



**THE POTENTIAL BENEFITS OF SIMULTANIOUS USE OF MEDIA MIX
MODELING AND ATTRIBUTION MODELING FOR ADVERTISING
EFFECTIVENESS**

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ABSTRACT

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The potential benefits of simultaneous use of media mix modeling and attribution modeling for advertising effectiveness

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The topic of advertising effectiveness has gained a considerable attention as companies are becoming more data driven and focusing on the advertising effectiveness on business objectives. The purpose of this thesis is to find out if the simultaneous use of both media mix modeling and attribution modeling can be advantageous for improving advertising effectiveness and what could be the potential drawbacks and limitations. The thesis also investigates how well companies understand the aspects of effectiveness.

The data in this thesis was collected by using semi-structured interviews, which were conducted for five company representatives.

The results of the study highlight the benefits of both modeling approaches that can be complementary if used correctly. Findings also demonstrate lack of understanding about advertising effectiveness in many companies which further supports the use of especially media mix modeling. While the results support the simultaneous use of both tools, there are clear shortages in companies' abilities to use both and the scale of benefits depends on multiple factors.

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Avainsanat: mainonnan tehokkuus, media -mix mallinnus, ekonometrinen mallinnus, attribuutiomallinnus

Mainonnan tehokkuus konseptina on saanut paljon huomiota, kun yritykset ovat enenevässä määrin datavetoisia ja keskittyvät mainonnan tehokkuuteen liiketoiminnan tavoitteissa. Tämän opinnäytetyön tarkoituksena on selvittää onko media mix -mallinnuksen että attribuutiomallinnuksen rinnakkaiskäyttö perusteltua mainonnan tehokkuuden parantamiseksi ja mitä mahdollisia haittoja ja rajoituksia siihen liittyy. Opinnäytetyössä tarkastellaan myös sitä, kuinka hyvin yritykset ymmärtävät tehokkuuden komponentteja.

Tämän opinnäytetyön aineisto on kerätty käyttämällä puolistrukturoituja haastatteluja, jotka toteutettiin viidelle yrityksen edustajalle.

Tutkimuksen tulokset korostavat molempien mallinnusmenetelmien etuja, jotka oikein käytettynä tukevat toisiaan. Löydökset osoittavat myös monien yritysten ymmärryksen puutetta mainonnan tehokkuudesta, mikä tukee erityisesti media mix -mallinnuksen käyttöä. Vaikka tulokset tukevat molempien työkalujen samanaikaista käyttöä, monille yrityksille niiden hyödyntäminen ei ole mahdollista ja hyötyjen mittakaava riippuu useista tekijöistä.

LIST OF ABBREVIATIONS

MMM	Media Mix Modeling
AM	Attribution modeling
CIC	Customer-Initiated Channel
FIC	Firm-Initiated Channel
ROI	Return on Investment
SEA	Search Engine Advertising
OOH	Out-Of-Home advertising

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Appendix 1. Interview questions

1 Introduction

'Half the money I spend on advertising is wasted; the trouble is I don't know which half.'

- John Wanamaker

Companies invest significant financial resources in advertising annually. Estimate on global advertising spending during 2022 was 827 billion USD (The Wall Street Journal, 2023), and the number has been on steady increase. Because of this, determining the advertising effectiveness for business objectives has become a priority for many companies. Advertising performance has traditionally been measured by using accounting tools such as balance sheet and income statements (Lavery, 1996) but due to the rise of digital analytics and improvements in data processing and storing, companies are increasingly basing their advertising investment decisions on data, even though many companies still lack robust tracking systems that allow this and use rule of thumb approach in various decision (Abedi, 2017). In optimal scenario, sufficient measurement of effectiveness would allow evaluation of advertising investment level, establishing budget allocations and modifying certain advertising elements, thus potentially leading to improved business performance.

The ability to demonstrate the total impact of advertising is crucial as a lack of understanding can lead to unjustified reduction on the resources allocated for advertising. According to a CMO survey (Moorman, 2019), demonstrating marketing impact and its financial outcomes is the greatest communication challenge among c-suite executives. Because of this, Chief Marketing Officers (CMOs) often do not last long in their position (Nath & Mahajan, 2011). Rossiter (2001) points out that marketing knowledge as a concept lacks a clear consensus, which has further contributed to the problem with accountability in the discipline. Webster, Malter and Ganesan (2005) observed that marketing has the greatest influence in the firms that have clear measures to quantify the impact of marketing for overall business performance.

While advertising has been proven to be a crucial part of business and most companies spend large portions of their earnings on it, it is often the first place of cutting costs, especially during uncertain times as it is commonly perceived as non-essential (Deleersnyder, Dekimpe, Steenkamp & Leeflang, 2009). Although understandable, and sometimes even advantageous in the short term, this typically has detrimental long-term consequences for businesses. According to Ratajczak et al. (2023), cutting down investments on brand advertising has a direct negative impact on key metrics such as total shareholder return, sales growth and market share. Besides this, they also found out that regaining the lost market share requires 1.85 dollars for every 1 dollar saved from near-term reductions in brand advertising spending. This is also illustrated by a study from Baveja, Postma, and Pritzl (2002) where the authors revealed that 70% of the companies that managed to increase their profits or revenues during 2001 recession sustained their gains after the following economic recovery, while less than 30% companies that decreased profits or revenue managed to gain back the lost ground. Although these effects are clear, they are not often immediate (Tellis, 2004, 16), which might create a disconnect when evaluating the effects of advertising. While larger, well-established brands can generally tolerate some underspending on advertising without experiencing significant market-share erosion, they are not immune to the negative consequences of excessive investment reductions (Hansen & Christensen, 2004). Although this is widely understood in companies, it can easily be overlooked in practice without concrete evidence, again highlighting the need for being able to quantify effectiveness of advertising for business performance.

On top of being able to demonstrate the total contribution of advertising, determining the effectiveness of different mediums in order to determine optimal allocation and investment level is equally important. It has become one of the most prevalent challenges in modern advertising, and thus it has also gained attention in academia. The Marketing Science institute has raised the attribution problem as one of the priorities in marketing research (Niemand, Kraus, Mather & Cuenca-Ballester, 2020). Using multiple advertising channels has proven to provide synergies and positively affect return on investment (e.g. Naik & Raman, 2003; Chang & Thorston, 2004) and because of this, it has become the preferred

way to advertise. This, paired with the appearance of new advertising channels, has made the process of media planning and credit attribution more challenging (Abedi, 2017). According to Fulgoni (2014), online and offline activities are inherently linked in the consumer journey to product purchase, which has increased the complexity of data and demand on the models used.

In addition to establishing and allocating advertising budgets, measurement systems are used to evaluate the performance of micro level elements, such as individual ad copies and target audiences. This applies especially to digital advertising, which is highly dynamic and often relies on constant optimization on campaign or even ad copy level. This challenges the modeling systems that need to provide information quickly and on granular enough level in order to keep up with the demands of marketers today. While the high-level advertising decisions such as investment levels and budget allocation across the media mix are in the core of effectiveness and focus of this thesis, the execution of advertising within channels plays a substantial role in the advertising performance.

The importance of the previously mentioned factors and challenges associated with them has prompted marketers to explore optimal method for accurately measuring their advertising efforts for justifying the investments and improving overall advertising effectiveness. Randomized experiments have been used by companies for determining advertising effects and have been widely accepted as a standard way of answering causal questions (Chan & Perry, 2017). However, they are typically expensive and time consuming (Jin et al., 2017), and cannot answer all questions that other approaches can. Experiments also often need to be run multiple times with different conditions over time (Chan & Perry, 2017).

Because of the challenges associated with randomized experiments, companies have sought alternative methods to achieve these objectives. Two other common methods used to accomplish these are attribution modeling (AM) and media mix modeling (MMM), which rely on different ways for attributing value to different advertising actions. Both

tools have maintained their relevance although popularity has varied in accordance with the prevailing beliefs of the time. According to IAB (2019), 72% of industry respondents were using at least one of the mentioned methods to assess advertising effectiveness, majority being more familiar with MMM. Even though MMM and AM are often used for similar objectives, they differ considerably in their underlying principles and are not necessarily suitable for all purposes they are intended to serve. While the comparison between the two is ongoing, they are not mutually exclusive. Rather, the granular, individual-level tracking capabilities of AM might complement MMM's macro-level insights derived from aggregated data. Consequently, this thesis focuses on potential benefits of simultaneous use of both MMM and AM for achieving higher advertising effectiveness.

Although the importance of quantification of advertising effectiveness is well-acknowledged in many companies, it has proven to be a complex task. Rust, Ambler, Carpenter, Kumar & Srivastava (2004) list three primary challenges in measuring marketing performance: difficulty in determining long-term effects, isolating marketing activities from other actions and purely financial metrics being inadequate for justifying marketing investments. Out of these challenges the problem of determining long-term effectiveness is especially problematic as it has led many marketers to optimize their advertising activities towards short-term profits as they are easier to quantify, which is usually not a sustainable approach as long-term effects of some efforts (especially above the line) tend to be vastly greater than short-term effects (e.g. Dekimpe & Hanssens, 1999; Pandey, Gupta & Chhajed, 2021; Stürze, Hoyer, Righetti & Rasztar 2022). Besides this practical reason for favouring short-term performance, there is also still significant ignorance about the concept of advertising effectiveness in companies and the magnitude of long-term effects is often not understood entirely (Binet & Field, 2013).

While marketing departments have been shown to be more long-term oriented compared to other departments on average (Homburg, Jensen & Krohmer, 2008), the pressure from the organisation can often shift the focus more towards short-term sales goals (Nikolov, 2018). In many organisations there is also significant distrust in marketing department, which is

demonstrated by a study that found that only 6 percent of firm executives believe their marketing is effective (Kotler & Keller, 2011). The concept of short-termism is well recognized phenomenon in academic literature (e.g. Rappaport, 2005; Ladika & Sautner, 2020), in which management places too much emphasis on short-term results over long-term results due to pressure to meet quarterly goals, which often results in outcomes such as reduction in innovation and erosion of customer trust (Peppers & Rogers, 2008). According to a survey from Graham, Harvey and Rajgopal (2005), majority of managers attest that they would cut back or at least delay advertising expenditure and sacrifice long-term performance to reach short-term performance goals. Personal bonus systems are also typically tied to short-term performance, compounding the issue. As advertising often accounts for a major portion of total marketing budget, it also gets a lot of attention from the finance department, that requires a clear justification for the expenditures (Doyle, 2004).

Digital advertising has relied on third-party cookies to track user actions for optimization and AM (Anderl, Becker, Von Wangenheim & Schumann, 2016). In recent years, the disappearance of third-party cookies has been a prominent topic and large platforms such as Google are actively trying to discontinue using them due to privacy concerns and growing number of regulations on them. Because of the decline in available data, the efficacy of measurement capabilities has also decreased (Accenture, 2022). Third-party cookies remain widely used due to the potential disruptions their removal could cause for various stakeholders, including technology companies themselves but currently Google is planning to discontinue using them on summer of 2024 (Google, 2022). As AM has primarily relied on cookies (El Hana, Mercanti-Guérin & Sabr, 2023), placing complete trust on a single measurement system poses significant risks. While this has generated significant and justified critique against AM, it does not necessarily render it completely invalid as many parties are eager to claim. Advertising technology companies are actively trying to figure new, privacy regulation abiding, tracking systems that would provide the same benefits as third-party cookies However, this has proven to be challenging and new solutions are still in their early stages.

1.1 Research gap

While research exists on both AM and MMM, little has been done to investigate the simultaneous use of the tools, despite appearing complementary on paper and potentially offering advantages for marketers. Prior research has also often overlooked the factors that largely determine which companies are able to, or should use the given modeling approach, such as company size, media spend and target audience size. In contemporary advertising, especially in digital format, technological advancements are fast, thus vast majority of the research on the ways to measure advertising effectiveness is outdated. Concerns about privacy have also increased with the tracking of consumer behaviour online, affecting the regulations around the subject. Changes in these regulations deeply affect the relevance and reliability of tools such as AM, thus justifying new research about the one of the most prevalent topics in advertising today.

1.2 Research questions and objectives

The objective of this thesis is to investigate whether companies can benefit from the simultaneous use of both MMM and AM in their advertising decision making on strategic level as well as day to day tactical level with the goal of enhancing advertising effectiveness. The thesis also aims to explore how well companies understand the concept of advertising effectiveness and its key components. Besides these, the study provides awareness of the potential challenges and limitations about the combination of these tools, and how relevant or reasonable the use of both models is for companies of different sizes and business areas.

Aside from gaining deeper understanding on the topics discussed, the goal is to provide knowledge for companies trying to improve their advertising effectiveness and ultimately drive business objectives. While the methods being discussed are not novel to the

advertisers, there is still a lot of ignorance and outdated information concerning them, which can harm the position of the marketing function in companies and eventually firm performance.

Based on the research objectives, the main research question is as follows:

Research question 1

“Can the simultaneous use of both attribution modeling (AM) and media mix modeling (MMM) provide value for companies in increasing advertising effectiveness?”

To gain better understanding of the main research problem, the first and second sub-question are formed to further elaborate the potential benefits, and challenges in this dual modeling approach:

Sub-research question 1

“How can the application of MMM and AM guide companies with the approach to advertising?”

Sub-research question 2

“What are the potential problems and limitations associated with MMM and AM, and how can companies avoid these?”

1.3 Preliminary literature review

This chapter will provide a brief overview on the existing literature on AM, MMM as well as advertising effectiveness. It is also meant to identify potential gaps in literature.

MMMs are a specialised, paid media focused, subset of marketing mix models, which are statistical models used by companies to measure the effectiveness of their marketing actions and have been around since the 1960s (Chan & Perry, 2017). They are designed to answer the difficult question of how much sales the different marketing activities bring and quantify that into measure such as return for investment (ROI). Marketing mix refers to a set of tactical marketing tools that are blended to produce the desired market response in the target market (Kotler & Armstrong, 2014, 76). The original marketing mix, or 4Ps of marketing, was introduced by Jerome McCarthy in 1960, and it has product, price, place and promotion as variables (Kotler & Armstrong, 2014, 76). In the context of advertising, these models are often referred to as media mix models as the purpose is to quantify the effects of different paid media activities. While marketing mix modeling has been around for decades, the fundamental principles remain effective, and developments in advanced models, such as improved accuracy in quantification of the long-term effect of advertising have improved their efficacy. For a decades old and well-established modeling approach, the amount of literature is relatively low, and large portion of that can be considered outdated as the models of today have addressed some of the shortcomings of the earlier models. Although the amount of up to date literature is surprisingly scarce compared to the attention it has gained in the industry, there are still recent articles demonstrating the usefulness of MMM (e.g. Chan & Perry, 2017; Fareniuk & Chornouk, 2023), and Stürze et al. (2022, 64) even going as far as arguing that for companies with larger brand portfolios and omnichannel sales, there is no reasonable alternative for MMM when trying to accurately determine allocation of advertising investments. While there are many challenges with the modeling approach reported (e.g. Chan & Perry, 2017; Cain, 2008), majority of them are not inherent limitations of the approach itself but rather suboptimal construction of the model, poor data quality, or lack of proper interpretation of the modeling results among other avoidable factors.

Attribution can be defined as “the process of identifying a set of user actions ("events") that contribute in some manner to a desired outcome, and then assigning value to each of these events” (IAB, 2016). While the term attribution has been used loosely when discussing different methods to assign credit to channels, attribution modeling refers to tracking and allocating credit to various digital touchpoints in a customer's individual journey, from initial interaction to the final transaction or other desired conversion (Stürze et al., 2022, 60– 62). The data from attribution models has been used to validate numerous advertising decisions from budgeting allocations to optimizing attributes such as advertising creatives and target audiences (Berman, 2018). While there are studies recommending AM as a standalone method to determine contributions of advertising activities and budget allocation based on that (e.g. Gaur & Bharti, 2020; de Haan, Wiesel & Pauwels, 2016; Geyik, Sanexa & Dasdan, 2014), many still argue against relying solely on AM due to flaws in the modeling approach (e.g. Danaher & van Heerde, 2018; Nisar & Yeung, 2019; Stürze et al., 2022).

Advertising effectiveness is a well-researched topic as it is in the core of marketing practises. Les Binet and Peter Field (2017) have studied the topic, focusing on effectiveness in the digital era, as the landscape of advertising has changed considerably in recent decades and even years. They divide the effects of marketing communications into sales activation (short-term) and brand building (long-term). This aligns with earlier literature where advertising was found to have effect on both immediate sales as well as future expected sales (Joshi & Hanssens, 2010). According to Thinkbox (2018), the long-term effects cover 58% of total advertising effectiveness while short-term effects cover the remaining 42%. This is supported by 1972 research by Bass and Clarke, who revealed that advertising 's greatest impact may not in fact be the initial moment but may occur after a certain period. This is why Osinga, Leeflang and Wieringa (2010) suggest that the marketing models being used should accommodate these effects. Lehmann and Reibstein (2006) used two broad categories when measuring advertising effectiveness: diagnostic marketing metrics such as awareness, customer satisfaction and loyalty, and evaluative marketing metrics such as sales, profits and return on investment. This thesis will mostly focus on the latter.

1.4 Theoretical framework

The objective of theoretical framework is to summarize the main concepts of the study into one figure, which visualises the relationship between them. In order to achieve the optimal performance in advertising, companies need to both understand the components and main principles of effectiveness in advertising and also be able to quantify those effects, which is only possible with right tools that can guide the decision making. Deep industry and technical knowledge are then used in interpreting the data from the modeling tools in both tactical and strategic decision making for improving the overall effectiveness and the return on advertising investment. This framework is illustrated in figure 1.

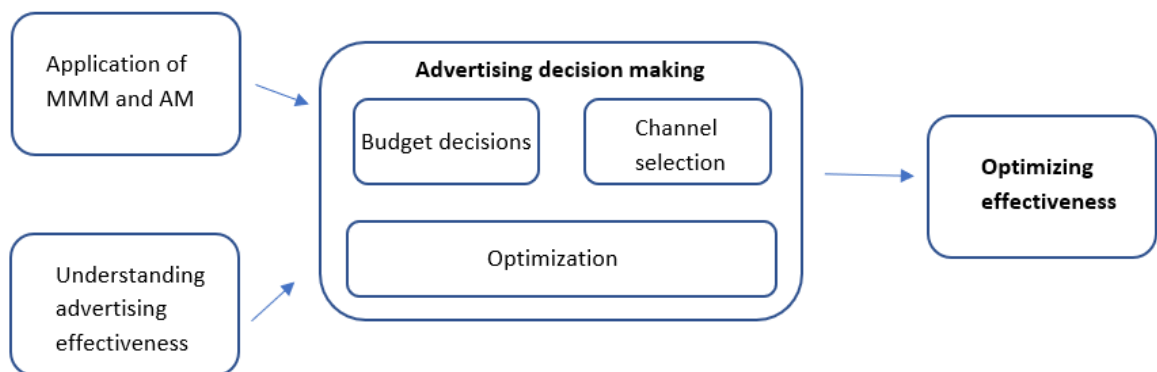


Figure 1. Theoretical framework of the thesis.

1.5 Research methodology

This study is conducted as qualitative research by using semi structured interviews from experts on the subject from one of the leading media agencies in Finland. Qualitative method was chosen as it is suitable for gaining in-depth understanding of the topic and examine it as comprehensively as possible (Hirsjärvi et al., 2009). Data for this research was collected using semi-structured interviews as they are well suited for scarcely

researched topic (Metsämuuronen, 2011) and offer the ability to do a deep dive into the subject (Saunders, Lewis & Thornhill, 2019). They also provide the opportunity to capture perspectives and insights from respondents who are directly working with the models and have first-hand experience with the implementation processes as well as knowledge about their strengths and limitations. Interviews were held in the Helsinki office of the agency and sample size for the study was 5 participants. All the interviewees work in different positions but are all involved in AM, MMM and/or strategic planning of advertising for both local and international companies.

The methodology of the research has two parts. First, review of existing literature is conducted for gaining understanding about the key concepts related to the topic. After that, the empirical study is conducted with interviews for gaining insight about the potential benefits of utilizing AM and MMM for improving advertising effectiveness. Interviews from experts working in media agency also provide valuable information about the potential downfalls of the practical implementation and possible short-termism among decision makers that has been observed in literature.

1.6 Delimitations

The study is conducted as a qualitative study and the interview questions are broader, so the number of individual respondents is lower. All the respondents also work in the same company, which can induce possible sampling bias. Despite this, compared to the low sample size, the study does provide versatile insights as the agency works with wide range of clients from different industries and many of the interviewees have experience from in-house positions as well. The media agency also primarily works with Finnish companies and branches of international companies operating in Finland, which does affect the generalizability of some of the information gained from the interview due to factors such as market size.

The technology involving the AM and MMM is changing continuously, so some aspects of the study might not be accurate in the future. There is a significant potential for artificial intelligence-based solutions for both modeling methods but as for today, there is insufficient evidence to assess their reliability. In addition, there are numerous ways of conducting both modeling techniques, and this thesis does not delve deeply into the mathematical side of them but instead provides a generalized overview of their principles.

This thesis is also limited to research paid advertising activities and excluding aspects such as sales promotions or PR campaigns. Because of this marketing mix modeling is mostly referred as media mix modeling (MMM). Regarding advertising effectiveness, the focus is mainly on paid advertising channels and their effectiveness across different time frames, and the components of the effectiveness. This study does not focus on the effectiveness stemming from type of content included in advertising but rather the medium being used.

1.7 Structure of the thesis

This thesis consists of 7 chapters in total. The first chapter is an introduction to the thesis and provides background and reasoning for the research. This is followed by the theory portion of the thesis, which introduces the reader to the academic literature on the research topics. The theory portion is covered in the chapter two, chapter three, and chapter four. Chapter five will present the research design and illustrates the data collection and analysis methods being used, which is followed by a discussion about the reliability and validity of the study. Chapter six presents the research findings. Finally, in chapter seven, conclusions and answers to the research questions are provided, followed by discussion of the limitations of the thesis and suggestions for future research.

2 Advertising effectiveness

This chapter discusses the concept of advertising effectiveness and its measures, as well as the time frame of advertising effectiveness due to its pivotal role in this thesis. The final sub-chapter will cover the key pillars that are in the core of conducting effective advertising.

2.1 The concept of advertising effectiveness

In order to measure and quantify advertising effectiveness, it has to be defined. Hanssens and Pauwels (2016) define the purpose of marketing as “creating and stimulating favourable customer attitudes with the goal of ultimately boosting customer demand”, which will ultimately result in increased sales and profits. As a subset of marketing, advertising aims for the same objective through paid communication mediums. Effectiveness refers to ability to reach the desired goal (Hanssens & Pauwels, 2016).

The mechanisms of advertising and its efficacy can be illustrated with 1898 AIDA model from Lewis, which is still widely used despite being over 100 years old (Turnbull, 2022, 18 – 19). Lewis divides the effects of advertising into 4 sequential stages: attention, interest, desire, and action. While there are several alterations suggested to the model in more recent literature (e.g. Heath & Feldwick, 2008), the AIDA model still captures fundamental components through which advertising operates. The effectiveness of advertising is ultimately derived from generating awareness and interest, reshaping consumers' perceptions of the brand, and driving them to take action.

To quantify the advertising effectiveness, companies have tried to find simple metrics for the answer. These metrics are usually divided into financial and non-financial metrics (e.g. Mintz & Currim, 2013). Examples of widely used financial metrics are profitability ratios

such as return on investment (ROI) whereas examples of non-financial metrics include brand recognition and share of advertising (Solcansky, Sychrova & Milichovsky, 2011). While financial metrics are directly tied to monetary results of advertising, research from Mintz and Currim (2013) found that the use of non-financial metrics is equally important, despite not being as closely linked to firm performance. The use of relevant metrics allows companies to benchmark the advertising performance to previous actions but also to the competitors.

While the use of both financial and non-financial metrics has been linked to increased advertising performance (Mintz & Currim, 2013), the number of available metrics has become a problem for many companies. According to Lehmann and Reibstein (2006), managers often have difficulty in deciding which metrics to monitor and to use as a basis for decisions. This can lead to confusion and poor advertising performance over time. The rise of digital advertising has also brought a plethora of new metrics to assess the performance and effectiveness of advertising efforts, which can further worsen the problem even though many of these metrics have demonstrated clear utility. Determining the true effects of advertising is also difficult as consumers buy products and services for multiple reasons, and there are countless triggers that might have ultimately affected the purchase decision (Tellis, 2004, 5). Furthermore, the effects are not always instantaneous, which is a topic that will be discussed later.

When talking about the impact of advertising, it is necessary to distinguish between effectiveness and efficiency. Effectiveness refers to a scale of effect on a given measure relevant to the context without relating it to the level of investment, while efficiency refers to what is achieved per unit of investment made (Binet & Field, 2013). Example of a widely used efficiency metric is return on marketing investment (ROMI), shown in figure 2.

$$\text{ROMI} = \frac{\text{Incremental Income} - \text{Incremental Variable Cost} - \text{Marketing Investment}}{\text{Marketing Investment}} = \frac{\text{Incremental Gross Margin} - \text{Marketing Investment}}{\text{Marketing Investment}} = \frac{\text{Incremental Revenue}}{\text{Marketing Investment}}$$

Figure 2. ROMI formula (Suárez & Estevez, 2016).

Even though both effectiveness and efficiency are important and should be monitored, Hanssens and Pauwels (2016) argue that companies should pay more attention to effectiveness as the goal is ultimately to aim to maximize the net profit rather than highest return on investment. While effectiveness and efficiency are closely related in practise (Binet & Field, 2013), there are evident trade-offs when looking at short-term and long-term effectiveness of advertising actions (Hanssens & Pauwels, 2016). More short-term and sales activation focused channels or campaigns tend to usually be highly efficient but are not often the most effective choice. This why Hanssens and Pauwels (2016) suggest that efficiency-driven marketing decisions should only be supported when they do not compromise the long-term brand equity. While certain media channels, which will be discussed later, can be highly efficient, advertising investments in these channels can only be scaled to a certain extent before reaching the limit. This applies especially to customer-initiated channels such as search engine advertising.

2.2 Time frame of advertising effectiveness

Measuring advertising effectiveness is a complex challenge not only because of the numerous external factors affecting it, but also because it occurs across different time frames. Advertising has been found to have both short-term and long-term effects (e.g. Dekimpe & Hansses, 1995; Breuer & Brettel, 2012; Binet & Field, 2013). The total advertising effectiveness can be seen as the instantaneous effect plus the carryover effects (Tellis, 2004, 93), which will be discussed more in depth later. The total return for

advertising investments can only be measured if both short and long-term effects are being considered.

Binet and Field (2017) divide these effects into brand building and sales activation. The purpose of brand building is to create mental brand equity and influence future sales, which yields long-term benefits after the campaigns are over. Sales activation on the other hand will take advantage of this earlier achieved mental brand equity to create immediate action among the individuals who are likely to purchase. Components of both effects are illustrated in table 1.

Table 1. The differences between brand building and sales activation (Binet & Field, 2017).

BRAND BUILDING	SALES ACTIVATION
CREATES MENTAL BRAND EQUITY	EXPLOITS MENTAL BRAND EQUITY
INFLUENCES FUTURE SALES	GENERATES SALES NOW
BROAD REACH	TIGHTLY TARGETED
LONG TERM	SHORT TERM
EMOTIONAL PRIMING	PERSUASIVE MESSAGES

Both long-term brand building and short-term sales activation contribute significantly to the effectiveness of advertising, so focusing on both is essential to achieve optimal outcomes. Based on the data from UK-based Institute of Practitioners in Advertising (IPA), Binet and Field (2017, 12) suggest a ratio of approximately 60% brand building and 40% sales activation for maximizing the effectiveness of advertising. However, this ratio is based on averages and the true optimal allocation varies based on the industry and other variables, thus it cannot be applied directly to obtain optimal results.

2.2.1 Long-term effectiveness

While earlier literature argued that the effects of advertising on sales would be relatively short in duration and most of them dissipate in few months (e.g. Clarke, 1976; Leone, 1995), more recent literature demonstrates that the effects can last well beyond that (Dekimpe & Hansses, 1995; Binet & Field, 2013;). According to a 2018 study by Thinkbox, long-term (3 months to 3 years) effects cover 58% of advertising ROI, while short-term (less than 3 months) cover the remaining 42%. Mela, Gupta and Lehmann (1997) also showed that advertising has modest effect on short-term sales but substantially larger long-term effect on brand loyalty.

As discussed in the introduction, marketers often tend to willingly focus on short-term results due to the pressures from the management or other earlier stated reasons such as easier quantification of results or monetary incentives. Discounting the long-term effects would ignore over half of the potential value that advertising brings. Because of this, without attention to these long-term, carryover effects, primarily brand building channels such as TV, will be systemically undervalued (Herrington & Dempsey, 2005). Dekimpe and Hansses (1995) state that advertising is characterised to have persistent, long-term effects on sales if a portion of the short-term effects will transfer to the long-term baseline of sales. However, Binet and Field (2013, 9) argue that the long-term effect always produces some short-term effects, but the opposite is not true, and the long-term effects are not the accumulation of short-term effects. Besides understanding the total value of advertising, understanding the scale of carryover effects is also important when planning new campaigns as sometimes the subsequent advertising pulse should only be scheduled once the carryover effects have decayed (Tellis, 2004, 93).

Having a strong brand has also been linked to decreased price sensitivity among consumers and it allows companies to charge premium for the products and services (Erdem, Swait & Louviere, 2001). Chu and Keh (2006) also link advertising directly to increased brand value, which on micro or consumer level positively influences behavioural outcomes such as purchase intent (Cobb-Walgren, Ruble & Donthu, 1995). This is generally achieved

most effectively by targeting a broad audience instead of strictly targeting the current core audience. Strong brands also get stronger response rates from the activation focused advertising (Binet & Field, 2017). The issue lies in the challenge of quantifying those effects.

2.2.2 Short-term effectiveness

The short-term effects of advertising are the immediate effects on sales or brand, often measured in weeks or few months (Mela, 1997). While the short-term effects of advertising on brand equity are typically weak (Mela, 1997), the effect on sales are usually significant and direct but also decay quickly (Binet & Field, 2017). While the focus on short-term effects have been widely criticised, they still play an important role in business, and allocating some resources for sales activation is important as it is an effective way to generate revenue and maintain cashflow. Campaigns focusing solely on long-term brand building tend to perform poorly in short-term and do not effectively trigger the purchase intent among potential customers, thus emphasising the need for short-term activation (Binet & Field, 2013). This phase will usually focus on information rich format for highly targeted groups of individuals who are already emotionally primed for the message (Binet & Field, 2017). If short-term revenue is the primary goal, sales activation will always yield better results compared to brand building, which is obvious considering the tight targeting on consumers that are already likely to purchase (Stürze et al., 2022, 69). However, if sales activation is emphasised too much, benefits from increasing the budget will start to fade as the pool of potential buyers is not growing due to lack of brand building with wide reach.

2.3 Key components of advertising effectiveness

This subchapter will provide an overview of budget decisions and optimizing advertising, which are both important elements that have substantial effect on effectiveness of advertising and need to be carefully evaluated.

2.3.1 Budget setting and allocation

Setting the total advertising budget and determining the allocation is one of the most important decisions when it comes to advertising in companies as it is often one of the largest expenses (Doyle, 2004). Since in literature there is a strong consensus that advertising positively correlates with sales and firm performance (e.g. Lodish et al., 1995; Leone, 1995; Sridhar, Narayanan & Srinivasan, 2014), setting budget too low will inhibit growth whereas decreasing it will often have detrimental effect on market shares and long-term performance, as discussed in the introduction. This applies to the potential reach of the advertising but also the frequency and intensity the individual is exposed to the advertisement, which has considerable impact on the effectiveness (e.g. Schmidt & Eisend, 2015). However, advertising spending can have little to no effect in certain cases, especially if saturation point is reached. Tellis (2006) claimed that S-shape curve would be the most likely illustration to explain effects of advertising intensity, as low amount of advertising will get drowned in the noise, while too high intensity will face diminishing returns due to market saturation and negative consumer response to repetitive advertising. This view however has been challenged in literature and Hanssens et al. (1990) propose a concave shape to resemble the response more accurately.

The existing literature on the optimality of the scale of advertising in companies remains mixed. Early literature largely suggests that companies tend to overspend on advertising rather than underspend, and that is often caused by organisational pressures within both advertisers and agencies (Aaker & James, 1982). Cheong, De Gregorio, and Kim (2014) noted that approximately 60% of advertisers overspent over the time period from 1985 to

2022. However, as discussed in the introduction, for many companies advertising is the first place to cut costs during uncertain times, which has been linked to decrease of firm performance (Ratajczak et al., 2023). While there is a strong interest in academia for researching optimality of advertising investment levels in companies, lack of knowledge on firm or brand objectives among researchers at given moment has made it extremely difficult (Hanssens & Pauwels, 2016).

As discussed by Stürze et al. (2022, 6), companies tend to place a lot of value on optimizing total advertising budget for achieving the desired goals. While this is important, according to literature, there seems to be a considerably higher leeway in the optimal investment level compared to the actual allocation of the total advertising budget. This is illustrated in figure 3, which is based on the “principle of the flat maximum” by Tull et al. (1986). According to this principle, even deviations of $\pm 25\%$ from the “optimal” investment level have negligible impact on profit and in a case of over advertising, can even produce positive results in the long term from increased market share.

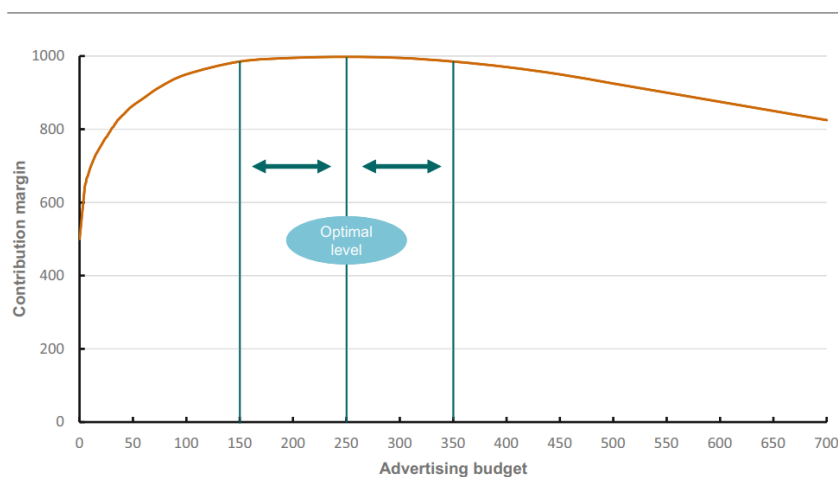


Figure 3. Principle of flat maximum (Tull et al., 1986).

While employing simple heuristics, such as the previously introduced 60/40 ratio, between brand building and sales activation may be convenient for budget allocation, they are solely based on averages and historical data, and do not take factors such as industry into

consideration. Furthermore, they often overlook factors in allocation, such as specific channels being used. TV for instance has demonstrated its effectiveness as a great medium for brand building but it might not be the optimal choice when targeting a predominantly young demographic due to the preferences in media consumption. While advertising effectiveness was earlier believed to be constant over time (Niemand, et al., 2020), research has shown that it varies substantially based on factors such as consumer behaviour, and competition (e.g. Jedidi, Mela & Gupta, 1999; Binet & Field, 2017), which further highlights the inadequacy of simple heuristics. According to Raman (2010), optimal resource allocation in advertising can potentially improve the firm profitability up to 400%, so it warrants a high priority in organisations.

2.3.2 Advertising optimization

Optimization can be defined as an action of making the most effective use out of a situation or resource (Merriam Webster). In advertising context, it typically refers to making changes to elements such as ad copies, budgets, bidding or targeting settings based on the performance (Aksakalli, 2012). One of the benefits of digital advertising is the ability to make quick changes to advertising, depending on the platform and the form of advertising being used. While traditional media channels such as print advertising and TV cannot be easily changed during a campaign that is already airing, in digital advertising, minor changes and experiments can typically be done during campaigns, thus not having to waste considerable budgets.

One key aspect of optimization is targeting. This can be done for example by location, demographic criteria or browsing habits (Shin & Shin, 2023). With well-structured targeting of advertising, companies can effectively reach consumers who are more likely to find their advertisements relevant and engaging (Shin & Yu, 2021). Targeted advertising has also been linked to improved consumer response (Goldfarb & Tucker, 2011), although this view has been contested in recent literature when targeting was based on highly granular customer data (Despotakis & Yu, 2023). While the recent trend of overemphasis

on tight targeting over wide reach has been criticized (e.g. Binet & Field, 2017; Stürze et al., 2022, 73), targeting still plays a large role in digital advertising, especially when geared towards activation.

Modifying the actual content of advertising or ad copies is also in the core of optimization. While some more visual forms of digital advertising may require more time to modify, some formats such as search engine advertising (SEA), which is mostly text-based, can be altered easily. Content of the advertisement will largely dictate the effect it has on consumers and response within individuals can vary substantially (Tellis, 2004, 7), and because of that testing alternative ads and tailoring them to different segments can be beneficial. According to Wood (2009), creative copy is the foremost driver of advertising effectiveness, and that a powerful copy can produce up to 20 times more results than a mediocre copy. Because emotions have been reported to drive stronger action than cognition in advertising (Sudhir, Roy & Cherian, 2016), the style of messaging has a large impact on effectiveness. Different consumers can also appreciate different features of the products or services, so highlighting them is important.

3 Advertising channels

As established in the introduction, utilization of multiple paid advertising mediums offers synergies for advertiser in both short-term performance objectives and long-term brand building. Different mediums tend to have distinct ways of delivering impact, and some of them might appear ineffective in tracking systems such as Google analytics. Although all forms of advertising produce some effects in both short and long term, the ratios differ vastly. For long time there has persisted a notion that online advertising equates to performance goals and offline advertising to brand building (Stürze et al., 2022, 26). This simplified idea is not however supported by existing literature (e.g. Binet & Field, 2017). The effectiveness of a given channel can also vary based on the customer positioning, and some channels work better during the awareness phase, while some are more attractive to consumers during the consideration phase (Niemand, et al., 2020). Consumer behaviour also differs across different target groups, favouring diverse channel strategy. This chapter covers various popular advertising mediums and their unique characteristics as well as strengths and limitations.

3.1 Offline channels

While digital advertising has received most of the attention in the recent years due to digital revolution, traditional offline channels such as TV, print or radio, have still maintained their relevance and proven effective in many situations. In United States only, companies spent 203,5 billion USD on offline advertising in 2022, dropping only 11% from 2018 despite all the new digital channels available (Statista, 2023a).

As companies increasingly try to analyse the advertising performance, offline advertising has been a challenge as it is difficult to determine factors such as the true number of impressions, and even more difficult to evaluate the impact on purchases. Compared to digital advertising, lack of precise targeting is also a challenge for traditional offline media.

However, studies often link offline channels with poor short-term ROI but strong long-term effect, which is connected to the lack of tight targeting (e.g. Stürze et al., 2022). Binet and Field (2017) note that as the fundamental role of advertising is to “want to consumers buy their brands to such an extent they do not have to discount them”, broad, early targeting is crucial as reach and long-term effectiveness still have a strong correlation. Traditional advertising is also sometimes discredited because it does not necessarily provide immediate results as well as some more performance oriented digital channels. Although this is frequently the case, according to research (de Vries, Gensler & Leeflang, 2017) offline channels are superior in long-term brand building. Binet and Field (2017) also demonstrate that offline channels improve the effectiveness of online channels and vice versa.

TV is one of the most popular advertising channels, but in same way as other traditional advertising channels, it has lost some of its popularity and is predicted to decline due to growing number of online mediums and interest towards them (Statista, 2023c). According to study from Nagar (2009), TV advertising was viewed as less informative compared to online advertising but was more effective in capturing attention and creating purchase intent after exposure. This goes in line with features that Binet and Field (2017) attributed to strong long-term brand building effect, that TV is generally known from (Wildner & Modenbach, 2015). While there has been critique towards TV advertising due to reduced attention among consumer who are usually in relaxed state while watching TV, this has reported to facilitate stronger emotive associations with brands (Heath, 2012). Although a study from Bright, Kiewell and Kincheloe (2006) demonstrated that TV advertising has lost its effectiveness considerably during the last 20 years, more recent data from Binet and Field (2017) report that including TV in the media mix increases the overall business effectiveness by 40% compared to the campaigns that do not, and that TV is particularly effective in gaining market share. This can most likely be attributed to the wide reach and the ability to effectively grab attention. Stürze et al. (2022, 21) report that long-term effect of TV advertising is usually roughly twice as high as the short-term sales uplift. TV advertising has also been shown to stimulate the repeat purchases as well as maintain healthy consumer brand perceptions (Cain, 2008).

Print advertising is one of the oldest forms of advertising, and because of this often discredited. This is demonstrated by year-by-year decline in print media spend (Statista, 2023b), caused by the growing interest in online media channels. Data from IPA still demonstrates that campaigns utilizing print advertising tend to overperform ones without print when budgets are equal, and this positive effect has only increased during the last 10 years despite the lower circulation levels (Binet & Field, 2017). Venkatraman, Dimoka, Vo and Pavlou (2021) also found that print advertising results in superior memory recall when compared to digital advertising.

Outdoor advertising, also known as Out-of-home advertising (OOH), refers to advertising that reaches consumers outside their home. A significant advantage of OOH is the ability to reach increasingly elusive and mobile consumer and associate the brand with given location such as high-end shopping centre (Wilson & Till, 2011). In recent years OOH has been showing modest results and even decline in performance compared to other channels but the recent rise of digital outdoor formats has been able to revitalise the medium and increase the effectiveness (Binet & Field, 2017). This combination of traditional and digital channels continues to have its place in modern multichannel advertising.

Radio has been a popular advertising medium for decades and has managed to maintain its popularity despite the rise of digital mediums, although it is frequently undervalued by certain advertisers (Michelon, Bellman, Faulkner, Cohen & Bruwer, 2020). Although radio advertising is often deemed inferior to digital channels, recent finding by Binet and Field (2017) show that including radio into the media mix increased the share of voice metric by 38% and has increased over time. They argue that because radio is often played in background while using computers and other devices, it can create clear synergies with other channels. Similar positive results were also reported by Danaher and Dagger (2013), who found that radio advertising significantly increased purchase intent. Despite a lack of visual component, radio advertising can evoke imagery in consumers' mind and create powerful experiences (Barwise & Ehrenberg, 1988).

So, while traditional advertising mediums go against certain megatrends such as younger demographic moving away from newspapers and linear TV, they still seem to hold their effectiveness in many situations, and sometimes even surpass digital mediums. This applies especially in the context of long-term brand building. They also seem to work synergistically with digital channels and enhance the total media mix being used.

3.2 Online channels

Search engine advertising (SEA) is one of the most popular forms of online advertising, covering approximately 40% of total digital advertising expenditures in 2022 with ad spend of 260 billion USD (Statista, 2023d). SEA works by targeting keywords that consumers have shown interest to by typing them into the search engines, thus it falls under the category of customer-initiated channels (Abou Nabout, Skiera, Stepanchuk & Gertsmeier, 2012). Despite being commonly perceived as a direct-response advertising channel with primarily short-term effects, SEA has also demonstrated a substantial carryover effect in studies (Yang, Zhao, Zeng & Jansen, 2022). According to Binet and Field (2017), search engine advertising, along with email, was the most effective medium for sales activation. One reason for not being among the strongest brand building channels is that consumers searching for a specific product or service are primarily searching for information about the features or prices and therefore are less receptive for brand messages (Stürze et al., 2022, 30). Additionally, SEA tends to be less visual compared to other advertising formats, and visuals of advertising are strongly linked to emotional response in consumers (e.g. Mitchell, 1986). However, Hyun et al. (2006) found that since users are highly involved with ads as they were actively searching for something similar, it enhances the user's memory of the ad, which explains some of the long-term effect on future sales. Search engine advertising has also been linked to improving effectiveness of organic search by increasing click-through rates as consumers are encouraged by the fact that the website is appearing twice in search results (Yang & Ghose, 2010).

Online video advertising is a video form advertising that is usually played on websites or social media and allows brands to advertise either through paid spots such as pre-rolls on YouTube or through owned video content (Binet & Field, 2017, 48). Online video is one of the most prevalent forms of digital advertising with third highest ad spend after display and search engine advertising (Jiang, Guan & de Haaij, 2020) and with one of the highest growth rates in all digital media (IAB, 2023). Online video, having the same ad format as TV, is also powerful in brand building and is suitable for smaller advertisers and, excellent results can be achieved with relatively small budget (Binet & Field, 2017). Online video is also highly versatile tool as it can be tightly targeted, which, is valuable when focusing on sales activation. Lee and Lee (2012) conclude that online video advertising can offer the branding power of traditional broadcast advertising as well as the direct and immediate response characters of internet advertising.

Display advertising refers to advertising medium where some form of visual advertisement such as image or video, is shown to user on third-party websites (Aksakalli, 2012). As stated, video advertising is a powerful brand building tool but regular image format display also has some long-term, carry over effect (Bayer, Srinivasan, Riedl & Skiera, 2020), although is still mostly used as a sales activation tool (e.g. Kireyev, Pauwels & Gupta, 2016; Binet & Field, 2017). With advancements in advertising technology, advertisers hold great control over frequency of display ad exposures on individual consumer level, thus potentially improving the overall effectiveness (Todri, Ghose & Singh, 2020). While the effectiveness of display advertising has been widely criticized in early literature, predominantly due to low click through rates (Lee & Ahn, 2012), this has been mostly disputed in more recent studies that have evaluated the effectiveness with more sophisticated measures (e.g. Binet & Field, 2017).

So, although digital advertising is frequently deemed mostly as activation, performance marketing, it is highly versatile and can be used for effective brand building with appropriate channel selection. Digital advertising is also changing constantly due to technological advances and new emerging platforms providing new ways for companies to communicate to consumers. As consumers have increasingly moved online, investments in

digital advertising have continued to grow, even during periods of economic downturns (Statista, 2023e).

4 Measuring advertising performance

This chapter provides a comprehensive overview on the literature from two primary methods that have been used for assessing advertising performance in companies, AM and MMM. First subchapter will delve into AM and its role in advertising as well current situation with uncertainty with third-party cookies. This is followed by a review of MMM and its history and modeling principles. Reported strengths and weaknesses of both modeling approaches are being discussed.

4.1 Attribution modeling

Attribution modeling can be defined as the science of using advanced analytics to allocate appropriate credit for desired customer action across media channels (Kannan, Reinartz & Verhoef, 2016). Digital touchpoints in a customer's individual journey are tracked, from the initial interaction to the final transaction or other desired conversion, providing a more granular understanding of the impact of each touchpoint (Stürze et al., 2022, 60– 62). This contribution is then quantified by the sum of conversions, which are usually purchases, leads or other relevant actions related to the business. These events, or interactions are ordered by the time the interaction happened and credited accordingly by the model being used (Sapp & Vaver, 2016). The way the credit is attributed is usually based on heuristic rules, which are often chosen based on company's intuition of a role of given advertising channel and its role in the customer path (Kannan et al., 2016). Due to the increased number of advertising mediums and online consumer interactions, the customer journey has become more complex over time. While recent literature and discussion on AM is mostly based around conversion attribution, early literature mostly revolves around click-through rates being the measure of effectiveness (Ansari & Mela, 2003), as the concept of internet advertising was new and knowledge with it was still in its early stages.

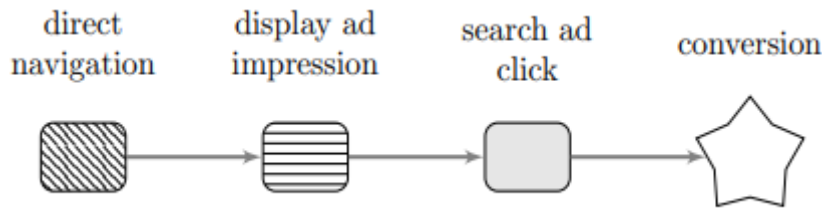


Figure 4. Example of conversion path (Sapp & Vaver, 2016).

These desired events along the customer journey are usually being tracked with third-party cookies that allow companies to collect more granular data (Anderl et al., 2016). Third-party cookies refer to unique identifiers that are placed on web browsers by advertising technology companies (Cooper, Yalcin, Nistor, Macrini & Pehlivan, 2023). These text snippets are used to identify users online, reveal their interests and collect other user specific information that is used by marketers (El Hana et al., 2023).

There are multiple different attribution models in use today ranging from the simplistic last click model that assigns all the credit to the last touch point in the customer journey, to more advanced model such as linear attribution and position-based attribution, which are referred as multitouch attribution models (MTAs). These more recent and sophisticated models try to allocate the credit more evenly to account for the synergistic nature of multichannel advertising. Examples of such models are:

- **Position based:** Model assigns 40% of the credit to the first touch point, 40% to the last touch point, and remaining 20% is attributed to other touch points along the user path.
- **Linear:** Model assigns equal credit to all touchpoints along the user path
- **Time decay:** Model attributes channels proportionally based on the position in the user path so that the closer the touch point is to the conversion, the more credit is assigned. Specific weights are decided by the marketer.

(Romero Leguina, Rumin & Rumin, 2020.)

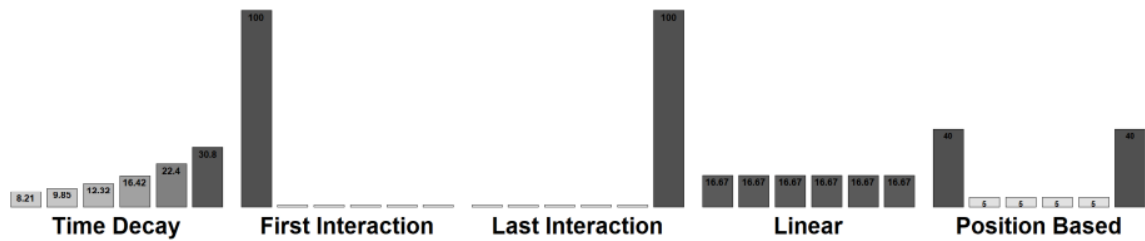


Figure 5. Different attribution models (Romero Leguina, Rumin & Rumin, 2020).

Although attribution models have progressed over the years, last touch models remain as the most common AM method used by companies, thus discrediting all the synergies provided by different channels (Berman, 2018). In a study by de Haan et al. (2016), the researchers estimated that the use of last click attribution model resulted in 10-12% decrease in revenue compared to status quo. This is a well-documented issue, which does not only affect smaller companies with fewer resources but has also been documented among well-known multinational companies (Stürze et al., 2022, 34). Relying on these early models will almost certainly lead to a brand erosion due to sub-optimal budget allocations (de Haan et al., 2016).

While the newer models address certain limitations associated with models such as last click, they are still based on simple heuristics that do not necessarily reflect reality and as mentioned previously, are often chosen based on intuition rather than data. Because of that referring to them as “modeling” tools can be misleading as they are not based on any statistical model (Stürze et al., 2022, 63). They also typically do not entirely consider customers whole purchase funnel and cannot account for consumer paths that do not result in a conversion (Li & Kannan, 2014). A 2012 study from Reiley, Lewis and Schreiner demonstrated that the conversion estimates by these heuristic based models differed significantly from randomized controlled experimental results.

The latest addition to AM are data-driven attribution models (DDAs), also referred as algorithmic or probabilistic models, that are often regarded as superior alternatives to older models as they are believed to better capture the value of advertising (Sapp & Vaver,

2016). Unlike the previously presented models, data driven attribution models rely on mathematical and statistical foundations and use the input data from previous campaigns, thus are proposed to be more reliable in attribution of conversions since they do not just work with predetermined set of rules (Romero Leguina et al., 2020). Data driven attribution models are also able to analyse non-converting user paths, thus more accurately credit touchpoints preceding the actual conversion event (Sapp & Vaver, 2016). One of the most common forms of DDA is Shapley model, which is being used by Google Analytics 4. Shapley value method is a general credit allocation method in cooperative game theory, which is applied to AM to treat individual advertising channels as players in the game (Zhao, Mahboobi & Bagheri, 2018). These algorithms assign credit on events in consumer path that led to conversion by comparing the conversion rates to users with similar path but do not contain the same marketing event (Sapp & Vaver, 2016). An equivalent model to Shapley value has been proposed by Dalessandro, Perlich, Stitelman and Provost (2012), which analyses the so-called joint effects of all advertising mediums being involved.

AM has been a prominent part of digital advertising during recent years as it has been used by marketers to track user actions and credit the conversions to different channels, thus helping to determine the ROI for specific digital advertising activities. With this information, companies have been able to allocate budget from less effective channels to better performing ones. In contrast to MMM, AM operates by user level, providing unique benefits for optimization that MMM as more macro level approach cannot offer.

One of the benefits of AM is the short time frame for which it can be used. As it works with near-real-time data, it can be used for precise optimization of digital campaigns at the customer level (Stürze et al., 2022, 64). This allows for instance the analysis of specific ad creatives, which is highly important given the strong relationship between advertisement quality and sales (Stürze et al., 2022, 45). As the data is user level, more advanced models can also provide unique insights about the interplay of different channels among the customer journey (Anderl et al., 2016). This insight is crucial as improvements in customer journey directly improve the overall customer experience, thus eventually leading to better financial outcomes (Lemon & Verhoef, 2016). Åkesson, Edvarsson and Tronvoll (2014)

also point out that understanding the factors that have influence on customer journeys need to be understood to create favourable customer experiences.

While having multiple use cases that have the potential to provide benefits to companies, AM has faced a lot of criticism especially when it comes to optimizing advertising investments between different channels. An evident reason is the inability to measure all offline activities due to the absence of tracking methods, which continue to account for a large portion of advertising budgets (Statista, 2023e). Due to this constraint, even the most sophisticated models are susceptible to the same flaw as the last-click models, as they do not account for early funnel exposure from offline channels. Another important reason for this is the tendency to credit some channels disproportionately high while discrediting others. Search engine advertising for instance is often shown to be by far the highest-performing channel, when compared to other digital channels. While SEA is shown to be an effective medium as a customer-initiated channel (CIC), other mediums such as display or tv advertising tend to increase the number of searches that result to website visits through ads, and eventually conversions. This is well illustrated by the study from Ghose and Todri (2015), which demonstrated that the mere exposure to display ads increased the tendency for consumers to do searches for both the brand and corresponding products. This effect is often discarded by attribution models, especially by models such as last click that ignore early interactions. This typically leads to over allocating budgets into search engine advertising and under allocation in firm-initiated channels such as display (Anderl et al., 2016). Advertising in customer-initiated channels is also dependent on the customer searches, and thus limiting the potential for scaling investments in the same manner as with firm-initiated channels (FIC) such as display.

Another common issue with AM is the fragmented touchpoint data, caused by the use of multiple platforms. These platforms rarely share information due to reluctance stemming from the competition dynamic or legal reasons and they register touchpoints differently (Berman, 2018). This makes accurate attribution of contribution significantly more challenging and partially erases the benefits of multitouch attribution models. Attribution models are also typically provided by the advertising platforms such as Google and

Facebook, which creates a conflict of interest since marketers have to rely on publishers to accurately report the effectiveness (Berman, 2018).

Overall, the reliability of tracking touchpoints with third-party cookies remains questionable and the lack of complete data has hampered the studies trying to establish the accuracy of the models. Cookie deletions by media and web users have reduced the number of tracked touchpoints resulting in incomplete attribution. Conversely, issues with formats such as display advertising registering impressions but not actually viewed by the user due to being below the fold of the webpage, have raised concerns about the validity of the tracked interactions (Kannan et al., 2016). Scottmay (2016) also note that ad blockers have become popular among users, especially in emerging markets as they reduce the data usage, which also hampers with the AM studies. Currently third-party cookies are set to be blocked by all major browsers by 2024 (El Hana et al., 2023). While platforms such as Google analytics 4 are attributing conversions based on both observed data as well as modelled data which does not rely on cookies (Google support, 2023), research on its reliability is currently non-existent due to novelty of the method.

4.2 Media mix modeling

Media mix modeling (also widely referred to as marketing mix modeling) is an approach of using econometric modeling for quantifying the sales contributions of different advertising activities (Cain, 2008). While marketing mix models are designed to analyse all marketing related activities such as pricing and promotions, MMMs are a subset of marketing mix models that are used to assess the effectiveness of media channels and tactics and improve them over time. The goal is to isolate and measure the interdependencies between influencing factors and drivers, and economic targets such as sales or leads (Stürze et al., 2022, 51). The structure of the model is rooted in microeconomic theories of consumer demand ranging from individual product sales equations to full interactive systems of brand choice (Cain, 2010). MMM is time tested modeling method that has been around in various forms since the 1960s and is still actively

being used (Chan & Perry, 2017). The popularity of econometric modeling rose in the 1980s in retail with the usage of UPC scanners that provided the models with accurate sales data (Fulgoni, 2018). There are also several other enabling factors that have led to the current development of marketing mix modeling such as the availability of granular internal and external data needed for the analysis, technology to store and process data and sophisticated analytical techniques such as forecasting and behavioural modeling (Doyle, 2004).

MMMs leverage aggregate historical time series data to model sales outcomes over time as a function of advertising variables, other marketing variables, and control variables such as seasonality, weather and competition landscape, from which the metrics such as ROI and optimized advertising budgets are derived (Chan & Perry, 2017). Crucial part of the model development is to select target variables such as sales or leads that are close to the marketing impulse and ultimately have close relationship to the commercial success of the firm (Stürze et al., 2022, 51). Sales (or other target variable) is divided into baseline sales representing the long-term trend, and short-term incremental sales. This baseline is an indicator of underlying consumer preferences, while the incremental sales are a representation of weekly variations caused driven by factors such as advertising or price promotions (Cain, 2008). Ideally, the model should provide high explanatory value with low baseline that cannot be broken down further (Stürze et al., 2022, 55).

On top of crediting different advertising channels, it also separately takes into consideration external factors such as economic outlook, weather and overall market growth (Perrey & Spicllecke, 2013, 162). This is a significant advantage as many micro- and macroeconomic factors can have strong effect on sales (Bendixen, 1993), and thus can skew the interpretations gained from the models. However, since the number of important outside variables tends to be high, including all of them can become a challenge. In certain cases, additional media metrics besides expenditure data such as clicks and impressions can also be incorporated into the models (Chan & Perry, 2017).

One of the primary advantages of MMM is the ability measure and forecast the value of both online and offline activities as the calculations are based on aggregate data instead of

granular, individual-level data. Additionally, it does not require expensive experiments, which has also contributed to its widespread adoption. After the models are built, marketers can simulate alternative scenarios with different advertising allocations and budgets. and use that data for future planning (Fulgoni, 2018). This is a substantial benefit in comparison to randomized experiments, which are only capable of testing a single scenario at a time (Chan & Perry, 2017).

The MMM analysis typically provides answers to three main questions:

- **Performance driver analysis:** Recognizing the actual drivers of the topline performance and identifying which of them are under our direct influence and which are not.
- **Impact analysis:** What is the return on investment with the advertising activities and how does it compare to other line items withing the advertising budget?
- **Optimization of advertising spend:** What is the optimal allocation of advertising funds and how would a reallocation affect the revenue and profit?

(Jesko & Spillecke, 2013, 162.)

The quantification of the long-term effect can be achieved in multiple ways. Typically, it is achieved via carry-over effect or some kind of brand equity metric (Hein, Schlereth & Mueller-Klockmann, 2019). In the carry-over approach, the regression model directly quantifies the continuing effect of campaign after it has stopped airing (Stürze et al., 2022, 20). In contrast, the brand equity approach measures the effect by including the desired brand equity key performance indicator (KPI) such as add awareness into the regression model. This can be done either directly as an additional influencing variable or indirectly quantified in two step process, “statistically highly condensed as the influence of brand equity on sales” (Stürze et al., 2022, 20). Srinivasan, Vanhuele and Pauwels (2010) found that incorporating mindset metrics into market response models such as MMM, significantly increased the explanatory value of the models. More recent example of this is a metric called Share of search, which is defined as the share of searches for given brand,

divided by searches for all brands in the competitor set. This new metric proposed by Binet and Hankins (2021) concluded that Share of search (SOS) represented 83% of firms market share, reinforcing the insight that SOS is a strong proxy to demand side of market share, thus being well suited for a brand metric used in MMM.

A benefit of a proper use of econometric modeling is also the ability to develop a saturation curve estimate, which helps to identify the windows of highest advertising spend effectiveness for given channel used (Perrey & Spillecke, 2013, 114). This enables companies to avoid the trap of diminishing returns in their advertising, which is common when strictly looking numbers from simplistic tracking systems. Although these estimates are efficiency based rather than effectiveness, they can be used in the analysis when trying to maximise total returns. The function of S-curve is demonstrated in figure 6.

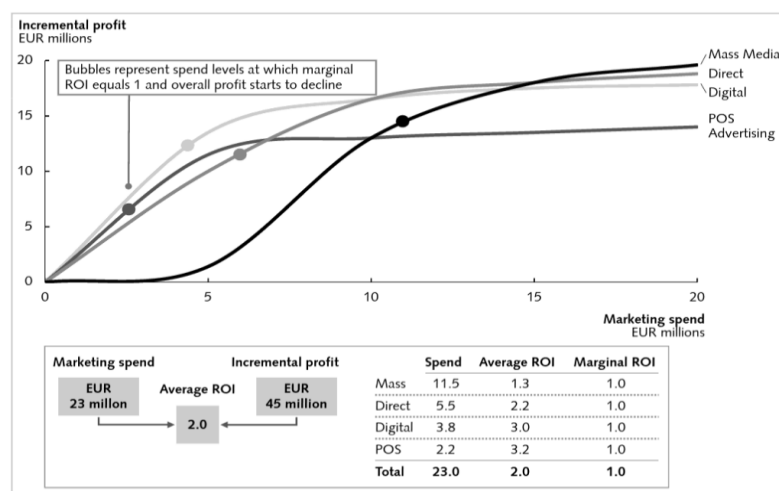


Figure 6. Example advertising spend curve (Perrey & Spillecke, 2013).

Despite its recent surge in popularity (e.g. Farenius & Chornouk, 2023; Mank, Rich, Bona, de Bellefonds & Recchione, 2019), MMM is not without its limitations and has limited utility in some situations. It primarily provides macro level data about the advertising effectiveness and cannot be used for micro-level, day-to-day optimization (Stürze et al., 2022). Since MMM is a top-down approach, the underlying data is aggregated, thus all the individual interactions are averaged and ignored (Liu, Laguna, Wright & He, 2014). As MMM is also based large quantities of historical data, it requires relatively stable market

conditions so the data can safely be assumed to resemble current business environment to produce reliable ROI estimations and suggestions for the future (Jesko & Spillecke, 2013, 114). While MMMs attempt to answer causal questions, the results from MMMs can typically only be considered correlational not causal as the regression models are based on limited amount of aggregated observational data (Chan & Perry, 2017). Selection bias is also a potential limitation when measuring the advertising effectiveness with MMM (Chan & Perry, 2017).

Data quality can also pose a challenge for organisations trying to establish the MMMs. As noted by Karmann, Köster, and Meyer (2015), a common issue faced by many companies is their inability to accurately assess the total advertising expenditure. Chan and Perry (2017) also add that in order for the data to fit the model, the response data needs to be on the same level as the advertising expenditure data, which is often not the case. Besides the data quality, data quantity is also a prevalent issue with MMM. Stürze et al. (2022, 55) propose a weekly granularity as it seems to typically be the optimal compromise between accuracy and data availability. In order to produce reliable results, MMMs need at least 2-4 years' worth of historical data (e.g. Stürze et al., 2022; Chan & Perry, 2017), which can limit the use for some organisations. As is the case with all statistical models, the efficacy of the model is dependent on the quality and accuracy of the input data provided.

Furthermore, MMM is only a tool to support the analysis and cannot completely replace experience and expertise. As Jesko and Spillecke (2013, 168–170) note, as with any management information system, it is dependent on the wisdom of the users, and should be used as a basis for wider discussion. Chernyak and Fareniuk (2020) also state that results of MMM are unique to each business as they are a combination of multiple factors, thus require an individual review on the recommendations given by the model being used. Because of this, effective use of MMM also requires deep commercial knowledge to accurately interpret the results and apply them into advertising strategies.

In addition, it is important to acknowledge that MMM is not a single model but rather a modeling technique, which can be structured differently and provide results with variable accuracy. Despite the long-standing use of MMM, many early models failed to accurately assess the long-term brand building effects of advertising due to deficiencies in the model construction. Unfortunately, many models being used today remain susceptible to the same flaw (Stürze et al., 2022, 16). In traditional models the long-term trend is typically represented by the regression intercept plus a linear deterministic growth factor, which adjusts the regression intercept by proportional amount over each time interval within the data sample, resulting in linear trend line that does not account for variance in sales data trend that tends to evolve over time (Cain, 2008). According to Cain (2010), this sole focus on incremental sales will be biased towards activities that promote short-term gains such as promotional activity and ignoring the benefits of brand building, thus resulting in brand erosion. In the context of media channel decisions, and division of sales activation and brand building suggested by Binet and Field (2017), it would shift in favour of mediums such SEA or hyper targeted display. Another common method to estimate the long-term effects in conventional models is to simply multiply the short-term effects by three, which is based on the 1995 study by Lodish et al. (Cain, 2010). A meta-analysis from Köhler, Mantrala, Albers and Kanuri (2017) suggested a lower multiplier of 2.54. However, while simple, using a multiplier to quantify long-term effects is usually not an accurate measure as the size of the multiplier is affected by factors such as the definition of short-term effects, media channels being used and the product category (Stürze et al., 2022, 17–18).

In conclusion, MMM is seen as helpful tool in literature for many companies equipped with the necessary resources to utilize it. Nevertheless, it is important to acknowledge its inherent limitations, particularly its limitation in providing granular insights due to its reliance on aggregated data. Constructing a model that is capable of generating realistic estimations also requires expertise and relying on conventional MMMs erases many the benefits that econometric modeling is able to provide. Despite these shortcomings and potential challenges, Stürze et al. (2022, 64) argue that for CMOs with large brand portfolios and omnichannel sales, there is no viable alternative for MMM when it comes to optimizing marketing investments for offline and online activities, while also incorporating long-term brand development.

5 Research design and methodology

This chapter will begin by providing an overview of the research design and methods of the thesis. The subsequent subchapters will go over the data collection and analysis methods used in the research. Finally, the concepts of validity and reliability in qualitative research are being discussed.

5.1 Research approach

This thesis was conducted as qualitative research. Qualitative approach was chosen as it allows gaining deeper understanding about relatively new topic that lacks previous research (Hirsjärvi et al., 2009). Although MMM and AM have been widely used for years, the advertising landscape has drastically changed and especially tracking digital advertising with third-party cookies has already been disrupted due to new privacy regulations, which alters the way these tools can be used and the role they play in decision making. Qualitative methodologies are ideal for understanding the perspectives of the participants in their words and allow in-depth observation of the process (Groenland & Dana, 2019, 32). Additionally, qualitative research also allows learning directly from the research subject, thus reducing the likelihood of measurement errors, which are frequently encountered in quantitative research (Groenland & Dana, 2019, 33).

Research approaches can be divided into three categories: deductive, inductive, and abductive (Saunders et al., 2016, 144). Deductive approach starts by forming a general theory or hypothesis based on the existing literature, which is then tested against the empirical data (Dubois & Gadde, 2002). Inductive approach on the other hand begins by collecting data to explore new phenomenon and build theory (Saunders et al., 2016, 145). Abductive approach combines deductive and inductive approaches, and it begins from collecting data to explore phenomenon, identify themes and explain patterns to generate or modify existing theory, which is then tested against new collected data (Saunders et al.,

2016, 145). Given the absence of existing literature on simultaneous use of the models to improve advertising effectiveness, abductive approach was chosen for this thesis, as the goal is building on and continuing from existing literature on individual models.

The nature of the research can be divided into exploratory, descriptive, explanatory, evaluative or a combination of these. This thesis is both exploratory and evaluative in nature as it seeks to gain insights on potentially improving effectiveness with simultaneous use of AM and MMM while also evaluating the effectiveness of both tools in the current advertising environment. Exploratory research is suited for studies, in which the goal is to gain insights on a subject that has not been studied previously. Evaluative research is concerned with how well something works. This combined approach is warranted due to the lack of prior research on the simultaneous use of MMM and AM, as well as the recent changes in privacy regulations affecting performance measurement and the rapid pace of advertising technology development. (Saunders et al., 2016, 164–176.)

5.2 Data collection

The data for this thesis was collected using interviews, as it is a common practise in qualitative research and provides advantages over other data collection methods. These advantages include flexibility, ability to repeat questions, correct misunderstandings and have a conversation with respondents (Tuomi & Sarajärvi, 2018). Interview questions are presented in appendix 1. Research interviews can be categorized as structured, semi-structured or unstructured interviews, the latter two being non-standardized approaches (Saunders et al., 2016). Semi-structured interviews are flexible interviews where the researcher has specific themes and key questions predetermined, which serve as the blueprint for the discussion (Saunders et al., 2016, 391). Questions can also be omitted, or new ones can be added based on the flow of the interview or the person being interviewed (Saunders et al., 2016, 391).

This study was done by conducting 5 semi-structured interviews with representatives from the case company. This interview method was chosen because it allows interviewees to bring up relevant factors that might not have been identified by the researcher (Puusa & Juuti, 2020). This method is also well suited for both exploratory and evaluative research (Saunders et al. (2016, 392 –393). The data was collected anonymously to get as honest answers as possible. Interviewees were chosen by using purposive sampling. This refers to an approach where the researcher uses their own judgment when selecting the participants for interviewees to achieve the objectives of the study and answer the research questions (Saunders et al., 2016, 301). In this case, the decision criteria were based on the potential interviewees perceived familiarity to subjects being studied and the overall experience in the industry. Purposive sampling is suitable for research with small sample sizes and allows researchers to choose highly informative candidates (Saunders et al., 2016, 301).

Four interviews were conducted face-to-face at the company's office and one in Microsoft Teams due to time constraints. The interview language was Finnish as it was the native language of all interviewees and allowed more fluent and in-depth conversation about the research themes, and enabled interviewees to better articulate their conceptions of complex topics. The interviews lasted from 30 minutes to 65 minutes and were held between the 29th of May and 13th of June 2023. The participants were provided with the interview questions in advance to reflect their responses and to avoid any confusions as some of the terms related to the thesis topics are used imprecisely in the industry and can have various meanings depending on the context. This was also done to minimise the potential recall bias, thus improving the validity of the data. All interviews were recorded with approval of interviewees to avoid loss of attention during interview situations as it allows the interviewer to fully concentrate on the discussion, and for the ease of analysis later.

Table 2. List of the interview participants.

Interviewee	Title of the interviewee	Date	Length of interview
Interviewee A	Senior manager, digital & media	29.5.2023	40 minutes
Interviewee B	Chief technology officer	1.6.2023	38 minutes
Interviewee C	Advisor, marketing & media	5.6.2023	30 minutes
Interviewee D	Senior manager, digital marketing	6.6.2023	56 minutes
Interviewee E	Business strategist	13.6.2023	65 minutes

Table 2 presents the interviewees and their role in the company. Date and duration of the interview are also being presented.

5.3 Data analysis

After the interviews, the recordings were transcribed and translated into English. The data was then analysed carefully. The analysis method chosen for this thesis was thematic analysis. Thematic analysis is a commonly used method for qualitative analysis that focuses on the contents of statements from the interviewees (Bennett, Barrett & Helmich, 2019). Braun and Clarke (2006, 78) refer it as a “foundational method for qualitative analysis”. The purpose of the method is to find themes or patterns in the collected data set, and the analysis process involves coding the qualitative data based on these themes and patterns involving the research topic for further analysis (Saunders et al., 2016, 579). Thematic analysis is a suitable method for analysing qualitative data since it is systematic and flexible as it provides logical way to process the data, but it is not tied to any certain philosophical position (e.g. Braun & Clarke, 2006; Saunders et al., 2016, 579). Braun and Clarke (2006) divide thematic analysis into six phases, which are displayed in figure 7.

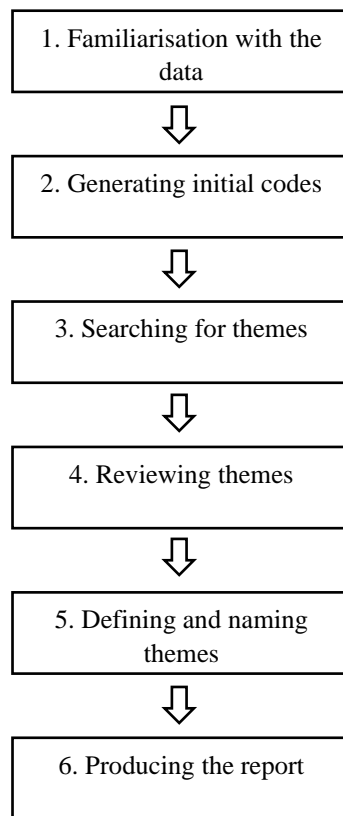


Figure 7. Phases of thematic analysis (Braun & Clarke, 2006).

During the transcription, the data was thoroughly familiarised and read multiple times. This was followed by coding the data to find the themes and patterns related to the research questions. After that, the themes were evaluated to make sure they were in line with the codes and named accordingly. Finally, the report was produced based on the results of the analysis.

5.4 Reliability and validity

This sub-chapter goes over reliability and validity, and their role in academic research. Reliability and validity are important concepts when assessing the quality and trustworthiness of a research. While their role in qualitative research is contested, they remain widely used (Saunders et al., 2016, 202).

According to Saunders et al. (2016, 202) reliability refers to reapplication and consistency, meaning that if the same research design would be replicated, it would still produce the same results. Reliability is typically separated into internal and external reliability (Thyer, 2001). Internal reliability implies to the consistency during the research project while external reliability refers to how well the data collection methods and analytic procedures can produce similar results if repeated on another occasion or by another researcher (Saunders et al., 2016, 202).

Validity on the other hand refers to the extent to which conclusions derived from the study provide an accurate description or explanation of what happened (Eriksson & Kovalainen, 2008). Validity can also be divided into internal and external validity. Internal validity refers to the extent to which causal relationship in study can be demonstrated while external validity is concerned on how well the findings of the study can be generalised to other relevant settings or groups (Saunders et al., 2016, 203-204).

According to Morse, Barrett, Mayan, Olson and Spiers (2002), there are several verification strategies to ensure reliability and validity of the research such as having methodological coherence, appropriate sample size, theoretical thinking and theory development. Morse et al. (2002) highlight that the concepts of validity and reliability have to be kept in mind during the entire research process to establish trustworthiness. While the concepts of reliability and validity have been criticised for not being suitable for qualitative research as they are difficult or even impossible to establish in qualitative research, they can be still applied if the researcher has understood the nature of qualitative research and difference in the concepts compared to when used in quantitative research (Puusa & Juuti, 2020).

6 Research findings

This chapter presents the results of the empirical research and analyse the interview responses. The chapter is divided into four sections based on the theme and topic of the questions.

The case company is a part of one of the largest media agency networks in the world. It serves both local and international companies and provides comprehensive range of services such as media buying and planning, advisory services, market research as well as modeling and measuring of the advertising performance. The agency has adopted a data-driven approach in its practices; therefore, the chosen interviewees were knowledgeable about the topics covered in this thesis.

6.1 Media mix modeling as a concept

First, the interviewees were asked to define MMM to avoid any misunderstandings about the method, as many terms related to advertising measurement are often used imprecisely in today's advertising. All the interviewees gave similar definition to the question.

6.1.1 Benefits of MMM

Then, the interviewees were asked about the benefits of econometric modeling (MMM) and its relevance in advertising. The most commonly mentioned and significant answer in every interview was that by using MMM, advertisers can obtain holistic view of their advertising performance and role of individual channels. Interviewee B also highlighted the fact that as MMM is based on regression analysis, it allows inclusion of control variables from numerous areas that can affect advertising performance and sales, thus more

accurately isolate the effect of advertising campaigns. This was also pointed out by interviewee E.

“It’s a very robust tool as we can include almost any time series data set that is believed to have impact on advertising and isolate the effect of advertising on sales”
– Interviewee B

“When we use econometric modeling, the benefit is that we don’t look advertising in a vacuum and understand that there are many outside factors affecting consumer behaviour. For example, fast food is consumed more on rainy days as people don’t want to leave house so they order food” – Interviewee E

An important benefit also mentioned in literature is the ability to track all forms of advertising also in offline environment. Since the case company is one of the leading media agencies in Finland, substantial portion of clientele are large companies that advertise across variety of mediums. According to interviewee A, this lack of knowledge in offline advertising effectiveness poses a challenge for advertisers who do not utilize econometric modeling.

“In many ways measurement of advertising is poor and insufficient in many cases. The challenge is that most of the measurement opportunities are only in digital media platforms. For example, in TV advertising, which is a major advertising channel, we cannot really get data easily about how it has affected the business. In digital channels we can at least still get information on views, clicks and conversions for example, even though these metrics cannot really tell the actual effect on sales or how substantial the branding effect has been” – Interviewee A

In the context of television advertising, this ability of getting data about effectiveness and using it to support future planning is especially important as the investments in this medium tend to be substantial. The effectiveness of TV advertising has also been questioned recently as people are increasingly consuming content on streaming platforms. This combined with the fact that the short-term ROI of TV tends to be poor, there is a need for supporting data.

“If we have enough data to make conclusions about the performance of TV, we can pretty confidently use it as a guideline to concentrate budget there for upcoming campaigns if the returns have been good compared to investments” – Interviewee A

Data from earlier econometric modelings also provides substantial assistance with new product launches, as many approaches can be applied to them, at least in cases where the products are somewhat comparable. Product launches are typically large investments for companies and even relatively small improvements in effectiveness can yield substantial absolute results.

“You can make informed decisions based on historical data. So, if I should launch a new product from the scratch, I would already have good base understanding of what has worked in previous launches and where we could have done better. Media mix modeling gives a lot better foundation for the planning process” – Interviewee D

As a further benefit of MMM, the ability to account for long-term performance was also mentioned multiple times in interviews, which goes in line with the literature. Since the long-term effect usually accounts for majority of total advertising effectiveness, it needs to be considered to determine total advertising effectiveness. This however requires that the model is set up to be able to measure that realistically.

“In a little bit more modern models we can set the sales baseline to stochastic, meaning that the baseline changes over time instead of staying constant, which gives more realistic picture on how the advertising actually effects the baseline sales [...] capturing the effect on brand equity.” – Interviewee B

Interviewee A also noted that while brand equity is primarily discussed as a positive attribute for companies, it can also be negative. This negative brand equity can be a result of certain advertising campaigns, and without proper measuring and modeling practises, can go on a long time before being noticed. This is something that can be largely avoided with the proper use of MMM, at least before it has caused severe damage to the brand.

“It’s worth noting that the brand effect can also be negative if company for example does a lot of discount advertising, that can increase sales substantially in the short term. That easily creates a notion if consumers that this company always has discounts, so they are only going to buy if the products or services are on sale. Every advertising action always gives some signal out” – Interviewee A

Another reason why MMM has been gaining traction recently is the continuous disappearance of third-party cookies, which are heavily used in online advertising today. Because MMM primarily uses first party data, the model is not reliant on any new possible privacy regulations that might appear in the future due to growing public concerns about data protection.

“As media mix modeling is based on econometrical modeling, it doesn’t depend on any kind of online tracking systems or other related technologies. You only need time series data on historical events [...] Because of this it doesn’t have any privacy dimension that might cause problems in the future”- Interviewee B

When asked whether the main advantage with MMM is primarily providing suggestions for minor allocation adjustments or about demonstrating the long-term effects of advertising, the sentiment was that both are equally important. While the effectiveness increases can be substantial even from small allocation changes, interviewee E notes that the use of MMM often shifts all advertising into more data led direction and raises the conversation about how to improve it, which is not always the case in companies.

A notable benefit of MMM is that the primary target variable is usually sales, which ensures that the attention is directed to right aspects. Interviewee D highlighted the number of available metrics especially in digital advertising, which can distract attention from the important metrics. This is especially true in case where individuals in charge of advertising lack experience.

“Media mix modeling is good for getting comprehensive view of the advertising effectiveness so that the focus is not on the smaller, less meaningful things. [...] Our clients should end of the day look at the big picture with their marketing management instead of putting too much effort on small details such as click through rate, which are tempting to get stuck on but don’t really measure the actual advertising effectiveness.” - Interviewee D

Interviewee E also emphasised the importance of focusing on a metric closely aligned with business objectives. While various, non-financial, marketing metrics have proven to be useful (Mintz & Currim, 2013), putting too much emphasis on the so-called “vanity metrics” can easily divert attention away from the core metrics.

“The biggest advantage is that marketing is able to speak the “language of business”. We are not measuring advertising in terms of reach but in terms of actual hard sales, which completely changes the position of marketing inside the company when we can actually show which things have impacted the outcome of success or failure. With this knowledge we can predict the future outcomes in the best case [...] and guide the future advertising actions.” – Interviewee E

Interviewee E noted that besides allocations of the budget, MMM is also a valuable tool for making a business case for increasing the advertising budget based on the growth demands of the management. This can help answering the accountability concerns towards marketing departments that have been growing in recent years (e.g. Moorman, 2019).

“If the client says that we have to grow our business by 5 million, we can say that based on the modeling data the total advertising budget has to be increased by this much. So, making the growth scenarios and business cases for additional investments for advertising is the “long game” and for that media mix modeling is an excellent tool” – Interviewee E

When asked about personal experiences with using marketing modeling with positive results, interviewee B shared a case with a FMGC client.

“With media mix modeling we were able to model how different campaigns affected the bread sales and optimized the advertising budget allocation based on those results. We were also able to see how new product launches affected the sales of other products. With that we were able to raise the advertising ROI by around 15% within the year” – Interviewee B

Interviewee A also had recent experiences on using media mix modeling with another client. In this case media mix modeling was used to validate new advertising medium used in the campaign.

“For example, beginning of this year we started testing a new media channel for our client, and with media mix modeling we were able to see that the new channel performed considerably better than one previously used one, so we made a replacement based on the data” – Interviewee A

Overall based on the answers, the media mix modeling enables a wholistic evaluation of advertising performance without having to worry about current or upcoming privacy policies. This data allows better allocation of resources, which had produced significant increases in advertising performance. It also focuses on actual metrics of business performance, thus decreasing the noise caused by various “vanity” metrics that are prevalent. Because of this it can shift the outlook on the role of advertising, and possibly justify the current scale of advertising activities or even increasing the investments.

6.1.2 Potential disadvantages and limitations of MMM

While MMM can be a valuable tool in assessing advertising effectiveness, there are some potential drawbacks and restrictions when using it for modeling performance. While MMM has been proven to be an effective tool, it is based in historical data, thus not necessarily able to accurately predict future.

“Media mix modeling is based on historical data, and there are no guarantees that future is going to resemble that exactly. So, it is simplification of future in a sense” – Interviewee B

The accuracy of the model is also dependent on available data. This applies to company’s internal data on sales and advertising actions, but also on any kind of control variables that are used in the model that might affect the performance. Interviewee B also raises a point on the actual explanatory value of the model being used.

“We can include variety of variables that might affect sales and marketing [...] but of course only those that we have available. [...] Then there is also the factor about how well the model manages to explain the chosen KPI. So, there is always some restrictions with the data like what data we have available and what is the overall quality of the data” – Interviewee B

These challenges with data availability and quality remain common despite the advancements in data processing and storing. According to interviewee E, the majority of clients still struggle with internal data, which is required to build models that have sufficient explanatory value.

Interviewee B also notes that there are always assumptions involved when using MMM.

“There are also always some assumptions like how to specific media channels behave or what effects do they have now or over time. When people see ads, the effect is not just immediate, but they will possibly remember it the next day for example. Estimating these factors into the model will bring its own challenges” – Interviewee B

Another risk mentioned in the interviewees was not related to the modeling protocol itself, but instead to the potential for human error in areas required for the modeling process. For example, the interviewees reported that an improper implementation of tracking protocols that can eventually interfere with the data used in models. This might cause delays in the

modeling process if noticed, or even result in suboptimal decisions in the future if undetected. Interviewee C highlighted the importance of communication along the modeling process as it commonly involves multiple individuals from different functions.

Another point was related to the actual interpretation of the modeling results. As stated in the literature, results gained from the models might not lead to optimal decisions without human expertise in advertising.

“Other issues are with the interpretation. If for example Meta doesn’t seem to provide good results based on the modeling, many people unfamiliar with marketing planning might think that because of that, Meta is not a suitable channel for them, when in reality the channel itself might be good but there might to something wrong with things such as message or audience targeting” – Interviewee A

“People who make the recommendations based on the models also have to have a broad understanding of advertising. Often the data analyst must speak about the findings from the data, the customer company has to figure out what it means, and the paid media specialists have to give the recommendations. [...] You can make 3 different recommendations from the same data based on your background” – Interviewee E

MMM can also provide recommendations based on efficiency rather than effectiveness that can skew future media planning if not taken into consideration. Interviewee E points out that models often cannot distinguish between absolute results but rather shows the size of ROI. This highlights the necessity of expertise in interpretation.

“Media mix models do not understand if we succeed in something, but the relative increase is the same. For example, in we raise the advertising investments from 10 000 to 100 000 and the absolute increase in sales is considerably higher but the ROI is the same, it focuses on that even though customer managed to increase the sales by 10x.” – Interviewee E

There are also requirements for organisations who would like to use MMM, and it is typically beyond the reach of for many smaller companies. For effective use of MMM, companies need around 3 years' worth of historical data and the annual advertising budgets need to be in the hundreds of thousands of euros, so that the model has enough data to work with, as pointed out by interviewee B.

As also stated in the literature, MMM only gives macro view on the advertising performance based on aggregated data, which is the reason it is not affected by loss of cookies or other privacy regulations. Because of that, it is not suitable for micro-level optimization, which is needed for digital campaigns to have optimal performance.

“It is not a tactical tool and can't be used for micro-optimization as the data used doesn't fit to that” – Interviewee B

MMM is also not suitable for modeling regional performance due to limitations in the models as noted by interviewee E.

“Media mix modeling is a poor tool to evaluate regional performance. The models do not understand that some advertising actions would only be done in some parts of Finland as its kind of mass modeling at the end of the day. In some models this has been tried to take into account by proportionally modeling different areas but in practise it hasn't worked, and the results have been very odd” – Interviewee E

To conclude, although MMM is a valuable tool according to the findings derived from the interviews, it does have its risks and limitations. These mainly stem from potential issues with available data, and its quality and granularity as well as human errors with the modeling process and interpretation. While it can be seen as an excellent tool for evaluating advertising performance, it does not give information about user specific behaviour and is not reliable in evaluating regional advertising performance. The model also contains some assumptions about advertising and results cannot fully be expected to resemble future as it is based on historical data.

6.2 Attribution modeling as a concept

After the MMM, interviews transitioned to AM. Similar to the previous section, the interviewees were asked to define attribution modelling to avoid any misunderstandings.

6.2.1 Benefits of attribution modeling

When respondents were asked about the advantages of AM, the primary reported benefit was the access to microlevel information about user behaviour and interactions with the touchpoints, which is missing from econometric modeling as it is based on aggregated data. While many companies can benefit from AM to some extent, according to interviews there is variance in utility depending on type of business. Interviewee D emphasised the benefits especially for e-commerce businesses.

“The benefits will largely depend on the type of business using it. For e-commerce businesses the benefits are pretty clear as they can analyse the point in the sales funnel where the customers are buying and understand better the factors that are leading to the purchase. [...]. We can also see the correlations of people first seeing a social media ad and then use Google to search for it later when they have time. [...]. It is important to understand the actual trigger for customer action” – Interviewee E

AM can also provide valuable insights about the content side of advertising, as pointed out by interviewee E.

“While attribution models usually track sales or leads but having content related event is also interesting because then we than attribute the scroll depth so you can see which channels and contents drive towards interest” – Interviewee E

Even though interviewees agreed that the conversions reported by the platform attribution systems might often not give accurate imagine of the overall effectiveness of the given

channel compared to other channels being used, interviewee A noted that these numbers can still be used to track improvements inside channels gained from optimizing elements such as ad copies or audiences. Main benefit over MMM in this case is the speed in which it can be done. As stated previously, gaining information from econometric modeling takes time, which hinders one of the benefits of digital advertising that is ability to make quick changes.

“We can look the number of conversions and the trend in attribution models and see how they react to changes without having to wait the results from econometric modeling” – Interviewee A

6.2.2 Potential disadvantages of attribution modeling

In literature, AM has been noted to have many flaws, which also appeared during interviews. Most prevalent were the lack of long-term performance measurement, inability to measure offline performance, as well as the inability to consider outside factors such as weather, economic condition, and other product launches.

One aspect which has not been widely discussed in previous literature was pointed out by few interviewees. One of the greatest potential benefits of AM is the ability to track the customer journey, thus providing opportunities to optimize overall customer experience. While this may be true in some cases, some practical challenges exist in the context of multichannel advertising. Interviewee A pointed the fact that AM platforms are rarely able to measure impressions from other platforms, and only report the clicks, which poses a problem when trying to accurately assess the customer journey and impact on advertising performance. While this would technically be possible, it would necessitate platforms such as Meta and Google to share their data with each other, which is not in their interests.

“The problem with Google analytics for example is that it can only attribute credit based on clicks in most cases and can’t do it with impressions, and mediums such as

display don't usually directly bring a lot of traffic. [...] Modeling the digital customer journey from most touchpoint would probably be possible, but the problem is with the closed ecosystems such as Meta and Google, who would never share their data. So that is the primary problem in my view” – Interviewee A

These problems in cross platform communication also inevitably lead to over attribution of some channels that tend to bring a lot of traffic due to their nature, mainly search engine advertising as well as organic search. This can lead to over allocation of budget into these channels and taking it away from channels that directly increase the demand and brand awareness, thus leading to higher search volumes in search engines such as Google. Interviewee D concluded that partially for these reasons, attribution modeling is not suitable for measuring the overall effectiveness of different channels and if used for this purpose, often leads to wrong conclusions about effectiveness on sales increases.

However, interviewee D pointed out that while the ecosystems such as Google and Meta do not communicate well with each other, it is still possible to gain insights on the customer journeys, but that requires analysis from multiple experts that are involved in different touchpoints. So, while attribution modeling may not necessarily provide sufficient answers by itself, it can give fragmentary insights about the journey that can be used as information by marketing professionals to formulate hypotheses for further testing and provide feedback for conclusions regarding specific areas of consideration.

“Utilizing attribution modeling usually requires multiple specialists, who are working with the customer journey. [...] In ideal scenario these people would sit together and discuss about the results and come up with possible improvements” – Interviewee D

The possible benefit gained from the analysis of the customer path is also dependent of factors such as size of the target group. Interviewee A noted that since the analysis part requires extensive manual work due to reason highlighted by interviewee D, it necessitates clear justification for the task.

“Doing the analysis takes a lot of manual work and in Finnish market we often have the problem that our target groups often tend to be small. [...] One obvious action to take from the analysis would be to customize the messaging in our ads based on the role of the touchpoint but is it even worth doing if our audience consists of only few tens of thousands, and then there is also the questions around data reliability so is it necessarily even worth it with the small potential gain? [...] It usually makes more sense when the audiences are larger” – Interviewee A

Interviewee B also noted that AM can work well in cases where the advertising is limited to one platform, such as Google. However, this style of advertising is rare among companies, and still does not address many of the flaws mentioned earlier if used to examine the total advertising performance.

“Of course, if you are only doing advertising in Google, and users are signed into their Google accounts all the time, then it can work relatively well” – Interviewee B

The disappearance of cookies was also discussed within the context of reliability and future of AM, as it has been reliant on third-party cookies. While there are alternative ways to do AM, the disappearance of cookies will have substantial effect at least in the short term according to interviewees. There was still a consensus among the interviewees that there will be a new method created to track digital touchpoints that will follow the new privacy regulations. Currently, the alternative solutions are based on probabilistic modeling, which raised some uncertainty in interviewees in terms of reliability. Example of this is Google Analytics 4, which is not reliant on third-party cookies. This however raises the question with potential conflict of interest as Google is one of the largest advertisement platforms in the world and has been criticized of giving favourable information of the performance of their advertising campaigns. Another way to avoid the use of third-party cookies is the requirement to log in with personal information inside the platform, but as interviewee A pointed out, it would require a large enough audience to work sufficiently.

So, while AM can offer certain advantages for companies, its efficacy as a standalone tool for decision making is questionable, even though that is how it is widely used. Even for the

areas it can be used successfully, AM often requires extensive analysis from professionals as technical limitations and closed ecosystems with service providers cause a fragmentation in the data, limiting insights. The disappearance of third-party cookies is also undermining the reliability of AM.

6.3 Advertising effectiveness

Subsequently, the interviews moved into questions regarding advertising effectiveness and knowledge regarding it companies.

One aspect that was mentioned in the interviews was the contextuality of advertising effectiveness and the importance of choosing the right metric to follow.

“For example, in fast food industry one of the key metrics should be brand salience, meaning that if you would choose to buy a pizza in the next 5 minutes, where would you buy it from. So, it is important to not only measure the top of mind for example, but how that translates to action” – Interviewee E

Interviewees were also asked about their perception on understanding of advertising effectiveness in companies. Many interviewees had professional experience in both media agencies as well as in-house marketing teams, so they had sufficient general understanding on the topic.

Although there was some variance in the answers, the common sentiment was that there is still a lot of room for improvement when it comes to understanding on advertising effectiveness, especially in long term effect of brand building with advertising. Interviewee E also pointed out that the more siloed the organisation is, the less emphasis is usually placed on the relevant metrics that should be monitored. She also noted that according to her experience, there are still relatively few companies in Finland that properly utilize econometrics in their advertising decision making.

“There is still a lot to learn about it. It’s surprising how much attention is still placed on metrics that do not really make a difference, for example clicks volumes. Common occurrence is that we build dashboards with a lot of data, but they are not utilized well as the attention is on the wrong things. That’s why I usually tend to prefer the “kill your darlings” approach, where we only report the most important metrics for us” – Interviewee A

The focus particularly on clicks in digital advertising was a reoccurring theme in the interviews. While this is understandable and does give some information about the scale of potential buyers, judging the effectiveness of advertising based on click volumes is largely inaccurate. Letting advertising platforms optimize towards clicks can also have unexpected negative consequences such as platforms preferring misleading ads or accidental clicks, leading to website traffic with no value to the business. As mentioned earlier, different channels bring different number of clicks, and it does not necessarily signal how well they perform. Because of this, having click volume as the primary metric of effectiveness can lead to ineffective channel selection and allocation. Many interviewees highlighted how display advertising for example is not done primarily to drive website traffic but rather to cause some kind of recollection later. Despite this, optimizing towards clicks remains a common practise and often leads to undesired outcomes.

“Optimizing towards clicks often leads to low quality traffic and this can be done in every channel in digital advertising. [...] Also, if we only optimize towards clicks in let’s say display advertising without having set conversion points, it often leads to optimizing towards ad placements with poor loading speed that leads to accidental clicks that are still often registered” – Interviewee D

Digital advertising has also brought a lot of data to companies, which easily creates a lot of noise. Interviewee A further notes that paid advertising is only one focus area of the marketing function of firms, so it is not necessarily realistic to assume that companies would have perfect understanding of all key components of advertising.

“Understanding the key components of advertising effectiveness is very difficult if you don’t do paid media with the same intensity that is done in agencies like ours. For many of our clients’ paid media is only one aspect in their entire marketing. Many companies also have a lot of different partners, so keeping up with everything is hard. There are also a lot of digital media channels that have appeared recently, and understanding the effectiveness requires deep understanding of all of them” – Interviewee A

Interviewee C also noted that while many companies are focusing on short-term performance, it is not necessarily because of lack of understanding the long-term effects but rather about the need of cash flow in current situation. This is especially relevant considering recent years that have been extremely challenging for many companies due to COVID-19 and overall economic situation.

“In my experience many companies understand the effects of advertising pretty well, but due to recent events like the Ukraine war and economic hardship, many companies have started to focus more on the short-term performance as it has been vital for surviving and being able to carry out the business” – Interviewee C

There are also still misconceptions about the advertising channels being used. Interviewee D pointed out that all digital channels are too often lumped together, even though their effects tend to be vastly different and the consumer behaviour around them varies substantially. This behaviour can also change over time.

To conclude, there is notable variance in companies when it comes to understanding of advertising effectiveness when it comes to factors such as time frame, relevant metrics and channel selection. Even though some companies might opt for strategies that are not optimal in the long-term out of necessity rather than ignorance, there is still an observable need for deeper expertise and tools that can demonstrate the effectiveness of actions with concrete data.

6.4 Simultaneous use of models

Finally, interviewees were asked about their opinion of utilizing both MMM and AM simultaneously when measuring and optimizing advertising performance. For the most part, interviewees saw the benefit of using both tools, as they serve a different purpose and can complement each other. Consensus was that at least using MMM is essentially mandatory for larger companies who truly want to measure the effectiveness of their advertising performance. While especially attribution modeling has been shown to be a flawed technique when trying to accurately estimate the wholistic performance of different channels or campaigns, it can provide some insights that would otherwise be unattainable for advertisers. Both tools have often been used for tasks they are not meant to or capable, so using both requires understanding of their strengths and weaknesses.

“I do think both tools have their place. Attribution models can be useful especially in optimizing advertising inside platforms such as Google or Meta and guide the process. For comparing different channels to base budget allocations on, it doesn’t really work, and it does require econometric modeling behind it. [...] Both tools are complementary but can never replace each other” – Interviewee A

“I do see use cases for both tools but for different things. It’s not smart to do budget allocations based on attribution modeling as its often goes badly and produces sub-optimal results. [...] Upper-level budget decision should be based on econometric modeling.” – Interviewee B

“Media mix modeling is mostly for analysing the big picture and adjusting the media mix while attribution modeling provides information for getting the most out of the digital channels being used” – Interviewee E

Interviewee A agreed that even though attribution models are not able to track all interactions happening online, they can still be used to detect certain trends and patterns for example during the customer path if done correctly. This, however, increases the amount of data needed for reasonable analysis since large portion of it is lost. For the observations

to be even somewhat reliable, it requires a lot of customer touchpoints, and might be difficult in small market or niche industry.

In terms of potential resource commitment, interviewees did not see a problem when utilizing both models, at least if the justifications discussed in previous section are in place. MMM is seen crucial for companies who want to base their advertising investment allocations on modeling data and cannot really be currently substituted with anything else. For these companies using AM for optimizing campaigns ads relatively small resource commitment when compared to MMM. Interviewee A also notes that typically these tools are used on different levels of the marketing function, especially in agency setting.

“Often media mix modeling and attribution modeling are tools for different people. Media mix modeling is for those who handle the entire marketing planning process such as marketing managers. Attribution modeling on the other hand is more for those who actually do the media buying and optimization and can compare the results with different ad copies or target groups.” – Interviewee A

While the use of AM for general optimization purposes does not consume many resources in terms of time or money, if free tools such as Google analytics are used, trying to analyse the consumer path in optimal fashion described by interviewee D will take time from multiple specialists. The ROI for this time investment is therefore related to size of the business as well as potential insights that can be derived and to translated into business performance.

Possible problems with using both tools simultaneously were related to the potential misinterpretations of the results. As stated previously, AM has been widely used for purposes where it is not suitable, in particular, media budget allocation. If individuals responsible for analysing results from both tools are not educated on their strengths and weaknesses, it can lead to confusion and suboptimal decisions in planning, refuting the benefits of dual model approach completely.

In terms of possible technical problems, none were specifically mentioned in the interviews. Many interviewees did mention the lack of reliability when it comes data from attribution models. While this does not discredit the tool altogether, it does bring certain limitations especially in cases where companies are combining the tools into one modeling solution and merging the first party data with attribution data. Although the distrust on the attribution data will hinder the possibilities to make important decisions based on it, it can be used for various experiments to confirm its utility.

When asked about the potential future relevance of this combination of tools, interviewees agreed that its highly unlikely that there will be something to replace this approach in the near future. Econometric modeling has been used since the 1960s, and it remains widely used today, although the models are more robust, and some new “best practises” might change over time. AM has been criticised for not being able to capture all the touchpoints and this criticism has increased in recent years but even if this would change in the future, it does not resolve the shortcomings when it comes to getting wholistic view of the advertising performance. While AI and its different applications are currently receiving substantial attention, they will most likely complement the existing modeling techniques instead of replacing them.

All and all, while the combination of modeling tools has its weaknesses and limitations like all other currently available tools, it provides companies with ability to optimize digital campaigns and potentially analyse their interplay, measure the wholistic effectiveness of all advertising and use the information for planning upcoming campaigns with more data driven approach. Whether companies should utilize both tools, depends on various factors such as scale of advertising investments, size of the market and/or target audience, available resources as well as state of data quantity and quality in the company. It is also important to understand that simply using the modeling tools does not provide the full value but requires users to understand the concept of advertising effectiveness thoroughly. For example, in the context of e-commerce, the conversion being used in AM is typically transaction, but there are other potentially valuable target metrics that could be employed. While there are no foreseeable risks in MMM as a modeling method, AM is in

an uncertain state and its future is dependent on many external factors such as public concerns about data privacy and new laws and regulations that service providers encounter.

7 Discussion and conclusions

The aim of this thesis was to examine whether the simultaneous use of AM and MMM can provide benefits companies with determining the effectiveness of their paid media actions and use that information to drive their business objectives in the future. Additionally, the thesis also studied the potential shortcomings in utilizing both modeling tools simultaneously and when it might not be realistic or advisable.

The objective of this chapter is to offer comprehensive answers to the research question as well as the accompanying sub-questions, utilizing the insights derived from the conducted interviews and connecting them to the existing theory presented. Lastly, limitations and potential future research suggestions are being discussed.

7.1 Answers to the research questions

Research question 1. Can the simultaneous use of both attribution modeling (AM) and media mix modeling (MMM) provide value for companies in increasing advertising effectiveness?

Utilization of both MMM and AM provides companies with comprehensive view of advertising performance, that would not be available using only a single modeling method. The combination can offer realistic effectiveness estimates by using first party data and including outside variables to the regression models while also providing insights about consumer behaviour and individual advertising elements that can be used to optimize various aspects of advertising. It also accounts for online and offline performance and can in optimal scenario provide information about the interplay of both types of advertising mediums. While based on the results of the research it can be argued that the use of MMM provides most of the benefits for companies that have the prerequisites for using it, the

addition of AM to the toolkit can enable companies to access more granular data such as information on the digital consumer paths. With that insight, companies can improve the overall digital customer experience, thus potentially lead to better advertising effectiveness and eventually better business outcomes.

Optimal approach derived from the interviews would involve utilizing MMM to determine general guidelines for advertising actions, including budgets and channel selection, and use AM for optimizing performance within those parameters, as demonstrated in figure 8.



Figure 8. Suggested approach for simultaneous use of MMM and AM.

An additional potential benefit of AM is the short time frame, as adjustments can be made quickly without having to wait the results from econometric modeling. In digital advertising, campaign lengths often fall below the time frame of econometric modeling and investments can be large, so even minor improvements can have a significant impact on overall effectiveness. However, benefits from AM require the use of multitouch models, which divide the credit for multiple channels.

If implemented correctly, MMM will also provide information on the long-term, brand building effects that have the potential to increase the baseline demand that carries on over time, and according to research, mitigate the negative effects of temporary under-investments in advertising. With this information companies can allocate the advertising

budget on different channels and campaigns in order to grow the long-term demand while also capturing the benefits of the created brand equity with more activation-based advertising. MMM can also provide reassurance about the effectiveness of advertising for business performance, thus supporting marketers in justifying the investments, which is a well acknowledged problem in current literature (e.g. Kotler & Keller, 2011) and has only grown more attention during this era of accountability.

Sub-research question 1. How can the application of MMM and AM guide companies with the approach to advertising?

Besides giving concrete recommendations on factors such as budget allocations and channel selection, the use of MMM and AM can substantially change the way advertising is done. While the use of these modeling tools will benefit companies when trying to make small to medium scale changes in aspects such as budget allocation or ad copy modifications, especially MMM can change the wholistic view of advertising effectiveness for many companies. While there is a lot of previous literature on the importance of brand building for long-term performance, management can be hesitant in making decisions based solely on theory without supporting data. MMM can provide concrete data on the effect of long-term brand building effect and show the return on investment of these actions, and potentially change the whole approach on advertising strategy even if the measuring itself is discontinued.

Based on the interviews, the use of modeling tools can also shift the advertising practises towards more data-driven direction, especially when this has not been the norm in the past. This data-driven approach will also facilitate marketers' justification of advertising actions to upper management, even if they do not necessarily seem to produce short-term results, which is often the case. They can also highlight the importance of granular elements of advertising that might otherwise be overlooked.

Sub-research question 2. What are the potential problems and limitations associated with the MMM and AM, and how can companies avoid these?

Many of the potential problems in the simultaneous use of MMM and AM are related to the unavoidable risk of human error, as well as the lack of expertise among the individuals who are interpreting the results and making decisions based on them, whether on tactical or strategic level. The noise caused by growing number of metrics in especially digital advertising is a prevalent problem in companies and addition of tools can amplify that to certain extent especially if roles and attributes of MMM and AM are not clear. This is why deep understanding in both technical side of the tools as well as the principles of different media channels and advertising is required for positive outcomes. The poor data quality is also a risk that can undermine the use of the modeling tools. For companies there is a need for expertise in data collection and management as without it there is no base for the analysis, and the data requirements only increase when multiple modeling tools are being used.

While in the optimal scenario the use of both tools is recommended for companies based on the results of the study, it is simply out of reach for most small companies with limited paid media budget and/or resources in general. Especially MMM requires a lot of historical data for building reliable models that will explain the dependent variable in sufficient way. Because the requirement for historical data, media mix modeling is also out of reach for new companies, albeit this typically coincides with small media budgets regardless. It is also worth mentioning that because MMM is based on historical data, it is not guaranteed to predict future outcomes. While this is not usually a problem if this factor is understood by companies, it can limit the possibility for utilization if the market conditions are highly volatile, in which case the history data does not provide reliable point of comparison for future.

For established companies with larger media budgets on the other hand, the utility of the use of AM depends also on the type of business. While it is a negligible resource investment considering the typical the size of these companies, some businesses that only operate for example in traditional retail industry and do not conduct any online business, it might not offer much additional value. Interviewee D provided an example of a beverage company that does not engage in online sales and whose customers typically do not need to visit the website to look for specific information as the product itself is uncomplicated in nature. While AM does not require as much data as MMM, if used for analysing customer paths and digital touchpoints, it will still require large enough audiences to be reliable especially with the ongoing disappearance of cookies further limiting the data. The complete disappearance of third-party based cookie tracking is a substantial risk as there is still a considerable uncertainty around the new methods. The data from attribution models is also highly fragmented due to closed ecosystems that do not share the data optimally. Because of this it requires more in-depth analysis of consumer paths also takes more experts to extract useful insights. Because of this, potential benefits have to be weighed against the workload from the analysis, which is also largely related to the size of the audience. This which can be an issue in smaller markets or niche industries.

7.2 Theoretical contributions

The findings of this study are consistent with the majority of the previous research, although there is a lot of variance regarding topics such as AM and understanding of advertising effectiveness among companies in the literature. The main contributions of this study relate to the potential benefits of simultaneous use of MMM and AM.

With MMM, the findings support the utility and importance for large advertisers to use MMM to measure the actual effectiveness of different channels and campaigns and get a wholistic view of advertising efforts. Results from interviews support the claim from Stürze et al. (2022) that there are currently no alternative methods for accurate performance measuring that would cover external factors such as weather or economic

conditions and would also recognize the long-term impacts of advertising discussed in length by Binet and Field (2017). Critique of short-termism of MMM (Cain, 2008) is also addressed as current models being used do account the long-term performance with more sophisticated methods that more accurately represent reality.

Findings from the interviews also highlight the importance of focusing on metrics with close proximity to overall business performance such as sales. This supports the research from Stewart (2009) where he discusses the accountability of marketers to financial outcomes and ability to be able to justify the marketing actions. He also emphasises the need for metrics for both short- and long-term effects that are somehow linked to financial results. Besides sales, example of this mentioned in interviews was share of search, which measures the brand visibility and demand compared to other competitors and can be used in MMM depending on the industry. According to Binet and Hankins (2021), share of search correlates strongly with future market shares, offering a predictive measure for financial metrics.

Regarding the overall short-termism and understanding effectiveness in companies when it comes to advertising, the results were somewhat inconclusive. While many interviewees recognized the phenomenon of short-termism appearing in literature (Lavery, 1996; Binet & Field, 2017; Ladika & Sautner, 2020), according to interviewees there is notable variance in knowledge. Sometimes the focus on short-term gains arises from necessity rather than ignorance. Overall, the findings indicate that there are still opportunities for companies when it comes to balancing short-term sales with long-term brand building as well as focusing on the right metrics rather than vanity metrics that have become a trend due to the rise of digital advertising and consequential noise. It also highlights the necessity of being able to quantify the long-term effectiveness, thus supporting the use of modern econometric modeling.

In terms of AM for budget allocation, literature is also inconclusive. While many earlier studies endorse using AM to at least assist in decisions regarding advertising investment

allocation (e.g. Kannan et al., 2016; Xu, Duan & Whinston, 2014), most of more recent studies are not in favour of it (e.g. Danaher & van Heerde, 2018; Nisar & Yeung, 2019). There are however exceptions to this. The main argument in more recent literature supporting attribution for budget allocation (e.g. Gaur & Bharti, 2020) is that the improvements from the utilization of data science in more sophisticated models will resolve the problem of ignoring the often-complex consumer path that led to conversion as well as and not accounting for the non-converting paths. According to results of thesis, AM is not suitable for budget allocation, even when only digital channels are being used.

While attribution models of today have improved significantly, they still cannot address problems in earlier models such as inability to model the effects of offline channels and long-term effectiveness, both of which were addressed in the interviews of this thesis. The latter point remains relevant for companies that solely rely on online advertising. Even though most of the shortcomings of AM have been discussed in previous literature, majority of it is outdated in terms of the risks associated with the disappearance of cookies and the effects it potentially has on the method. This adds a new layer to the risk management when it comes to optimization of advertising campaigns and reliance on a single tool. This thesis contributed to the literature by examining the current state of AM as standalone tool and concluding that it does not offer realistic or reliable enough estimates, thus is not suitable for that purpose.

Even though based on the previous literature presented in this this thesis, MMM and AM could have been expected to be complimentary, there was little to no body of academic evidence to support it. This thesis contributed with the finding that these modeling tools do have potential to be used together as a dual approach for increasing advertising effectiveness, even though the utility is questionable and simply out of reach in some instances. Potential benefits must be weighed against the costs and risks associated with the process. In this case the costs mostly relate to having to spend resources for utilizing both modeling tools and analysing the results deeply enough to utilize the findings for improving the effectiveness of advertising. Risks on the other are mainly dependent on the expertise withing the company as well as the state of data management. While the usual

risks with interpretation are prevalent with both tools when used alone, analysing data from both tools can cause mistakes in planning if the users are not aware the areas where each tool are better suited to be used, as discussed in previous chapter. The risks with data quality can be higher in case these models are tried to be combined into one model as this would allow data issues in either model to affect the modeling results altogether. This however is not established practise yet and is difficult to speculate further.

7.3 Managerial implications

This thesis has provided valuable information about MMM and AM as well as their strengths and weaknesses for companies wanting to optimize their advertising actions. The study also considered the circumstances when the use of both tools will bring the most value and when it is most likely not realistic or otherwise reasonable. With MMM, the thesis also provides information on factors to consider when creating the model or buying it from another service provider, such as the importance of incorporating dynamic baseline sales to account for long-term brand impact. While both tools are widely used and recommended, companies still struggle to reap the full benefits of the tools and may even make worse decisions based on the data provided if the understanding of the models or principles of advertising channels is not sufficient. This study also highlights the potential risk with human error in various points of the process that are needed for accurate implementation of MMM. By focusing on these, companies can put additional emphasis on these steps and mitigate the risk of undermining the results of the long process and avoid poor decisions from results of false data.

The thesis also sheds light on the time frame of advertising effectiveness and how it should be accounted in advertising decisions. Although many companies are not able to use MMM due to data unavailability, lack of expertise, the age of the business, or other related factors, the long-term effects of advertising and attributes of different mediums have to be kept in mind when interpreting AM data. Sometimes, companies may need to make

decisions that contradict the suggestions of attribution platforms, which can still provide valuable information on some areas.

The study also examined the reliability of attribution data, which is typically derived from third-party cookie tracking or alternatively from probabilistic models from publishers such as Google. While companies can choose to use this data, it is important to know the defects in it. The reliability is also dependent on type and number of platforms being used. If companies only use platforms and placements from Google, attribution data can be seen as more reliable due to only having one ecosystem, especially if third-party cookies are still being used. The technology with cookieless attribution is also novel and advertising technology companies are continually introducing new tracking solutions that comply with the current privacy regulations, so individuals in charge of advertising should follow the ongoing development with these solutions and make informed decisions about the reliability of the data.

Due to the high demand for tools for measuring advertising performance, many marketing technology companies are now providing or creating solutions that combine the data from econometric modeling and AM into one unified measuring system. While these systems might be able to provide reasonable estimates and suggestions, mixing partially unreliable data from attribution models into company's own internal data might create problems, particularly in the absence of adequate skepticism. This is especially true due to the uncertain situation with third-party cookies. In attribution models based on probabilistic modeling such as Google analytics 4, the service providers have a clear interest to inflate the role of their own platform. These models usually work with black box principle, and thus users are not being able to evaluate the factuality of the models. Understanding the basic principles behind these solutions is crucial as taking the recommendations from them at face value can yield counterproductive results.

7.4 Limitations and future research

The research was done as a single case study, which places some limitations. All the interviews were conducted from individuals working in the same company. Even though the case company as a media agency offers a comprehensive perspective on relevant areas such as understanding of advertising in companies, different agencies as well as other companies in general still have their own practises when it comes to utilization of tools such as MMM and AM. The case company as well as majority of the clients operate in Finland, thus cannot be completely generalized to other markets due to differences such as market and audience size.

The sample size for the study was also relatively small, which does decrease the generalizability of the study results. While a greater number of interviewees can offer a wider range of answers and views on the topic, it should be noted that the answers gained from the interviewees were mostly aligned and many observations were repeated multiple times. This does signal that the saturation point, which refers to a point where collecting additional data provides little or no additional information or themes about the research topic (Saunders et al., 2016, 297), could have been reached. This could partially be attributed to the fact that all the interviewees worked in the same company.

Bias is also a risk factor when conducting qualitative research and can decrease the overall validity and reliability. Saunders et al. (2016) divide potential bias in to 3 types: Interviewer bias, interviewee or response bias and participation bias. Interviewer bias refers to interviewer imposing his/her own beliefs and frame of reference through comments, tone or non-verbal communication, which might alter the answers, or letting bias affect the interpretation of the answers in the analysis part of the study (Saunders et al., 2016, 397). In this study, all the interviewees were conducted by a single person, which can pose the risk for interviewee bias. Interviewee bias on the other hand refers to bias caused by interviewees perception about the interviewer or perceived interviewer bias (Saunders et al., 2016, 397). It can also stem from interviewees unwillingness to reveal certain things to cast himself/herself or the organisation they work in in certain light.

Because of this, the interviews were conducted anonymously, and name of the company was not mentioned in the thesis. Lastly, participation bias refers to bias that is caused from nature of individuals that are willing to partake in interviews, thus skewing the sample the data is collected from (Saunders et al., 2016, 397). This was minimized by making the interviews as convenient as possible for participants, so that schedule wouldn't prevent certain individuals from partaking.

Data quality is another frequently encountered problem with qualitative research, especially when conducting semi-structured or in-depth interviews. Saunders et al. (2016, 401) suggest considering three measures to avoid these: Interviewer level of knowledge, developing interview themes and providing participants information prior to interviews, and appropriateness of the interview location. These factors were considered when planning the data collection process. First aspect was addressed through comprehensive research on the topics discussed while doing the literature review portion of the thesis. The case organisation was already familiar to researcher due to current employment. Both factors allowed interviewees to present more detailed answers to the questions as the knowledge on topics and the context of marketing industry was addressed. With second measure, as stated earlier, interviewees were provided the interview questions and themes being discussed so that they could both prepare answers to the questions as well as bring up topics that they consider relevant to the research being conducted. Lastly, for the interview location, meeting room of the case company was selected due to being convenient for interviewees, and providing uninterrupted conditions for the interview, which helps with the fluency of the conversation as well as recording.

Additionally, to ensure the validity of the research, participant validation was done after the analysis. Participant validation involves giving the research data back to interviewees for them to review it and potentially make corrections on the data or interpretations derived from it by the researcher (Saunders et al., 2016, 207). Interview questions are attached to the appendix for increased reliability but due to conducting the research with semi-structured interviews, the additional questions presented to some interviewees are not documented.

For future research, it would be advantageous to extend the scope of interviews across multiple companies and especially different types of agencies as the practises and beliefs around different tools and their practical utility might differ substantially. Even though the case company works with international clients, media activities are predominantly done for Finnish market, so having companies from different markets would also make the study easier to generalize. The number of interviews was also limited due to time constraints of the thesis and could be expanded for the future research.

Marketing technology is evolving rapidly and there are new privacy focused solutions being planned to replace third-party cookies. When these are being deployed with major browsers and deemed sufficient, the role and status of AM should be revisited and studied again. There are also companies providing models that combine MMM and AM, usually referred to as unified systems. As they are still in a novel stage, they provide interesting topic for future research due to potentially providing more efficient utilization and other advantages that are not possible with approach suggested in this thesis.

References

- Aaker, D. A & Carman, J. M. (1982) Are You Overadvertising? *Journal of advertising research* 22, 4, 57–70.
- Abedi, V. S. (2017) Allocation of advertising budget between multiple channels to support sales in multiple markets. *The Journal of the Operational Research Society* 68, 2, 134–146.
- Abou Nabout, N., Skiera, B., Stepanchuk, T. & Gertsmeier, E. (2012) An analysis of the profitability of fee-based compensation plans for search engine marketing. *International journal of research in marketing* 29, 1, 68–80.
- Accenture. (2022) Growth through Privacy-First Measurement: A guide to evolving MMM for Marketing Executives. [Online]. [Accessed 10.5.2023] Available <https://acn-marketing-blog.accenture.com/wp-content/uploads/2022/03/Growth-Through-Privacy-First-Measurement-Traditional-Brands-MMM.pdf>
- Aksakalli, V. (2012) Optimizing direct response in Internet display advertising. *Electronic commerce research and applications* 11, 3, 229–240.
- Anderl, E., Becker, I., von Wangenheim, F. & Schumann, J.H. (2016) Mapping the customer journey: Lessons learned from graph-based online attribution modeling. *International journal of research in marketing* 33, 3, 457–474.
- Ansari, A. & Mela, C. F. (2003) E-Customization. *Journal of marketing research*. 40, 2, 131–145.
- Barwise, P. & Ehrenberg, A. (1988) *Television and its audience*. Vol. 3. London, Sage.
- Bass, F. M. & Clarke, D. G. (1972) Testing Distributed Lag Models of Advertising Effect. *Journal of marketing research* 9, 3, 298–.
- Baveja, S., Postma, G. & Pritzl, R. (2002) How to bounce higher out of recession. *European business journal* 14, 4, 193.
- Bayer, E., Srinivasan, S., Riedl, E. & Skiera, B. (2020) The impact of online display advertising and paid search advertising relative to offline advertising on firm performance and firm value. *International journal of research in marketing* 37, 4, 789–804.

- Bendixen, M. T. (1993) Advertising Effects and Effectiveness. *European journal of marketing*. 27, 10, 19–32.
- Bennett, D., Barrett, A. & Helmich, E. (2019) How to...analyse qualitative data in different ways. *The clinical teacher* 16, 1, 7–12.
- Berman, R. (2018) Beyond the Last Touch: Attribution in Online Advertising. *Marketing science (Providence, R.I.)* 37, 5, 771–792.
- Binet, L. & Field, P. (2013) The Long and the Short of It: Balancing Short and Long-Term Marketing Strategies. *Institute of Practitioners in Advertising*.
- Binet, L. & Field, P. (2017) Media in Focus: Marketing Effectiveness in the Digital Era. *Institute of Practitioners in Advertising*.
- Binet, L & Hankins, J. (2021) The Institute of Practitioners in Advertising. New findings from the cross-industry IPA Share of Search think tank data. [Online] [Accessed 20.3.2023]. Available <https://ipa.co.uk/news/share-of-search>
- Braun, V. & Clarke, V. (2006) Using thematic analysis in psychology. *Qualitative research in psychology* 3, 2, 77–101.
- Breuer, R. & Brettel, M. (2012) Short- and Long-term Effects of Online Advertising: Differences between New and Existing Customers. *Journal of interactive marketing* 26, 3, 155–166.
- Bright, J. K., Kiewell, D. & Kincheloe, A. H. (2006) Profiting from Proliferation. [Online]. [Accessed 15.5.2023]. Available <https://www.mckinsey.com/~/media/McKinsey/Business%20Functions/Marketing%20and%20Sales/Our%20Insights/Pricing%20in%20a%20proliferating%20world/Pricing%20in%20a%20proliferating%20world.pdf>
- Cain, P.M. (2008) Limitations of conventional marketing mix modeling. *Admap Magazine* 493, 48-51. [Online]. [Accessed 15.5.2023]. Available <http://www.timberlake-consultancy.com/mainWebsite/pdf/limitations-of-conventional-marketing-mix-modeling.pdf>
- Cain, P.M. (2010) Marketing mix modelling and return on investment. In *Integrated brand marketing and measuring returns* (pp. 94-130). London, Palgrave Macmillan UK.

- Chan, D. & Perry, M. (2017) Challenges and opportunities in media mix modeling. Google Inc. [Online]. [Accessed 20.5.2023]. Available <https://storage.googleapis.com/pub-tools-public-publication-data/pdf/2d0395bc7d4d13ddedef54d744ba7748e8ba8dd1.pdf>
- Chang, Y. & Thorson, E. (2004) TELEVISION AND WEB ADVERTISING SYNERGIES. *Journal of advertising*. 33 2, 75–84.
- Chernyak, O. & Farenjuk, Y. (2020) Modeling of Effectiveness of Media Investment Based on Data Science Technologies for Ukrainian Bank. *CEUR Workshop Proceedings*, 2732, 282–289.
- Cheong, Y., de Gregorio, F. & Kim, K. (2014) Advertising Spending Efficiency Among Top U.S. Advertisers from 1985 to 2012: Overspending or Smart Managing? *Journal of advertising* 43, 4, 344–358.
- Chu, S. & Keh, H. T. (2006) Brand Value Creation: Analysis of the Interbrand-Business Week Brand Value Rankings. *Marketing letters* 17, 4, 323–331.
- Clarke, D. G. (1976) Econometric Measurement of the Duration of Advertising Effect on Sales. *Journal of marketing research* 13, 4, 345–.
- Cobb-Walgren, C.J., Ruble, C. A. & Donthu, N. (1995) Brand equity, brand preference, and purchase intent. *Journal of Advertising* 24 (Fall) 25–40.
- Cooper, D. A., Yalcin, T., Nistor, C., Macrini, M. & Pehlivan, E. (2023) Privacy considerations for online advertising: a stakeholder’s perspective to programmatic advertising. *The Journal of consumer marketing* 40, 2, 235–247.
- Dalessandro, B., Perlich, C., Stitelman, O. & Provost, F. (2012) Causally motivated attribution for online advertising, in *Proceedings of the Sixth International Workshop on data mining for online advertising and internet economy*. 2012 ACM. 1–9.
- Danaher, P. J. & Dagger, T. S. (2013) Comparing the Relative Effectiveness of Advertising Channels: A Case Study of a Multimedia Blitz Campaign. *Journal of marketing research* 50, 4, 517–534.
- Danaher, P. J. & van Heerde, H. J. (2018) Delusion in Attribution: Caveats in Using Attribution for Multimedia Budget Allocation. *Journal of marketing research* 55, 5, 667–685.

- Deleersnyder, B., Dekimpe, M. G., Steenkamp, J-B. E. M. & Leeflang, P. S. H. (2009) The Role of National Culture in Advertising's Sensitivity to Business Cycles: An Investigation across Continents. *Journal of marketing research* 46, 5, 623–636.
- Dekimpe, M. G. & Hanssens, D. M. (1995) The Persistence of Marketing Effects on Sales. *Marketing science (Providence, R.I.)* 14, 1, 1–21.
- Dekimpe, M.G. & Hanssens, D.M. (1999) Sustained spending and persistent response: A new look at long-term marketing profitability. *Journal of Marketing Research* 36, 4, 397-412.
- Despotakis, S. & Yu, J. (2023) Multidimensional Targeting and Consumer Response. *Management science* 69, 8, 4518–4540.
- Doyle, S. (2004) Software review: Which part of my marketing spends really works? — Marketing mix modeling may have an answer. *Journal of database marketing & customer strategy management* 11, 4, 379–385.
- Dubois, A. & Gadde, L.-E. (2002) Systematic combining: an abductive approach to case research. *Journal of business research*, 55, 7, 553–560.
- El Hana, N., Mercanti-Guérin, M. & Sabri, O. (2023) Cookiepocalypse: What are the most effective strategies for advertisers to reshape the future of display advertising? *Technological forecasting & social change* 102, 1, 6-25
- Erdem, T., Swait, J. & Louviere, J. (2002) The impact of brand credibility on consumer price sensitivity. *International journal of research in marketing* 19, 1, 1–19.
- Eriksson, P. & Kovalainen, A. (2008) *Qualitative methods in business research*. Los Angeles; London, SAGE.
- Fareniuk, Y. & Chornous, G. (2023) Optimization of Media Strategy via Marketing Mix Modeling in Retailing. *Ekonomika - Vilniaus universitetas* 102, 1, 6–25.
- Fulgoni, G. M. (2014) Omni-Channel' Retail Insights and The Consumer's Path-to-Purchase: How Digital Has Transformed the Way People Make Purchasing Decisions. *Journal of advertising research* 54, 4, 377–380.

- Fulgoni, G. M. (2018) How Limited Data Access Constrains Marketing-Mix Analytical Efforts: Why Data Barriers Are Preventing Marketers From Optimizing Marketing Spend. *Journal of advertising research* 58, 4, 390–393.
- Gaur, J. & Bharti, K. (2020) ATTRIBUTION MODELING IN MARKETING: LITERATURE REVIEW AND RESEARCH AGENDA. *Academy of Marketing Studies Journal*, 2, 4, 1-21.
- Geyik, S., Saxena, A. & Dasdan, A. (2014) Multi-Touch Attribution Based Budget Allocation in Online Advertising, in *Proceedings of the Eighth International Workshop on data mining for online advertising*. 2014 ACM. 1–9.
- Ghose, A. & Todri-Adamopoulos, V. (2016) Toward a Digital Attribution Model: Measuring the Impact of Display Advertising on Online Consumer Behavior. *MIS quarterly* 40, 4, 889–910.
- Goldfarb, A. & Tucker, C. (2011) Online Display Advertising: Targeting and Obtrusiveness. *Marketing science (Providence, R.I.)* 30, 3, 389–404.
- Google Privacy Sandbox Progress Report. (2022 [Online] [Accessed 15.6.2023]. https://assets.publishing.service.gov.uk/media/63d7b357e90e0773e17b27d3/Privacy_Sandbox_Progress_Report_to_the_CMA_2022_Q4.pdf)
- Google support. (2023) About modeled conversions. [Online] [Accessed 20.6.2023]. Available <https://support.google.com/analytics/answer/10710245?hl=en>
- Graham, J. R., Harvey, C. R. & Rajgopal, S. (2005) The economic implications of corporate financial reporting. *Journal of accounting & economics* 40, 1, 3–73.
- Groenland, E. & Dana, L-P. (2019) *Qualitative Methodologies and Data Collection Methods: Toward Increased Rigour in Management Research*. Vol. 1. Singapore, World Scientific Publishing.
- de Haan, E., Wiesel, T. & Pauwels, K. (2016) The effectiveness of different forms of online advertising for purchase conversion in a multiple-channel attribution framework. *International journal of research in marketing* 33, 3, 491–507
- Hansen, F. & Christensen, L.B. (2004) Long-term advertising effects and optimal budgeting. *Proceedings of the EMAC Conference, Murcia, Spain*.

- Hanssens, D.M., Parsons, L.J. & Schultz, R.L. (1990) Response Models in Marketing. In: Market Response Models: Econometric and Time Series Analysis. International Series in Quantitative Marketing. Vol. 2. Springer, Dordrecht.
- Hanssens, D. M. & Pauwels, K. H. (2016) Demonstrating the Value of Marketing. *Journal of marketing* 80, 6, 173–190.
- Hein, S., Schlereth, C. & Mueller-Klockmann, T. (2019) Long-Term Brand Equity Measurement - Status Quo and Challenges. *Zeitschrift für Kommunikation & Markenmanagement* 65, 3, 6-11.
- Heath, R. & Feldwick, P. (2008) Fifty years using the wrong model of advertising. *International Journal of Market Research* 50, 1, 29– 59.
- Heath, R. (2012) *Seducing the subconscious the psychology of emotional influence in advertising*. Chichester, West Sussex, Wiley.
- Herrington, J. D. & Dempsey, W. A. (2005) Comparing the Current Effects and Carryover of National-, Regional-, and Local-Sponsor Advertising. *Journal of Advertising Research* 45, 1, 60-72.
- Hirsjärvi, S., Remes, P., Sajavaara, P. & Sinivuori, E. (2009) *Tutki ja Kirjoita*. Vol. 15. Helsinki, Tammi.
- Homburg, C., Jensen, O. & Krohmer, H. (2008) Configurations of Marketing and Sales: A Taxonomy. *Journal of marketing* 72, 2, 133–154.
- Hyun, Y. J., Gentry, J.W., Park, C. & Jun, S. (2006) An Investigation of Newspaper Ad Memory as Affect Context Involvement and Ad Size—A Korean Case. *Journal of Current Issues & Research in Advertising* 28, 1, 45-56
- IAB Attribution Working Group. (2016) DIGITAL ATTRIBUTION PRIMER 2.0. [Online] [Accessed 20.4.2023]. Available <https://www.iab.com/wp-content/uploads/2016/10/Digital-Attribution-Primer-2-0-FINAL.pdf>
- IAB. (2019) The Essential Guide to Marketing Mix Modeling and Multi-Touch Attribution: An overview of industry viewpoints on measurement techniques. [Online] [Accessed 20.4.2023]. Available https://www.iab.com/wp-content/uploads/2019/11/IAB_MMA_MTA-Guidebook_Nov-2019.pdf

- IAB. (2023) 2022 Video Ad Spend & 2023 Outlook. Defining the Next Generation. [Online] [Accessed 7.11.2023]. Available: https://www.iab.com/wp-content/uploads/2023/04/2023_IAB_Video_Ad_Spend_Report.pdf
- Jedidi, K., Mela, C. F. & Gupta, S. (1999) Managing Advertising and Promotion for Long-Run Profitability. *Marketing science* (Providence, R.I.) 18, 1, 1–22.
- Jin, Y., Wang, Y., Sun, Y., Chan, D. & Koehler, J. (2017) Bayesian methods for media mix modeling with carryover and shape effects. Google Inc. [Online]. [Accessed 20.5.2023]. Available <https://storage.googleapis.com/pub-tools-public-publication-data/pdf/b20467a5c27b86c08cceed56fc72ceadb875184a.pdf>
- Jiang, Z., Guan, C. & de Haaij, I. L. (2020) Congruity and processing fluency: An analysis on the effectiveness of embedded online video advertising. *Asia Pacific journal of marketing and logistics* 32, 5, 1070–1088.
- Joshi, A. & Hanssens, D. M. (2010) The Direct and Indirect Effects of Advertising Spending on Firm Value. *Journal of Marketing* 74, 1, 20–33.
- Kannan, P. K., Reinartz, W. & Verhoef, P. C. (2016) The path to purchase and attribution modeling: Introduction to special section. *International journal of research in marketing* 33, 3, 449–456.
- Karmann, T., Köster, L. & Meyer, T. Budget Sizing: The Million-dollar Question. In Perrey, J. & Spillecke, D. (2013) editors, *Retail Marketing and Branding*, chapter 8, pages 117–128. 2nd edition. Hoboken, NJ, USA, John Wiley & Sons, Inc.
- Kireyev, P., Pauwels, K. & Gupta, S. (2016) Do display ads influence search? Attribution and dynamics in online advertising. *International journal of research in marketing* 33, 3, 475–490.
- Kotler, P. & Keller, K. (2011) *Marketing management*. 14th ed. Prentice Hall, in Smith, T. A. (2022) *Marketing effectiveness and accountability in SMEs: a multimethodological approach*. Palgrave Macmillan.
- Kotler, P. & Armstrong, G. (2014) *Principles of marketing*. 15th ed, global ed. Boston, Mass: Pearson.

- Köhler, C., Mantrala, M. K., Albers, S. & Kanuri, V. K. (2017) A Meta-Analysis of Marketing Communication Carryover Effects. *Journal of marketing research* 54, 6, 990–1008.
- Ladika, T. & Sautner, Z. (2020) Managerial Short-Termism and Investment: Evidence from Accelerated Option Vesting. *Review of Finance* 24, 2, 305–344.
- Laverty, K.J. (1996) Economic “short-termism”: The debate, the unresolved issues, and the implications for management practice and research. *Academy of Management Review* 21, 3, 825-860.
- Lee, J. & Ahn, J.-H. (2012) Attention to Banner Ads and Their Effectiveness: An Eye-Tracking Approach. *International journal of electronic commerce* 17, 1, 119–137.
- Lee, J. & Lee, H. (2012) Canonical correlation analysis of online video advertising viewing motivations and access characteristics. *New media & society* 14, 8, 1358–1374.
- Lehmann, D. R. & Reibstein, D. J. (2006) *Marketing Metrics and Financial Performance*. Cambridge, MA: Marketing Science Institute.
- Lemon, K. N. & Verhoef, P. C. (2016) Understanding Customer Experience Throughout the Customer Journey. *Journal of marketing* 80, 6, 69–96.
- Leone, R. P. (1995) Generalizing What Is Known About Temporal Aggregation and Advertising Carryover. *Marketing science (Providence, R.I.)* 14, 3, G141–G150.
- Li, H. A. & Kannan, P. K. (2014) Attributing Conversions in a Multichannel Online Marketing Environment: An Empirical Model and a Field Experiment. *Journal of marketing research* 51, 1, 40–56.
- Liu, Y., Laguna, J., Wright, M. & He, H. (2014) Media mix modeling – A Monte Carlo simulation study. *Journal of marketing analytics* 2, 3, 173–186.
- Lodish, L. M., Abraham, M., Kalmenson, S., Livelsberger, J., Lubetkin, B., Richardson, B. & Stevens, M. E. (1995) How T.V. Advertising Works: A Meta-Analysis of 389 Real World Split Cable T.V. Advertising Experiments. *Journal of marketing research* 32, 2, 125–139.

- Mank, T., Rich, N., Bona, C., de Bellefonds, N. & Recchione, T. (2019) Marketing Measurement Done Right. [Online] [Accessed 4.5.2023]. Available <https://www.bcg.com/publications/2019/marketing-measurement-done-right>
- Mela, C. F., Gupta, S. & Lehmann, D. R. (1997) The Long-Term Impact of Promotion and Advertising on Consumer Brand Choice. *Journal of Marketing Research* 34, 2, 248–261.
- Merriam-Webster. (2023) “Optimization” [Online] [Accessed 6.9.2023] Available www.merriam-webster.com/dictionary/optimization
- Metsämuuronen, J. (2011) Tutkimuksen tekemisen perusteet ihmistieteissä. 4th edition. Helsinki, International Methelp.
- Michelon, A., Bellman, S., Faulkner, M., Cohen, J. & Bruwer, J. (2020) A New Benchmark for Mechanical Avoidance of Radio Advertising: Why Radio Advertising Is a Sound Investment. *Journal of advertising research* 60, 4, 407–416.
- Mintz, O. & Currim, I. S. (2013) What Drives Managerial Use of Marketing and Financial Metrics and Does Metric Use Affect Performance of Marketing-Mix Activities? *Journal of marketing* 77, 2, 17–40.
- Mitchell, A. A. (1986) The effects of verbal and visual components of advertisements on brand attitudes and attitude toward the advertisement. *The Journal of consumer research* 13, 1, 12–24.
- Moorman, C. (2019) The CMO Survey: Highlights & Insights Report. Technical Report February [Online]. [Accessed 15.3.2023]. Available <https://cmosurvey.org/results/february-2019/>
- Morse, J. M., Barret, M., Mayan, M., Olson, K. & Spiers, J. (2002) Verification Strategies for Establishing Reliability and Validity in Qualitative Research. *International journal of qualitative methods* 1, 2, 13–22.
- Nagar, K. (2009) Advertising effectiveness in different media: A comparison of web and television advertising. *IIMB Management Review* 21, 3, 245–260.
- Naik, P. A. & Raman, K. (2003) Understanding the Impact of Synergy in Multimedia Communications. *Journal of Marketing Research* 40, 4, 375–388.

- Nath, P. & Mahajan, V. (2011) Marketing in the C-Suite: A Study of Chief Marketing Officer Power in Firms' Top Management Teams. *Journal of Marketing*, 75, 1, 60–77.
- Niemand, T., Kraus, S., Mather, S. & Cuenca-Ballester, A. C. (2020) Multilevel marketing: optimizing marketing effectiveness for high-involvement goods in the automotive industry. *International entrepreneurship and management journal* 16, 4, 1367–1392.
- Nikolov, A. N. (2018) MANAGERIAL SHORT-TERMISM: AN INTEGRATIVE PERSPECTIVE. *Journal of marketing theory and practice* 26, 3, 260–279.
- Nisar, T. M. & Yeung, M. (2018) Attribution Modeling In Digital Advertising: An Empirical Investigation Of the Impact of Digital Sales Channels. *Journal of advertising research* 58. 4, 399–413.
- Osinga, E. C., Leeflang, P. S. H. & Wieringa, J. P. (2010) Early Marketing Matters: A Time-Varying Parameter Approach to Persistence Modeling. *Journal of marketing research* 47, 1, 173–185.
- Pandey, S., Gupta, S. & Chhajed, S. (2021) Marketing Mix Modeling (MMM)- Concepts and Model Interpretation. *International journal of engineering research & technology* 10, 6, 784-793.
- Perrey, J. & Spillecke, D. (2013) *Retail Marketing and Branding a Definitive Guide to Maximizing ROI*. 2nd ed. Chichester, West Sussex, Wiley.
- Peppers, D. & Rogers, M. (2008) *Rules to break and laws to follow: how your business can beat the crisis of short-termism*. 1st ed. Vol. 8. Hoboken, N.J: John Wiley & Sons.
- Puusa, A., Juuti, P. & Aaltio, I. (2020) *Laadullisen tutkimuksen näkökulmat ja menetelmät*. Helsinki, Gaudeamus.
- Raman, K. (2010) Resource Allocation in Marketing. *Marketing (Munich)* 32, (JRM 1), 81–90.
- Rappaport, A. (2005) The Economics of Short-Term Performance Obsession. *Financial analysts journal* 61, 3, 65–79.

- Ratajczak, D., Simon, M., Fascines, L., Kruger, E., Murphy, C. & Almeida, A. (2023) Don't Cut Your Brand-Marketing Budget. Rethink It. [Online] [Accessed 6.8.2023] Available <https://www.bcg.com/publications/2023/rethink-brand-marketing-budget>
- Reiley, D., Lewis, R. A. & Schreiner, T. (2012) Ad Attributes and Attribution: Large-Scale Field Experiments Measure Online Customer Acquisition. [Online] [Accessed 17.5.2023]. Available https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2049457
- Romero Leguina, J., Cuevas Rumín, Á. & Cuevas Rumín, R. (2020) Digital Marketing Attribution: Understanding the User Path. *Electronics (Basel)* 9, 11, 1822–.
- Rossiter, J. R. (2001) What Is Marketing Knowledge?: Stage I: forms of marketing knowledge. *Marketing theory*, 1, 1, 9–26.
- Rust, R. T., Ambler, T., Carpenter, G. S., Kumar, V. & Srivastava, R. K. (2004) Measuring Marketing Productivity: Current Knowledge and Future Directions. *Journal of Marketing* 68, 4, 76–89.
- Sapp, S. & Vaver, J. (2016) Toward improving digital attribution model accuracy. Google inc. [Online] [Accessed 6.4.2023] Available <https://storage.googleapis.com/pub-tools-public-publication-data/pdf/45766.pdf>
- Saunders, M., Lewis, P. & Thornhill, A. (2016) *Research methods for business students*. Seventh edition. Harlow, Essex, Pearson Education.
- Saunders, M., Philip, L., & Thornhill, A. (2019) *Research methods for business students* Eighth edition. Harlow, Pearson Education Limited.
- Scottmay, M. (2016) Rise of ad-blocking software threatens online revenue. *New York Times*, in Kannan, P. K., Reinartz, W. & Verhoef, P. C. (2016) The path to purchase and attribution modeling: Introduction to special section. *International journal of research in marketing* 33, 3, 449–456.
- Schmidt, S. & Eisend, M. (2015) Advertising Repetition: A Meta-Analysis on Effective Frequency in Advertising. *Journal of advertising* 44, 4, 415–428.
- Shin, J. & Shin, W. (2023) A Theory of Irrelevant Advertising: An Agency-Induced Targeting Inefficiency. *Management science* 69, 8, 4481–4497.

- Shin, J. & Yu, J. (2021) Targeted Advertising and Consumer Inference. *Marketing science* (Providence, R.I.) 40, 5, 900–922.
- Solcansky, M., Sychrova, L. & Milichovsky, F. (2011) Marketing effectiveness by way of metrics. *Economics and Management* 16, 1323-1328.
- Sridhar, S., Narayanan, S. & Srinivasan, R. (2014) Dynamic relationships among R&D, advertising, inventory and firm performance. *Journal of the Academy of Marketing Science* 42, 3, 277–290.
- Srinivasan, S., Vanhuele, M. & Pauwels, K. (2010) Mind-Set Metrics in Market Response Models: An Integrative Approach. *Journal of marketing research* 47, 4, 672–684.
- Suárez, M. M. & Estevez, M. (2016) Calculation of marketing ROI in marketing mix models, from ROMI, to marketing-created value for shareholders, EVAM 1/Cálculo del ROI de marketing en modelos de marketing mix, del ROMI, al valor creado del marketing para los accionistas EVAM. *Universia business review* 52, 18–75.
- Sudhir, K., Roy, S. & Cherian, M. (2016) Do Sympathy Biases Induce Charitable Giving? The Effects of Advertising Content. *Marketing science* (Providence, R.I.) 35, 6, 849–869.
- Statista (2023a) Marketing spending on offline channels in the United States from 2018 to 2023. [Online] [Accessed 16.3.2023] Available <https://www.statista.com/statistics/1028853/offline-media-ad-spend-us/>
- Statista (2023b) Print Advertising - United States. [Online] [Accessed 16.3.2023] Available <https://www.statista.com/outlook/amo/advertising/print-advertising/united-states>
- Statista (2023c) TV & Video Advertising - Worldwide. [Online] [Accessed 16.3.2023] Available <https://www.statista.com/outlook/amo/advertising/tv-video-advertising/worldwide>
- Statista (2023d) Digital advertising spending worldwide from 2021 to 2026. [Online] [Accessed 16.3.2023] Available <https://www.statista.com/statistics/237974/online-advertising-spending-worldwide/>
- Statista (2023e) Advertising - Worldwide. [Online] [Accessed 16.3.2023] <https://www.statista.com/outlook/amo/advertising/worldwide>

- Stewart, D. W. (2009) Marketing accountability: Linking marketing actions to financial results. *Journal of business research* 62, 6, 636–643.
- Stürze, S., Hoyer, M., Righetti, C. & Rasztar, M. (2022) *Agile Marketing Performance Management : 10 Success Factors for Maximizing Marketing ROI Dynamically*. Wiesbaden, Springer Fachmedien Wiesbaden GmbH.
- Tellis, G. J. (2004) *Effective advertising understanding when, how, and why advertising works*. Thousand Oaks, California, SAGE.
- Tellis, G.J. (2006) Modeling marketing mix. *Handbook of marketing research* 506-522.
- The Wall Street Journal. (2023) Global Advertising Forecast to Speed Up After a Slower Start in 2023. [Online] [Accessed 10.10.2023] <https://www.wsj.com/articles/global-advertising-forecast-to-speed-up-after-a-slower-start-in-2023-45b8953c>
- Thinkbox. (2018) Profit ability: The business case for advertising. [Online] [Accessed 30.3.2023] <https://www.gaintheory.com/wp-content/uploads/2017/12/Profit-Ability-The-Business-Case-For-Advertising-2018-Full-Report.pdf>
- Thyer, B. A. (2001) *The handbook of social work research methods*. Thousand Oaks, California, SAGE.
- Todri, V., Ghose, A. & Singh, P. V. (2020) Trade-Offs in Online Advertising: Advertising Effectiveness and Annoyance Dynamics Across the Purchase Funnel. *Information systems research* 31, 1, 102–125.
- Tull, D. S., Wood, V. R., Duhan, D., Gillpatrick, T., Robertson, K. R. & Helgeson, J. G. (1986) ‘Leveraged’ Decision Making in Advertising: The Flat Maximum Principle and Its Implications. *Journal of marketing research* 23, 1, 25–32.
- Tuomi, J. & Sarajärvi, A. (2018) *Laadullinen tutkimus ja sisällönanalyysi. Uudistettu laitos*. Helsinki, Kustannusosakeyhtiö Tammi.
- Turnbull, S. (2022) *Absolute essentials of advertising*. London, Routledge.
- Venkatraman, V., Dimoka, A., Vo, K. & Pavlou, P. A. (2021) Relative Effectiveness of Print and Digital Advertising: A Memory Perspective. *Journal of marketing research* 58, 5, 827–844.

- de Vries, L., Gensler, S. & Leeflang, P. S. H. (2017) Effects of Traditional Advertising and Social Messages on Brand-Building Metrics and Customer Acquisition. *Journal of marketing* 81, 5, 1–15.
- Webster, F. E., Malter, A. J. & Ganesan, S. (2005) The Decline and Dispersion of Marketing Competence. *MIT Sloan management review*. 46, 4, 35–.
- Wood, L. (2009) Short-Term Effects of Advertising: Some Well-Established Empirical Law-Like Patterns. *Journal of advertising research*, 49, 2, 186–192.
- Wildner, R. & Modenbach, G. (2015) The Long-Term ROI of TV Advertising in a Digital World. *GfK marketing intelligence review*, 7, 1, 54–60.
- Wilson, R. T. & Till, B. D. (2011) Effects of outdoor advertising: Does location matter? *Psychology & marketing*, 28, 9, 909–933.
- Xu, L., Duan, J. A. & Whinston, A. (2014) Path to Purchase: A Mutually Exciting Point Process Model for Online Advertising and Conversion. *Management science* 60, 6, 1392–1412.
- Yang, S. & Ghose, A. (2010) Analyzing the Relationship Between Organic and Sponsored Search Advertising: Positive, Negative, or Zero Interdependence? *Marketing science* (Providence, R.I.), 29, 4, 602–623.
- Yang, Y., Zhao, K., Zeng, D. D. & Jansen, B. J. (2022) Time-varying effects of search engine advertising on sales—An empirical investigation in E-commerce. *Decision Support Systems* 163, 163113843–.
- Zhao, K., Mahboobi, S. H. & Bagheri, S. R. (2018) Shapley Value Methods for Attribution Modeling in Online Advertising. [arXiv.org](https://arxiv.org/).
- Åkesson, M., Edvardson, B. & Tronvoll, B. (2014) Customer experience from a self-service system perspective. *International journal of service industry management* 25, 5, 677–69

Appendix 1. Interview questions

1. Media mix modeling

- Can you explain the concept of media mix modeling and its relevance in advertising effectiveness?
- What are the primary advantages and use cases for media mix modeling?
- Could you share an example where media mix modeling has improved advertising effectiveness for one of your clients?
- What are the main challenges and/or limitations in use of media mix modeling?

2. Attribution modeling

- Can you explain the concept of attribution modeling and its significance in evaluating advertising effectiveness?
- What are the primary advantages and use cases for attribution modeling?
- What are the main challenges and/or limitations in use of attribution modeling?
- Do you think the potential disappearance of cookies will drastically affect attribution modeling?

3. Advertising effectiveness

- How would you conceptualize advertising effectiveness and what are the key components?
- What metrics or key performance indicators (KPIs) do you commonly use to assess advertising effectiveness? Short-term/long-term?
- How would you assess the time frame of effectiveness of different channels?

- In your experience, do clients usually have good understanding of advertising effectiveness?

4. Utilizing media mix modeling and attribution modeling together

- Do you see potential in utilizing both methods simultaneously?
- Do you think utilizing both methods could provide insights that could not be achieved by only using one, and how would you do it in practise?
- If there is potential, do you think integrating the tools is an option or would it be better to just use them side by side?
- Do you think use of both tools would be a good idea in terms of time/resource commitment required?
- If you think the use of both tools is justified in some situations?
- Do you think MMM and AM will remain relevant in the near future with the current speed of technical innovation?