoretical contributions

The theoretical framework of this study reinforces the notion that adopting more advanced analytical approaches, such as MMM, necessitates specific qualities within an organization. Engaging in complex statistical analyses like MMM requires an organization to recognize that while these sophisticated methods can yield more rewarding results, as Delen & Ram (2018) suggest, an appropriate infrastructure must also be in place. This infrastructure encompasses technical capabilities, skilled personnel, a supportive organizational culture, and well-defined processes facilitating the analytical journey (Gupta & George, 2016; Tabesh et al., 2019; Wedel & Kannan, 2016). This comprehensive approach ensures that the organization is equipped with the necessary tools and fosters an environment where analytical methodologies are understood, valued, and effectively implemented. The successful application of complex analyses like MMM depends on the synergy between these various elements within the organization, where each plays a critical role in supporting and enhancing the overall analytical capability.

Furthermore, this study contributes to the academic discourse by empirically validating the practical application of MMM, building upon the foundational works of Chan & Perry (2017) and Jin et al. (2017). The study's findings demonstrate the effectiveness of MMM in real-world marketing scenarios, as evidenced by robust R^2 and MAPE values. This validation offers a significant academic contribution, as it corroborates the theoretical underpinnings of MMM and provides concrete evidence of its applicability and efficacy in practical settings. By bridging the gap between theory and practice, this study enhances the understanding of MMM's potential in real marketing data analysis, offering valuable insights for academicians and practitioners. The positive results regarding R^2 and MAPE values affirm that when correctly implemented in an adequately equipped organization, MMM can be a powerful tool for understanding and optimizing marketing strategies in diverse market contexts.

5.3 Managerial implications

This study has uncovered insights crucial for organizations aiming to incorporate MMM into their marketing organization. A key finding is the critical role of the organization's existing experience and expertise. For effective implementation, an organization must possess the necessary skills, capabilities, culture and processes to undertake complex analyses such as MMM. As Davenport and Harris (2017) suggest, these skills are typically developed incrementally over time. Following Figure 1 by Delen and Ram (2018), organizations could start with less complex analyses, gradually progressing to more complex analyses as their capabilities increase. However, possessing these capabilities alone is insufficient; it requires a cultural shift within the organization to fully embrace and facilitate more advanced analytical methods (Wedel & Kannan, 2016).

Furthermore, the organization's structure could significantly influence the success of implementing MMM. Effective communication across different units is paramount to identify and leverage the right skill sets for the planning and implementation. This cross-functional collaboration ensures that MMM is not just a siloed activity but an integrated effort leveraging diverse expertise, which can reduce errors and excessive resource drains during the implementation.

Additionally, managerial backing is vital for MMM's successful implementation and sustained support. Hughes et al. (2017) emphasize that projects are unlikely to succeed without this level of support. Managerial endorsement not only provides the necessary resources and authority but also signals the strategic importance of the project to the entire organization. This endorsement encourages broader engagement and commitment across different levels of the organization, thereby facilitating smoother implementation and more effective utilization of MMM.

Wedel and Kannan (2016) highlight the critical importance of data quality in modeling. It is essential for organizations to thoroughly inspect their data for quality and comprehensiveness before proceeding with any modeling activities. The adequacy and excellence of the data are fundamental, as modeling based on incomplete or substandard data can yield misleading results. Such outcomes, rather than adding value, may be detrimental to business operations. Therefore, ensuring the data's comprehensiveness and high quality is a crucial preparatory step in the modeling process.

5.3.1 Outcomes of the thesis project for the case organization

The thesis project has made the case organization more mindful of storing various types of crucial external data in their databases. Particularly to enhance the quality and comprehensiveness of their marketing data, of which quality is vital for more advanced models. This awareness has catalyzed the initiation of new projects aimed at further documenting the data, focusing on gaining a deeper understanding of what expenditures in offline marketing entail and how different analysts should consistently interpret them.

5.4 Limitations of the study

Like all research, this study has some limitations that should be considered when interpreting the findings. The first significant limitation of this study relates to internal bias and the scope of interviewees. The limitation stems from the inherent nature of this research, conducted as an internal project within the case company where I am currently employed. This setting potentially introduces a bias in both data interpretation and analysis. My role as an employee could influence how data is perceived and presented, possibly leading to a subconscious preference for outcomes that align with internal perspectives or goals. This internal approach also limited the range of interviewees to company employees, which may have restricted the diversity of viewpoints and insights obtained, potentially affecting the study's breadth and depth of analysis. Acknowledging this limitation is crucial for a balanced understanding of the study’s findings.

The second limitation is this study's narrow organizational scope. The focus was primarily centered on the sales function within the case company. This specific concentration means that the findings predominantly reflect the perspectives and experiences of those involved in sales, potentially overlooking valuable insights from other departments or functions. Such a limited scope may not capture the company's full complexity and interdepartmental dynamics, which could play a crucial role in understanding the broader application and implications of the study's findings. Including a more comprehensive range of departments, such as brand marketing, data and analytics, or finance, could have provided a more comprehensive view of the organization. This broader perspective might have revealed additional factors influencing the implementation.

The third limitation is the retrospective nature of such studies, which significantly impacts the reliability of interviewees' descriptions of past events. The primary concern is memory reliability: as time elapses, recall accuracy diminishes, potentially introducing biases or incomplete recollections. Participants might unknowingly modify their memories or omit essential details influenced by memory fading or subsequent events. Furthermore, retrospective interviews are prone to hindsight bias, leading individuals to reinterpret past occurrences based on present knowledge or outcomes.

The fourth limitation of this study is that the modeling faced a significant constraint concerning the dependent variable. It had to settle for a static 60-day care path to ascertain new bookings resulting from follow-ups. As indicated, these follow-ups are often not influenced by marketing efforts, given that bookings can be made immediately after the first visit. This approach to the dependent variable presents a limitation; a more thorough understanding of care paths would allow for a more precise definition of this variable. Consequently, with a better-defined dependent variable, the accuracy and efficacy of the model's results could see notable improvement.

The fifth limitation is that the study is subject to concerns regarding the generalizability of its findings. The study was conducted within the unique context of a single organization. Therefore, the study's findings may not universally apply to other settings. This limitation is particularly pertinent when considering the diverse nature of organizational structures, cultures, and market environments. Thus, while the study provides valuable insights into implementing MMM within a specific organizational setting, its conclusions may require validation and adaptation in other contexts. This highlights the necessity for additional research spanning various organizational settings, which could provide a more expansive understanding of MMM's applicability and effectiveness in different business environments.

Despite these limitations, this research contributes essential insights into the challenges and potential solutions for implementing MMM within a specific organizational context.

5.5 Future research

The current research on MMM has primarily focused on its theoretical aspects, as evidenced by studies like those of Chan and Perry (2017) and Jin et al. (2017). These investigations have significantly advanced our understanding of MMM's theoretical underpinnings. However, there is a noticeable gap in the literature concerning the practical organizational applications of MMM, which is the primary focus of this thesis. This gap is particularly evident when considering the application of MMM in real-world business contexts.

This study investigated the integration of MMM within a single organization, highlighting unique challenges and opportunities in adopting such analytics tools. The research reveals the need for broader studies involving diverse companies at different MMM adoption stages, from initial exploration to advanced integration. Future research should compare how various organizational structures and data maturity levels affect MMM implementation and use. Such studies would identify patterns and best practices for organizations seeking to adopt MMM and enhance academic understanding by providing empirical insights into MMM's practical applications across various business contexts. This expanded research could guide organizations in effectively leveraging MMM to measure marketing effectiveness.

Another key area for future research identified in this study is validating MMM results. During the modeling phase of this study, it was observed that varying adstock configurations in the lightweightmmm led to different outcomes, underscoring the need for dependable validation methods. While industry experts often propose lift tests as the primary method for validating MMM results, the current literature on MMM primarily focuses on testing model reliability with idealized, synthetic data, which may not accurately reflect real-world scenarios. This gap is especially critical in the case of MMM, especially given the Bayesian approach used in this thesis, which incorporates existing market knowledge to refine results. However, aside from lift tests and the application of recommended marketing strategies, there is a noticeable absence of comprehensive methods for effectively confirming these findings. Addressing this gap in research could significantly enhance the practical application and reliability of MMM in diverse marketing contexts.

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APPENDIX 1 INTERVIEW STRUCTURE

Warm-up question

1. Kerro omasta toimenkuvastasi

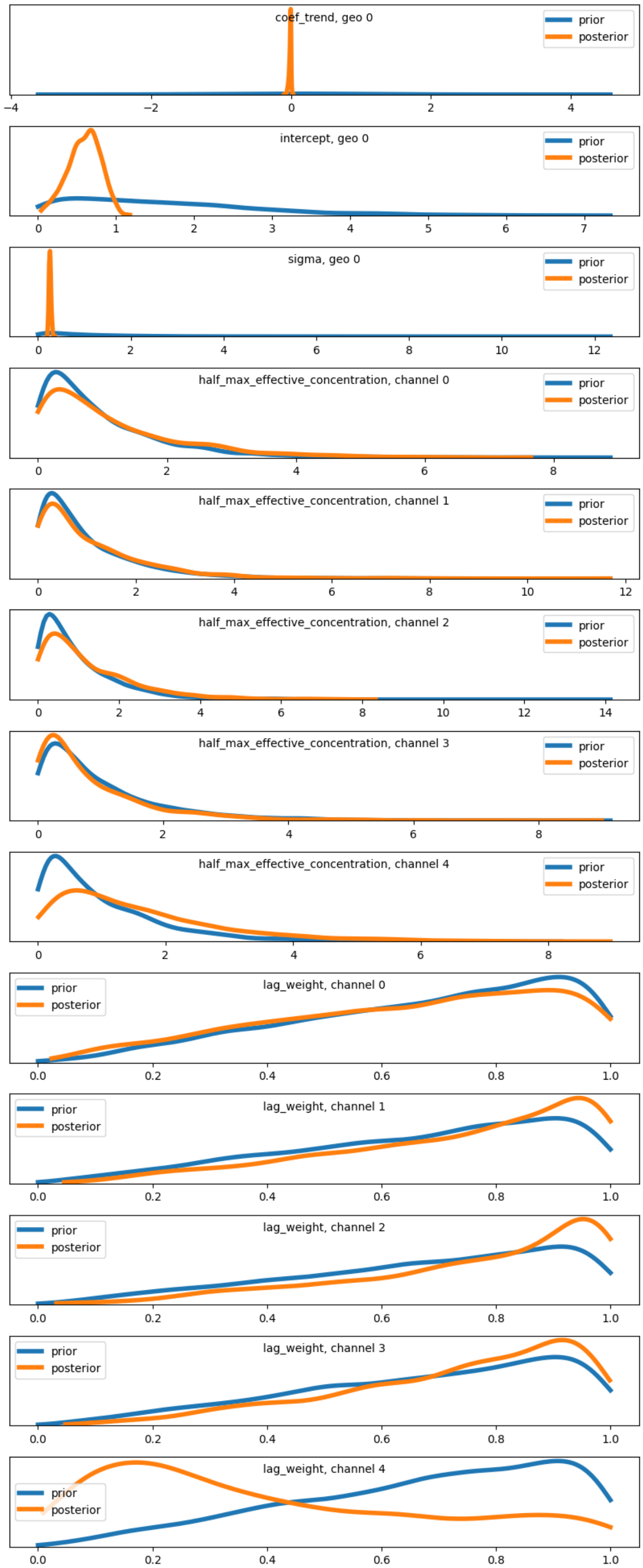
Organizational and process-related questions

1. Markkinointiorganisaation rakenne?
2. Miten paljon markkinointiorganisaatiossa panostetaan oman osaamisen kehittämiseen?
3. Mieti viimeisintä markkinointikampanjan suunnittelua.
    a. Miten markkinointia suunnitellaan tällä hetkellä?
    b. Kuinka päätökset tehtiin?
        i. Syventävä: mihin valittu linja perustui? (data/mutu/kokemus?)
    c. LISÄYS: miten läpinäkyvää päätöksenteko on?
    d. Millä eri tavoilla markkinoinnin dataa kerätään tällä hetkellä?
        i. Miten dataa analysoidaan?
        ii. Tekevätkö kaikki markkinoinnissa analyysiä vai tekevätkö vain tietyt henkilöt?
        iii. Millaisia KPI:tä te käytätte onnistumisen mittaamiseen?

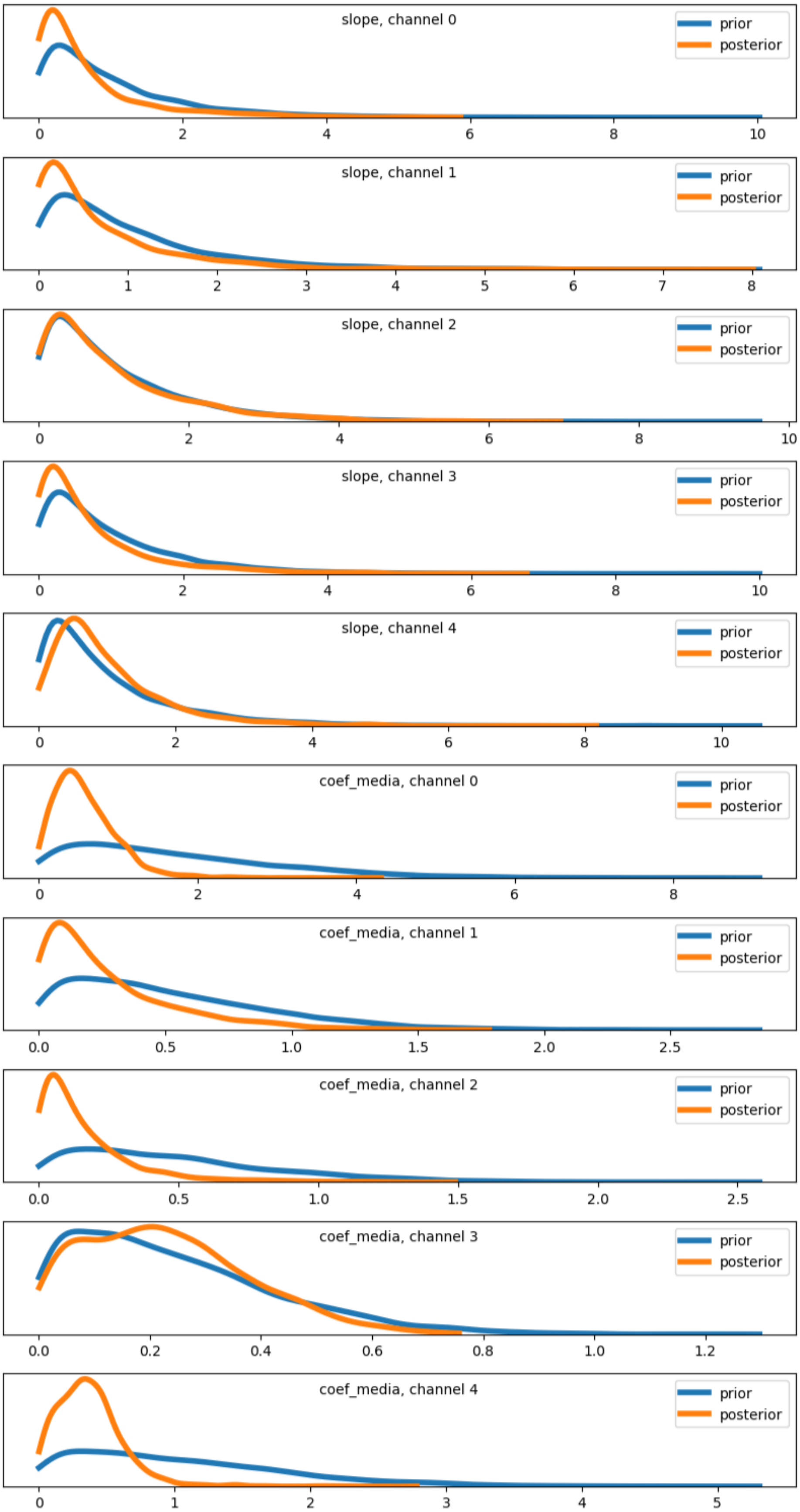
Marketing mix modeling-related questions

2. Mitä marketing mix modeling tarkoittaa? Mitä sillä tavoitellaan?
3. Miksi aiempi kokeilu marketing mix modelingin käyttöönottosta epäonnistui?
4. Minkälaisia tuloksia mallin pitäisi antaa, että se olisi hyödyllinen markkinoinnin suunnittelussa?

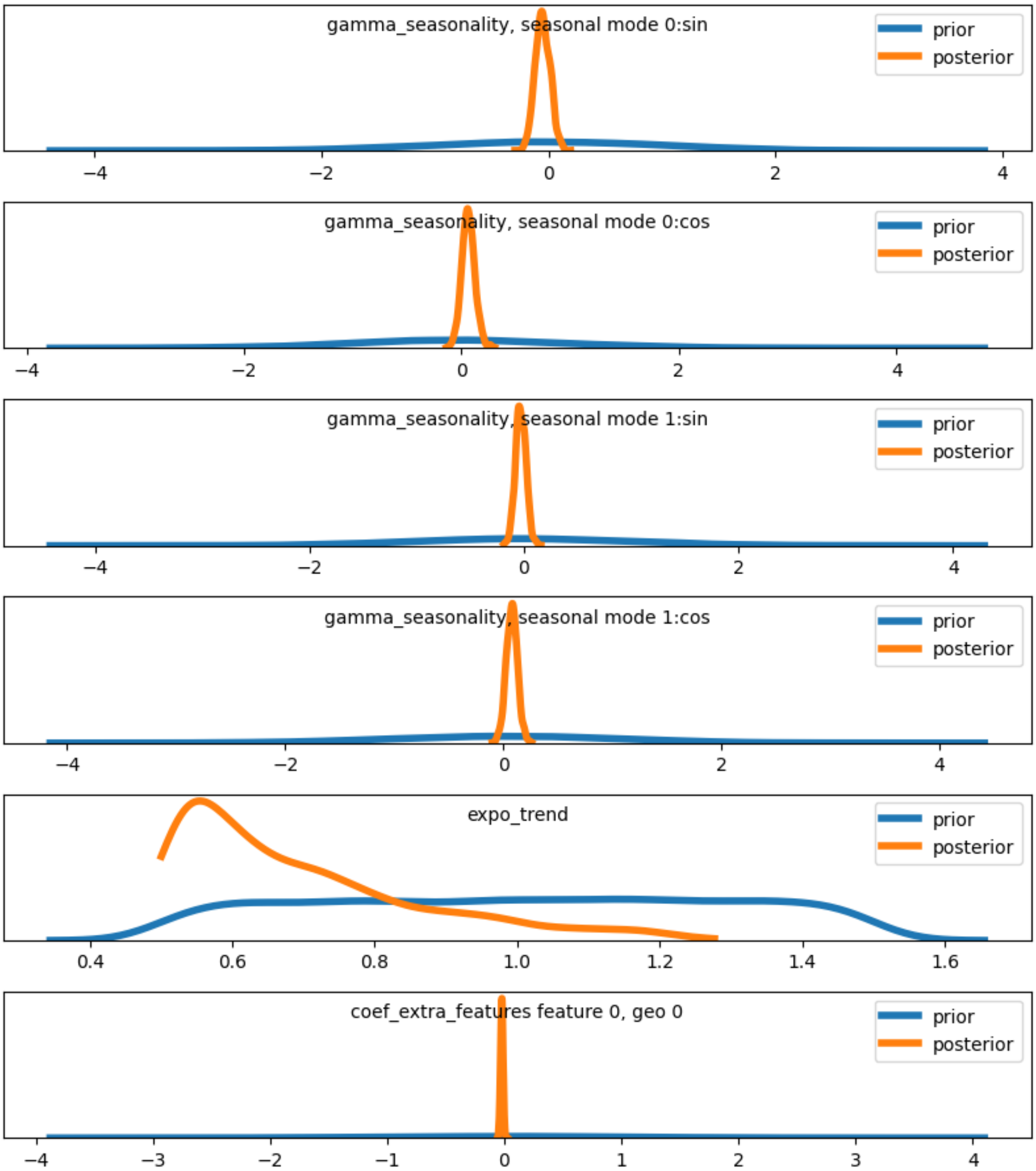
APPENDIX 2 PRIOR AND POSTERIOR RESULTS 1



APPENDIX 3 PRIOR AND POSTERIOR RESULTS 2



APPENDIX 4 PRIOR AND POSTERIOR RESULTS 3



APPENDIX 5 MEDIA CHANNEL POSTERIOR RESULTS