RECAST

OPERATIONALIZING

MMM for Modern Brands

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ABOUT THE AUTHORS

Tom holds a master's degree from the London School of Economics and an MBA from Wharton. Prior to co-founding Recast he built a quantitative market research firm consulting for clients such as Amazon, McKinsey and Nike.

TOM VLADECK
Co-Founder of Recast

Michael is a trained econometrician with a background in healthcare and environmental economics. He previously built the marketing science team at men's grooming brand Harry's before co-founding Recast.

MICHAEL KAMINSKY
Co-Founder of Recast

Mike was a co-founder at Ladder, a 50-person growth marketing agency, leading the ad operations, data science, and product teams. He is currently making online courses for data-driven marketers at Vexpower.

MIKE TAYLOR
Attribution Expert

MAKING USE OF THIS GUIDE

Welcome to “Operationalizing MMM for a Modern Brand,” a guide for CMOs and VPs of Marketing looking to use marketing mix modeling (MMM) to optimize their marketing strategy and improve business outcomes.

What is a modern brand? When we say “modern” we don’t just mean DTC (Direct To Consumer) brands founded in the last 10 years, but rather we mean brands that are attempting to make use of the breadth of marketing and distribution channels that are available to modern marketers. Modern brands are using TikTok to drive sales on amazon and measuring how influencer unboxing videos impact their sales at Target. Modern brands aren’t content to use the playbooks of the past but instead they’re working hard every day to meet their customers where they are across an ever-shifting landscape of media channels.

In this ebook, we’ll cover the key concepts and best practices for implementing MMM in modern brands. We’ll help you scope out the project, understand the deliverables, and take action on the insights gained from MMM. Whether you’re new to MMM or an experienced practitioner, this guide will provide valuable guidance for using MMM to inform your marketing decisions and drive results.

Many brands have shown particular interest in MMM in recent years, and it’s easy to see why. As growing brands increasingly rely on paid advertising and expand their marketing efforts to less measurable channels like podcasts, billboards, and influencers, MMM can provide valuable insights into the effectiveness of these tactics and help optimize resource allocation. Recent privacy changes such as iOS14 and GDPR have only further highlighted the importance of MMM for modern brands, who must learn to reduce their reliance on user-level tracking data.

Many examples in this guide focus on newer e-commerce and retail brands, but of course MMM is not just relevant in this domain – it can be applied to any business looking to better understand the impact of its marketing efforts on key performance indicators (KPIs). Whether you’re in mobile gaming, fintech, or any other consumer or prosumer industry, MMM can be a valuable tool for improving your marketing ROI.

In the following pages, we’ll cover the key concepts and best practices for operationalizing MMM in a modern brand. We’ll explore the history and evolution of MMM, the benefits and limitations of this statistical technique, and the types of data and goals that are essential for success. We’ll also delve into the various tools and software options available, and provide guidance on how to build, validate, and update your model automatically. We’ll address common challenges and objections, and provide suggestions for further learning and resources.

By following the steps outlined in this guide, you’ll be able to effectively operationalize MMM for your brand, and take your marketing attribution efforts to the next level.

1. INTRODUCTION TO MARKETING MIX MODELING

1.1: Marketing mix modeling past and present

Marketing mix modeling (MMM) is a top-down statistical method used to quantify the impact of various marketing efforts on sales and market share. MMM is used to analyze data from various sources, such as advertising spend, promotions, pricing, and sales data, in order to understand the relative impact of these inputs on sales. Businesses typically use MMM to optimize their marketing mix, identify which marketing initiatives are most effective, and make data-driven decisions about where to allocate their marketing budget. Additionally, MMM can help businesses forecast sales and predict the impact of future marketing efforts, which can be useful for budgeting and long-term planning.

MMM has its roots in the “Four P’s” of marketing developed by E. Jerome McCarthy in the 1960s. In its early application, MMM focused on measuring the impact of traditional marketing channels like TV advertising and promotions, for consumer packaged goods (CPG) brands, using linear regression, and econometrics techniques. The technique works by associating spikes and dips in sales to events and actions in marketing. MMM has evolved over time to incorporate more diverse data sources, automated data pipelines, and more sophisticated statistical techniques. For example, the release of Meta’s Robyn open source library, and publication of Google’s Bayesian MMM papers, as well as the launch of automated solutions like ours at Recast, has led to the modernization of the industry in just the last few years.

The efforts to overhaul the traditional approach to MMM have been driven partly by a new class of modern consumer startups maturing into full omnichannel brands. As they have expanded into non-digital advertising channels – TV, Billboards, PR – they've been in search of more holistic attribution methods. However, the main driving force behind this mass adoption of MMM is the backlash against "surveillance capitalism," as consumers become increasingly aware of and concerned about the ways in which their data is being collected, shared, and used by businesses. This has led to changes in technology, such as Apple's iOS 14, which has made it more difficult for companies to track the effectiveness of their digital advertising, as well as the rise of ad blockers, which can impede the delivery of online ads. Additionally, privacy legislation such as the General Data Protection Regulation (GDPR), California Consumer Privacy Act (CCPA) and upcoming American Data Privacy Protection Act (ADPPA) has turned data from a valuable asset to a potential legal liability.

In this environment, MMM is a much welcome privacy-friendly alternative to other marketing measurement methods, as it typically only requires aggregate data, such as ad spend and sales data, and does not rely on tracking individual users. This makes MMM a more compliant and ethical way for businesses to measure the effectiveness of their marketing efforts, especially when dealing with laws such as GDPR, CCPA, and ADPPA. Additionally, MMM's independence of any specific channel makes it a useful "tie-breaker" when comparing the effectiveness of different competing marketing efforts. With the rise of digital marketing, many of the measurement methods for different channels have become more complex and less transparent. MMM, on the other hand, is channel-agnostic, working across both online and offline channels regardless of how the data is being collected or how the results are being reported. This independence provides a neutral, data-driven approach for comparing the effectiveness of different marketing channels and making decisions on budget allocation.

1.2: Privacy backlash and channel diversification: the case for MMM

The digital landscape has seen a massive shift in recent years, with new laws and regulations such as the General Data Protection Regulation (GDPR), the California Consumer Protection Act (CCPA), and the upcoming American Data Privacy Protection Act (ADPPA). Privacy controls such as Apple's iOS14, ad blockers, and Intelligent Tracking Prevention (ITP) have dramatically reshaped the way digital advertising works, severely impacting marketer's ability to measure the performance of their campaigns. At the same time, as DTC startups mature into full Omnichannel brands expanding to traditional brick-and-mortar stores like Walmart as they scale, and figuring out how to measure how marketing impacts their sales on Amazon where they have no control over tracking and analytics. They are increasingly diversifying the channels they use to market their products, including TV, billboards, public relations, and other hard-to-measure channels such as podcasts, video streaming, and influencers.

This has made it increasingly difficult for companies to keep track of their marketing efforts and measure their success holistically.

The GDPR, CCPA, and ADPPA are all legal frameworks that have been put in place to protect the privacy of consumers. The GDPR was implemented in 2018, granting individuals the right to access their data, the right to demand that their data be deleted, and the right to restrict how their data is used. The CCPA, implemented in 2020, similarly grants individuals the right to access their data, the right to delete it, and the right to opt out of the sale of their data. Finally, the upcoming ADPPA will provide additional protections for consumers by allowing individuals to be informed of the data being collected from them, the intended use of the data, and the rights they have with regard to their data. This has necessitated a shift in how companies must measure their marketing efforts and has made it increasingly difficult to keep track of their success. These legislative efforts have put an end to the notion that data should be freely collected, and increased demand for more privacy-friendly attribution methods like MMM.

Privacy controls such as Apple's iOS14, ad blockers, and Intelligent Tracking Prevention (ITP) have broken the way digital advertising was attributed. Gone are the days when you could rely on tracking who had seen or clicked on an ad, all the way through to which of those people purchased your product. Apple's iOS14 release, for example, requires app developers to ask for user permission before tracking their data and activities. Ad blockers, on the other hand, block advertisers from gathering data or showing ads to users, who amount to over 40% of the web. There are also myriad other moves towards greater user control and respect for privacy, such as Apple's ITP which prevents advertisers from tracking users across multiple websites, and similar functionality in the Brave and Firefox browsers. Google is also openly planning to deprecate its use of cookies in Chrome, though this effort continues to be delayed (at least as of early 2023). All of these privacy controls limit the ability of companies to track user behavior, and in some cases, block the tracking altogether. This has led to a decrease in the effectiveness of digital marketing campaigns, as companies are now unable to accurately measure the impact of their efforts.

Additionally, companies are also utilizing hard-to-measure channels such as podcasts, video streaming, and influencers in order to escape the competitiveness of saturated channels like Meta (née Facebook) and Google. These channels provide unique opportunities for companies to reach their target audiences, but they are also more difficult to measure and track given that more of their impact derives from mid to long term brand awareness rather than short term return on investment (ROI). This has made it increasingly difficult for companies to keep track of their marketing efforts and measure their success.

1.3: Benefits and limitations of marketing mix modeling

In the last section we discussed the appeal of a privacy-friendly technique like MMM in the current macro-environment. However, MMM has been used since the 1960s by businesses looking to optimize their marketing mix and maximize their return on investment. What are its other benefits? Following on from that, what are the limitations that have kept it from being more widely adopted until now? In this section we'll discuss the benefits and drawbacks of using MMM, so you can decide whether the technique is right for you.

Because it works independently across all marketing channels and platforms – even hard to measure channels like TV, billboards, podcasts, and influencers – it is uniquely positioned to allocate budget between them. This feature of MMM has made it the default choice for large enterprises dealing with a complex marketing mix, who need a single source of truth for deciding between competing channels. You can't rely on in-platform reporting to do this, because every platform and channel measures performance differently: indeed, if you added up all of the conversions or revenue that each platform wanted to take credit for, you'd probably end up with a number that is many multiples of your actual revenue! In this situation MMM can act as the tie-breaker between all departments, independent from the biases of individual channel managers or operational teams.

When the Enron scandal led to the Sarbanes-Oxley Act in 2002, suddenly companies had to justify their marketing expenditure, alongside all other major expenses. In large enterprises, typically budgets are set by choosing a 'reasonable' advertising to sales ratio, and earmarking that percent of their sales target to marketing. For example if a company planned to generate $100 million in revenue next year, they would allocate 10% of sales to marketing, and set the budget at $10 million. The issue with this way of allocating budgets is that you're taking on blind faith that the marketing budget is "working". You have no way of knowing whether you could have hit your target with less marketing budget, or if you had an opportunity to achieve more. Marketing Mix Modeling added a level of scientific rigor to this decision, by allowing marketers to forecast what spend levels would achieve in terms of sales, within a (hopefully) well-calibrated margin of error.

MMM is not without its limitations. As with all predictive models, it's based on historical data, so it cannot predict future outcomes with certainty. Additionally, that means it's only as good as the data that goes into it, so it's important to have high-quality data. Gathering this data, especially for legacy brands that haven't been diligent in maintaining a centralized data warehouse, can be extremely difficult and time consuming, touching on every aspect of the organization. For example you may need to gather sales figures from the finance department, channel data from the various teams that run each of the marketing channels, as well as talk to customer service and various other departments who have what you need. In addition you may need to gather data from outside sources, such as macroeconomic indicators, market or industry trends, and seasonal events like holidays. It may also be necessary to purchase data on competitive moves like what your competitors are spending on TV advertising. These issues are somewhat mitigated by the move to more modern data management technologies like data warehousing and data pipelines that move data automatically between locations. However, this still tends to be the most time-consuming part of setting up MMM for the first time.

Furthermore, because MMM can be complex and time-consuming, it often requires specialized expertise or software. That requirement makes MMM expensive, which explains why until recently it has sat squarely in the domain of Fortune 500 companies. It may not be suitable for businesses with limited data or marketing complexity, for example spending less than six figures per month on fewer than 3 channels. As the process is still largely manual in most organizations, it is usually only done once or twice a year, meaning a significant amount of delay in being able to respond to the recommendations of the model. Relying on expertise can also be a significant source of bias: in complex modeling scenarios, the results can often be made to say whatever the analyst wants to say, or whatever they expect you (or the rest of your company) wants to hear. Most of the modernization of MMM has been in aid of removing this human bias or lessening its impact, by automating much of the feature selection and modeling process. This, combined with the introduction of automated data pipelines, has made it possible to update models in weeks rather than years, greatly increasing the usefulness of MMM as a real time decision-making tool.

However MMM is still in the process of modernizing. Not all best practices are distributed equally across the industry. The vast majority of models are still done by hand in Microsoft Excel by a (hopefully honest) external consultant, once per year in line with annual planning cycles. Even amongst the most cutting-edge MMM practitioners, there are still open questions around how best to account for the impact of advertising creative, how to factor in the long term impact of brand advertising, and how to get more granular campaign-level data for optimization. This exciting field will continue to innovate and improve, as large tech giants like Meta and Google invest in the area, as well as vendors like Recast, and in-house teams who continue to move the industry forward.

1.4: What makes marketing mix modeling so hard

Marketing itself is a complex process with many factors influencing the buying decision that no one will ever truly observe: did seeing the billboard influence your decision to buy a coke rather than a Dr Pepper at the convenience store? It's impossible to know for sure.

Marketing mix modeling is fundamentally an effort to statistically measure the relationships between marketing and buying behavior. Since the underlying system is incredibly complex, we should expect that the statistical problem will be very complex as well!

While some people believe that we can apply recent advances in machine learning to the problem, unfortunately it's not that easy. Most machine learning tools are designed for prediction problems and do not address the "why" behind the data, making them ineffective for MMM. This means

MMM requires specialized algorithms and domain knowledge to accurately measure and explain the effects of marketing activities.

Additionally, MMM is often limited by small data sets, with most datasets only containing a few hundred rows of data. Complex, unobservable processes, such as the time shift of channel spend to impact on sales, and diminishing returns, make MMM difficult to model. This means you must be able to accurately measure the effects of marketing activities, even on small samples, and be able to account for the effects of confounding variables that could distort your results.

MMM also requires modeling multiple channels, each with their own unique set of factors and interactions, adding to the complexity. In building models you're regularly confronted with multicollinearity – when multiple variables correlate with each other – and must learn techniques to deal with them. And you have to do this automatically and at scale, otherwise you'll start getting implausible results from your model as it updates each week.

Lastly, MMM must also account for external factors, such as seasonality and external events, which can significantly impact sales. These factors must be taken into account when building MMM models, as they can significantly affect the results and lead to incorrect conclusions, for example recommending to cut spending in periods of high demand!

When you step back to think about it, it can really seem like an impossible problem. At Recast, we've been working very hard for many years to build a statistical modeling platform sophisticated enough to address these complexities. We've effectively built a simulation engine (powered by Bayesian statistics) that incorporates all of these complex factors into our simulations and allows us to ensure that the assumptions our model is making line up with what marketers and marketing scientists actually believe.

2. DEFINING YOUR GOALS

2.1: Clearly define what you want to achieve with marketing mix modeling

MMM can be an invaluable tool for modern brands looking to maximize their return on investment. However, many brands don't actually have a clear picture in their mind of what a successful outcome would look like. By clearly defining your goals, you can ensure that your modeling efforts are focused and aligned with your business objectives. This will also help guide you in terms of what data to collect, what metrics to track, how to interpret the results of your model, and (most importantly) how to take action to improve your bottom-line. Every decision you make affects every aspect of your model, and so teams that aren't aligned around their goals tend to have painful experiences in trying to use marketing mix models.

When setting goals, it's important to consider the long-term and short-term objectives of your business. For example, you may want to analyze the impact of your marketing efforts on customer acquisition, revenue growth, or brand awareness. Targeting short term metrics can give you greater visibility and control over optimization, but you also can't ignore the long term impacts of your campaign. You should also take into account the limitations of the method, such as conversions that happen too far down the funnel or take too long to materialize, as these might be harder to associate with historic advertising spend. Anything more than a few weeks out is going to be much noisier and have a wider margin of error, so it's important to be prepared for less certainty in the recommendations of the model.

One common error we see is organizations trying to do too much with their MMM. A model that attempts to answer every question will effectively answer none. We believe it's wisest to focus on the most important and actionable questions for your business when developing an MMM strategy. For every modeling feature, you should ask yourself "if I knew the answer to this question, what would I do differently?". For example, knowing how much inflation impacted your sales last quarter is interesting, but if that isn't going to impact your strategy next quarter then it probably isn't the most important question to answer.

It's not just a case of knowing your KPIs and targets, it's also about figuring out what questions you want answered. One business might be looking for growth opportunities, or to evaluate the performance of a new channel, while another business could be looking to cut costs, and increase efficiency in an economic downturn. Once you have a clear understanding of your goals, you can begin to define the scope of your marketing mix modeling activities. This can include things such as the channels and campaigns you will analyze, the data you will collect, and the metrics you will track, all of which is fed into the model to train it. It's important to note that the data you collect should be comprehensive and accurate, as you will need it to build an accurate model that can be used to make informed decisions. Biased data will lead to biased results.

When it comes to interpreting the results of your model, there are certain key metrics that should be considered. These include things such as the effectiveness of each channel, the ROI for each campaign, and the overall impact of your marketing efforts. There are also cross-channel considerations, for example spending on one channel might have a 'halo effect', improving the performance of another channel. Often your model will force you to make tradeoffs. For example, once the model has worked out the diminishing returns of a channel, it can present you with the following choice: you can have the volume of sales you want, but it'll come at greater cost as the channel gets saturated, or you can improve efficiency but only by sacrificing volume by cutting spend. By understanding these metrics and complex interactions, you can identify which channels are the most effective and where improvements can be made.

Finally, once you have a clear understanding of your goals and the necessary data collected, you can then begin to think about how you will interpret your models. What scenarios do you need to forecast? What insights do you need to find? What charts and tables will be most helpful in aiding you to make budget allocation decisions. Having an idea in mind before you begin your project, will help your team format their final presentation, as well as ensure the model is useful in delivering on your requirements. Without thinking about this ahead of time, you run the risk of investing a lot of time and effort into a model that doesn't ultimately get used to make decisions. Failed projects like this can diminish trust in the technique itself, potentially eliminating any future plans you had to "do it right next time".

2.2: Identify the metrics that will be most important for your modeling efforts

In order to make your model actionable, it's essential to first identify the key performance indicators (KPIs) that are most important for your business. These KPIs will serve as the foundation for your modeling efforts and will help you understand the drivers of performance and optimize results after the model is built.

When identifying the most important KPIs, it's important to consider both short-term and long-term metrics. Short-term metrics such as revenue, signups or subscribers, new vs existing users, and orders or transactions are important for understanding the immediate impact of your marketing efforts on your business. However, it's also important to consider the long-term impact of your marketing efforts on your business. For example, an increase in brand awareness may not immediately translate to an increase in revenue, but it can have a positive impact on revenue in the long-term. This is difficult to directly measure and model, but it should at least be noted as a consideration, as it's bound to be questioned internally.

Another important consideration when identifying KPIs is to understand how the metrics differ by country and by business unit. For example, if your business operates in multiple countries, it's important to understand how the metrics differ by region and whether you need multiple models or one master model that can be applied across different regions or business units. Additionally, if your business operates in multiple business units, it's important to understand how the metrics differ by unit and whether you need multiple models or one master model that can be applied across different business units.

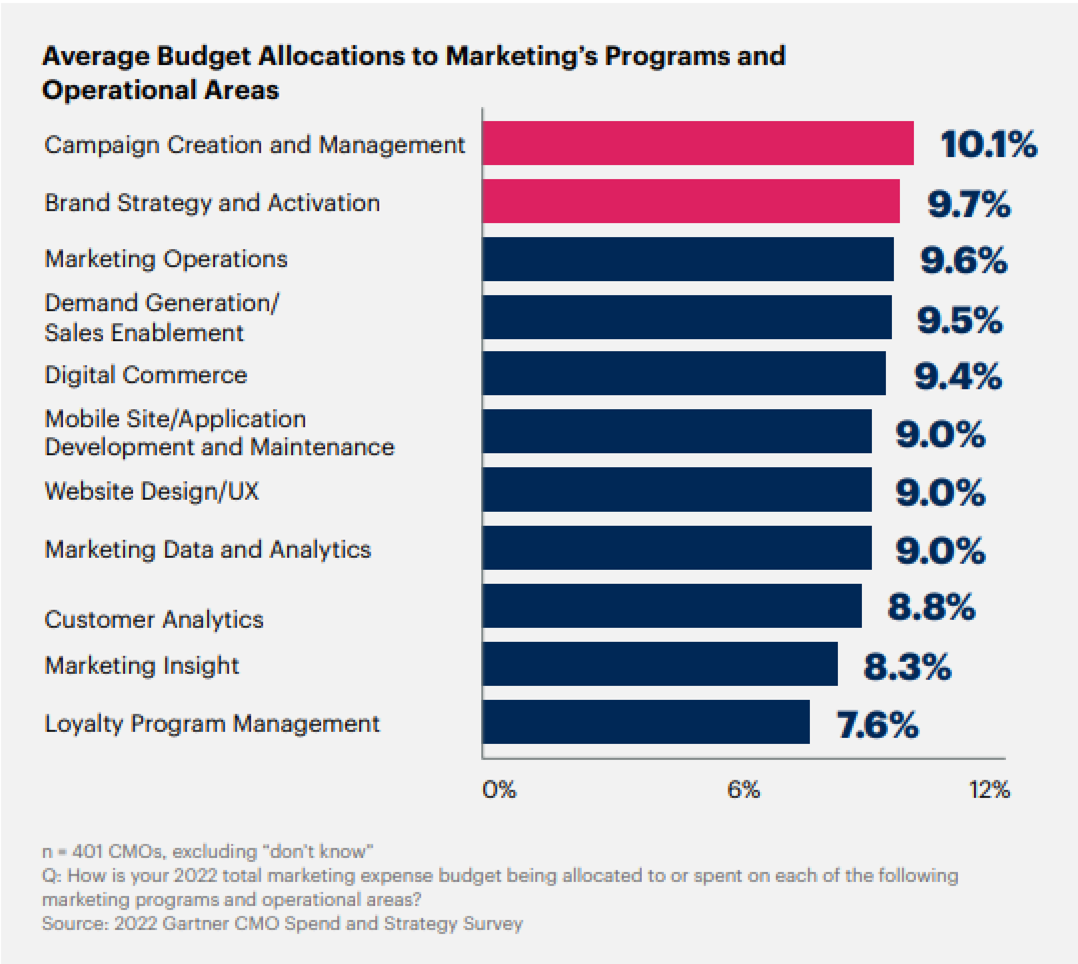
An approach we have seen practiced most often is to build your first model for your most important business unit, and biggest country by volume, as this will have the largest immediate impact on your business. Smaller countries and business units may justify their own model, or can be combined together if similar enough or when the granularity of the model is less important to the overall trajectory of the business and decisions that need to be made. It's also possible to build a geo-level model, which predicts region-level sales and then aggregates them globally, which can in some cases improve the accuracy and plausibility of your model.

In order to determine which KPI to use, it typically makes sense to align with whatever metrics your business goals are targeted on internally. In the case where sales take a long time to manifest, for example over 2-3 weeks, it's advisable to use a proxy metric that correlates with long term value. For example in Business to Business (B2B) leads are recorded immediately, but the actual sales may not close for months. Similarly in Business to Consumer (B2C) subscriptions, the majority of a customer's lifetime value is unlikely to be realized for many months or even years. In these cases you need to choose a shorter term metric, like qualified leads or activated subscribers, as the dependent variable (the KPI you're targeting) in your MMM. This is because models tend to get extremely noisy the further out they must predict, and already have to consider the natural lagged effect of advertising (ad-stocks). If you're a fast-growing ecommerce business it may be better to model first order revenue as you're likely to be oriented towards driving new customers. If your business is mature and primarily driven by repeat customers, consider modeling returning customers separately.

Identifying the most important KPIs for your business is a crucial step in operationalizing MMM. By considering both short-term and long-term metrics, understanding how the metrics differ by country and business unit, conducting a thorough analysis of your historical sales and performance data, you can gain a better understanding of the drivers of performance and optimize results. Additionally, it's important to take into account the long-term impact of your marketing efforts, including brand awareness, when identifying the most important KPIs for your business.

2.3: Calculating how much resource you should allocate to this project

MMM projects can vary in size and complexity, and allocating the appropriate amount of resources is crucial for the success of your project. There are several factors to consider when calculating how much resource to allocate to your MMM project.



https://www.gartner.com/en/marketing/research/annual-cmo-spend-survey-research

The first is the size and complexity of your marketing mix. A larger and more complex marketing mix will require more time and resources to model effectively, as MMMs suffer from multicollinearity: too many variables that are correlated with each other. If you have a sizable marketing budget, then every percentage point of error in the model might cost you millions.

Gartner's "State of Marketing Budgets" report in 2022 revealed they found that only 25% of marketers budgets are allocated to media spend, with the rest divided up more or less evenly between labor, agencies, and technology. Marketers spend 9% of their operational budgets on marketing data and analytics, the category where Marketing Mix Modeling resides.

For example a brand spending $10 million per year on marketing, might set aside 25% as media budget, and 9% of the remaining on marketing analytics. Of that $675,000 analytics budget let's say they allocate 1/3rd to Marketing Mix Modeling: that leaves $225,000. This buys either 1 model build and 3 quarterly updates, or an $18k per month budget for an "always on" solution. Larger brands spend many millions of dollars on marketing measurement, as they span multiple products and business units, and they invest significant amounts of money in advertising across multiple channels, as well as needing to account for a wider range of factors. Smaller brands might be fine building a simple model in Excel to a reasonable degree of accuracy, and using that to make directionally sound decisions. We generally advise against using an MMM unless you are spending at least $1 million per year across more than 3 or more marketing channels.

The investment and ongoing maintenance may need to be significantly higher if you decide to build an automated solution in house. You must consider the research and development phase of building a custom model, which for Recast took 3 years with multiple PhD-level researchers before we were satisfied with reliability and accuracy. This can be shortcut by using an open-source library like Meta Robyn, Google LightweightMMM, or Uber Orbit, but then you need to evaluate whether their unique strengths and weaknesses suit your business requirements (we will cover this more in a later section). Finally, you must build and maintain a front-end user interface for non-technical users, as well as put monitoring systems in place to detect when the model might be deviating from reality and degrading in accuracy. This last part is generally the most time-consuming and least "fun" part of the exercise, so make sure your analytics team is committed to ongoing support and not just the initial model-building phase.

The second factor to consider is the amount and quality of data available. Having a sufficient amount of high-quality data is crucial for the success of your MMM project, as it will allow for more accurate predictions and better optimization of marketing spend. In general you'll need at the very least historical marketing spend data for all marketing channels going back two years. That way the model can estimate what portion is attributed to seasonality, and how the channel performance has been trending over time. If you have limited data, you may need to allocate more resources to collecting and cleaning the data. The data engineering required to collect and clean your data into the right format for modeling automatically could be a significant undertaking, depending on how functional your data warehouse setup is. Depending on the quality of your data warehouse, this process could take anywhere from hours to months.

The third factor to consider is the level of expertise required for your MMM project. If you have in-house expertise in statistics and econometrics, you may be able to allocate fewer external resources to the project. However, if you lack expertise in these areas, you may need to allocate more resources to hiring outside consultants or training in-house staff. MMM is not like traditional "data science", because it can't be treated like a "black box" for making predictions: the model must make inferences and also be able to explain how, in order to determine what channels contributed to performance. This is key, and it's rarely possible with machine learning algorithms: you need either frequentist or bayesian statistics.

It's also important to consider the cost of deciding to build a model and the potential outcome, but also the counterfactual of what happens if you don't build a model. By calculating the potential ROI of your MMM project, you can make an informed decision about how much resource to allocate to the project. Also be mindful of the opportunity cost of dedicating resources to MMM. For example, if you allocate a significant amount of resources to your MMM project, you may have to scale back advertising spend, or cut other projects in order to do so.

It's important to weigh the potential benefits of your MMM project against the opportunity cost of dedicating resources to the project. For example, if you spend $10 million per year on advertising with a 4:1 Return on Investment (ROI), every percentage point of error in budget allocation may cost you $400,000 (that's the counterfactual). Assigning $225,000 from your advertising budget to building a model costs you $900,000 in potential revenue (this is the opportunity cost). Accordingly, your MMM must improve the accuracy of your budget allocation by 2.8 percentage points, in order to justify the cost of the project.

- Total cost of MMM: **$1.25m**
  - ✓ Cost of the model: $225k
  - ✓ Cost of potential revenue: $900k
- Cost of 1pp in error: **$400k**
- Accuracy uplift required: $1.25m / $400k = **2.8pp**

The required 2.8 percentage points is a relatively low bar to clear but if you run this calculation and find you need to realize a 15% improvement to make up the cost of the MMM, that's going to be much more challenging. It's essential to determine how much time and resources to allocate to your modeling efforts before you commit to them. Consider factors such as the size and complexity of your marketing mix, the amount and quality of data available, and the level of expertise required. Additionally, it's important to calculate the cost of building a model, the potential outcome and counterfactual of not building a model, and make sure you have sufficient resources to ensure the success of your project while also being mindful of the opportunity cost.

3. THE MARKETING MIX MODELING **LANDSCAPE IN 2023**

3.1: Modern MMM vs Traditional Econometrics

The MMM landscape has been changing recently and the approaches and firms that were once dominant are being displaced. MMM as a discipline has been around since the ‘Golden Age’ of advertising in the 1960s, and it was in need of a refresh. As modern brands started to explore and adopt MMM, they brought cutting edge data practices and modeling techniques with them, solving some of the main problems plaguing traditional MMM.

We’ll refer to the first era of MMM as “econometrics” to differentiate it, because that’s where the field inherited from. Econometrics is a set of statistical techniques, usually based on linear regression, which were applied in the government, finance, and medicine, as well as marketing. The application of Econometrics to marketing began to be known as marketing mix modeling based on the “4 Ps of the marketing mix”: Price, Promotion, Product, Placement, as those were the variables being modeled.

Zoom forward to today, and the fundamental concept remains the same. What has changed is the infrastructure supporting it. Traditional Econometrics was an expensive practice which required highly trained econometricians and statisticians to build custom models “by hand” fine tuning all of the inputs and assumptions. This was so expensive that even large companies typically only built a model once per year, to align with their annual budgeting cycles. This pace is too slow for modern brands, because they need to be able to adapt to rapidly shifting marketing platforms. They needed to optimize competitive digital channels and also be able to experiment with offline advertising in a more data-driven way. Automating MMM became the main focus of these modern entrants to the field.

The majority of the work is in data collection and cleaning, from 50 percent to 80 percent of the time according to Steve Lohr in the New York Times. However, modern brands have invested in unifying their data across sources, using data pipelines and connectors to the various platforms they use to run marketing campaigns or sell products. Today it's standard to fully automate this part of the process, so that data is always ready in the right format for modeling. This gave brands the promise of being able to update their model closer to real time rather than once per year. Automating the process also significantly brought down the cost of making a model, as did the release of open-source modeling software by Meta with Robyn, and the contributions from Google's papers on Bayesian MMM.

Automating the data collection step was a huge win, but it came with a problem: most of the modeling was still done manually and as such was prone to human bias. Brands wanted to update their models in real time, and they had the data infrastructure to do so, but that wouldn't be possible if a human analyst was still a necessary part of the model building process. Thankfully automation helped solve that problem too, as MMM moved towards more advanced algorithms, like Ridge Regression (used in Meta Robyn) or Markov Chain Monte Carlo (used by Recast) that could automatically handle many of the issues that normally needed an analyst. MMM isn't all the way modernized yet: there's still work to be done, and the traditional Econometrics vendors are still struggling to catch up to state-of-the-art.

3.2: The marketing mix modeling feature checklist

There are many important things to consider when evaluating an MMM vendor or building your own MMM to make sure that your model is following modern best practices. If you don't account for these features in your procurement or planning process, you risk ending up with a misleading and worse-than-useless model. Marketing is complex. In order to have a good model, you need to make sure that you're explicitly capturing the most important features of how marketing operates on eventual customers. Knowing what these options are before you start building your model, can make you a more informed customer of MMM services or software.

Here's a downloadable checklist template you can use to ensure you're following MMM best practices. For completeness we'll also compare each section against the leading open-source modeling libraries so you can see the benefits and limitations of each one. You can also use this as part of your procurement process if you're working with a vendor for MMM (though of course at Recast we'd pass with flying colors!).

RECAST

MMM Checklist

	Recast	Traditional MMM	Facebook Robyn	Google Lightweight MMM	Orbit
Model Features					
A. Changing ROI Over Time ROI per channel isn't estimated statically for the full time period, but updates daily or weekly as channel performance improves (or declines).	☑	☐	☐	☐	☑
B. Marketing Spend Time-Shift Not all of the impact of a marketing campaign will be felt the same day it happens, but must be modeled over time using adstocks, or lags.	☑	☑	☑	☑	☐
C. Declining Marginal Efficiency of Spend Marketing channels saturate at higher spend levels, meaning you get worse average performance (CPA, ROI) as you increase spend.	☑	☑	☑	☑	☐
D. Pull-Forward and Pull-Backward effects Customers will often wait for an anticipated sale or pull forward purchases to the sale period they otherwise would have made later.	☑	☐	☐	☐	☐
E. Model Seasonality (don't control for it) Periods of high demand change the way your marketing performs, so that effect needs to be modeled not isolated with a dummy variable.	☑	☐	☐	☐	☑

https://docs.google.com/spreadsheets/d/1A5XqvMegNanQTVsr7mhHP_BcjwoDSh1D9ZgDxKUvb4A/edit#gid=0

MODEL FEATURES

A. Changing ROI Over Time

This is something every marketer knows, but many modelers fail to appreciate: marketing performance in a given marketing channel changes over time. It's not uncommon for us to see ROI double (or halve!) in a marketing channel over the course of a week or two. There are lots of reasons why channel performance can change dramatically, from algorithm changes, to creative testing, or seasonal demand. Failure to allow for marketing performance to change over time can give you faulty results and cause you to make poor decisions when a channel goes from an under- to over-performer (or vice versa).

B. Marketing Spend Time-Shift

If you spend a thousand dollars on a podcast ad today, it's unlikely all of the conversions caused by that ad will occur today. You probably won't even receive them all by the end of next week. Since it takes time for listeners to download a podcast, listen to it, and eventually decide to make a purchase it could take many weeks for your marketing spend to have its full effect. The amount of time that it takes for your marketing spend to have its full impact will vary (a lot!) by channel, and this can cause tricky modeling problems if your model doesn't handle this correctly.

C. Declining Marginal Efficiency of Spend

Just because you spent $1,000 on Facebook this month and got a great return doesn't mean you can spend 10x that next month and get the same return. In fact, you'll probably get a much worse return as you scale up your spend. Why? Because there's declining marginal returns to advertising spend. This happens because Facebook will allocate your first $1,000 to the users that are most likely to convert and buy your product. As you spend more money, Facebook will have to keep expanding its circle of people to advertise to in order to spend those dollars, and by your millionth dollar, you'll be advertising to people who are much less likely to convert than with your first thousand dollars.

D. Pull-Forward and Pull-Backward effects

Holidays and promotional events are very important for many companies. Handling these events is crucial to correctly estimating the true effectiveness of your marketing dollars. Imagine this (very common) situation: a big promotional event is coming up, so the marketing team starts increasing spend into top-of-funnel channels in order to put customers into the marketing funnel who can then be converted by the sale. Many customers and potential customers, in anticipation of the sale (if, for example, you do the sale every year) will delay purchases that they were going to make to wait for the sale. And likewise, other customers might "pull forward" a purchase they were going to make in the future in order to take advantage of the sale. Treating these events as if they're totally independent of marketing activity (via the use of a "dummy variable") is a very common modeling mistake!

E. Model Seasonality (don't control for it)

The relationship between marketing and seasonality is devilishly tricky to handle correctly. The issue is that marketers (wisely) spend more marketing dollars when customers are most likely to purchase their products: advertise hot wings before the super bowl, sunscreen in the summer and sweaters in the winter. However, if you simply "control for" seasonality in an additive model, your MMM is going to tell you that your marketing spend is least effective during those times. That's because the model will "pull out" the effect of the season as if it were independent of the marketing spend, but really those two things are working together! Accounting for this "endogeneity" can be very tricky to get right in a statistcal model.

F. Handle Upper and Lower Funnel Channels Correctly

Some marketing channels, like branded search, are actually caused by other marketing channels. We expect that when brands spend more money on TV advertising they will drive more searches for their brand name and will end up paying the "Google tax" for all of those additional clicks. This relationship can wreak havoc on less sophisticated models since branded search spend will be highly correlated with other top-of-funnel marketing spend and the model will be inclined to over-credit branded search effectiveness. It's critical to model these relationships explicitly in order to make accurate forecasts and correctly identify which channels are driving incremental impact.

G. Incorporate Results of Lift Tests

It's critical to be able to anchor your model to reality and other gold-standard sources of information about channel performance. If you run a lift-test for your TV program in January, you want to make sure that you can include the results of that test in your model so that 1) the TV estimates are as precise as possible and 2) all of the other channels effectiveness can be estimated conditional on the results of the lift test.

H. Update Frequently

In order to make the results of the MMM actionable you can't just update the model once every 3 months. Performance marketers are making budget allocation decisions on a day-by-day and week-by-week basis, so you need to make sure that they have the most up-to-date estimates of channel performance possible. If you're relying on MMM results 6 months out of date, then you could be wasting hundreds of thousands or millions of dollars on channels that are no longer as effective as they once were, or failing to give credit to your team for all their optimization work.

MODEL OUTPUTS

I. Clear marginal ROI / CPA estimates per channel

Marketers care about marginal ROI and CPA because that tells them where they can invest their "next dollar" most effectively. The primary output of your MMM should be a clear communication of the current incremental ROI and CPA of the marketing channels your business is active in so that marketers can make effective budget allocation decisions. Sometimes modelers get so caught up in all of the bells and whistles of their model that they forget that at the end of the day the job of the model is to produce insights that are actionable for marketers.

J. Confidence intervals indicating model certainty

Correctly communicating uncertainty is critical to a good MMM. For every estimate that the model produces, the point estimate should be accompanied by a confidence interval expressing the amount of uncertainty in the estimate. In general (though not always!), channels with more spend will have more certainty associated with their ROI estimates, and channels with less spend will have less certainty. It's important to communicate this uncertainty to marketers so that they can make effective decisions about where to invest their dollars (and how big of a risk they might be taking). We think a Bayesian framework is really useful for MMM because it naturally generates these intervals for all of the parameters in the model.

K. Forecast future sales based on input budgets

While predictive accuracy isn't a sufficient condition for a good MMM, it is a necessary one. So, a good MMM should be able to predict how much revenue or customer acquisitions will be produced by a given marketing budget into the future. This is really useful for budgeting and planning processes (the finance team will love it!) and can help marketers adjust if they're not on pace to hit their targets. These forecasts of course should come with credible intervals expressing the uncertainty in the forecast based on the inputs!

L. Optimize media mix based on current performance

And finally, the model should be able to produce optimized budget subject to realistic complex constraints. Marketers often have constraints like "we want to spend as much as we can up to a blended CPA of $73 but we've already locked in TV spend for the quarter at $1.5M". A good MMM should be able to produce a realistic optimal budget based on those constraints that marketers can use for planning.

MODEL EVALUATION METRICS

M. Plausibility of coefficients

The first check you should make when evaluating an MMM is that the parameter estimates for the marketing channels are plausible. One issue we hear over and over again from CMOs is that they started working with an MMM vendor and the results that they're getting just don't make sense. While you don't just want to replicate your existing measurement strategies with your MMM (since then you wouldn't be getting an alternative perspective), you do want to make sure that the results you're getting are at least plausible and if the model is producing results that go against all of your other sources of information, it's probably your model that's wrong!

N. Out-of-sample predictive fit

The next check you should make when evaluating an MMM is its out-of-sample predictive fit. That is, you want to check that the model does a good job of predicting sales or customer acquisition even on data that the model hasn't seen before. If you're evaluating an MMM vendor, you absolutely must ask for this. The idea is similar to a "back test" that a hedge-fund might run to evaluate how a new strategy might perform based on historical data.

Too often, less-sophisticated modelers will rely on in-sample fit statistics when checking their model. This is problematic because MMMs are subject to "over-fitting" where the model is too fine-tuned to the data that it's seeing that it actually can't predict on new data at all. This is very bad! In-sample R2 in the case of MMMs is a meaningless metric. Any modeler that tries to convince you that their model is good because it has a high R2 does not know what they're doing and should be avoided!

3.3: Selecting the package that is most appropriate for your data and goals

3.3.1: Meta Robyn

Robyn is an open-source library for marketing mix modeling that was released by the marketing science team as a potential solution to Apple's devastating iOS14 update. The release of this tool by a large tech platform was a vote of confidence for MMM as a methodology, which until then had primarily been used by large Fortune 500 brands and was rarer amongst start-ups.

One of the positives of using Robyn is that it is open-source, which means anyone can look at the code and see exactly how it works. This level of transparency can help build trust with users and analysts. Additionally, Robyn uses the evolutionary optimization algorithm Nevergrad to automatically find the best combination of parameters for the model from 10,000 attempts, which can save time and resources.

However, there are also some negatives to using Robyn. One downside is that it requires knowledge of R, a programming language popular among statisticians, which may make it difficult for some users to implement. Additionally, the Decomp.RSSD metric, which is used to optimize the model, was invented by Facebook and is controversial. It effectively optimizes to not telling marketers that they were wrong, which could lead to questionable results. Finally, Robyn doesn't output 1 model, it outputs many "equivalent" models, some of which can be extremely different in recommendations! The final model is chosen by an analyst based on the most 'plausible one', based on what they know about the business, which is a source of bias.

3.3.2: Google LightweightMMM

LightweightMMM is another MMM library like Robyn, but is implemented in Python and has a few key philosophical differences. The tool uses Bayesian algorithms and is based on Numpyro with JAX for differentiation, as well as supporting Geo-level models out of the box. This allows for estimation of saturation curves and adstock rates as part of the model, rather than doing this step in a separate process as it is with Robyn via the evolutionary Nevergrad package.

The time it takes to run LightweightMMM can be significantly faster than Robyn, with a model with 5 media variables and 150 weeks of data taking around 12 minutes to estimate, compared to 2-3 hours for a similar model in Robyn in our testing. LightweightMMM optimizes the model based on accuracy alone as measured by MAPE, while Robyn also optimizes Decomp.RSSD, a metric that helps make the model more plausible.

In terms of building a model with LightweightMMM, the process is similar to building a model with Robyn, with both tools accepting data in the same way and taking approximately 8 to 14 weeks to complete. However, Google's project is less developed and supported than Facebook's, so there are less documentation and best practices available.

It is possible to get LightweightMMM running on a daily basis by self-hosting the code on a server like AWS or Google Cloud. However, the main cost would be the data engineering required to set it up, as the documentation and support is not as extensive as Robyn's. Additionally, using Python as the main language for LightweightMMM makes it more accessible to a wider range of users than R, which is traditionally used by econometricians and statisticians.

3.3.3: Uber Orbit

Orbit is another open-source library that can be used for MMM, but is actually more built for general time series forecasting. It has one superpower however: it allows for the performance of marketing to change over time.

It uses Bayesian Time-Varying Coefficients (BTVC) which is a advanced technique that allows for a range of answers for the return on investment (ROI) of each channel, rather than a single answer, which can be more accurate for dynamic bid-based channels like paid search or paid social. This is a significant advantage over traditional marketing mix models which assume that marketing performance remains unchanged across the modeling time period.

Orbit is built on the Python programming language and uses the Stan library for probabilistic modeling. The tool uses Priors to offer a flexible mechanism for incorporating existing knowledge to direct the model to more plausible results. However, not being a true MMM library, It lacks basic features like Saturation and Adstocks and it's more akin to Meta's Prophet time series forecasting library, than a direct comparison to Meta's Robyn.

However, the inclusion of Bayesian Time-Varying Coefficients (BTVC) is the first and biggest open use of this advanced technique, which is at the core of Recast's model also. The transparency of this tool helps a lot when you're dealing with a highly technical topic like marketing attribution, and we can all learn from Uber's contribution.

3.3.4: Building a custom model

Building a custom marketing mix model can be a powerful tool for understanding the impact of marketing efforts on business outcomes. However, there are several considerations to keep in mind when building such a model.

The choice of model will depend on the specific goals and objectives of the modeling project. For example, the linear regression model available in the SKLearn or Statsmodels libraries are simple and easy to interpret, but may not be appropriate for modeling complex relationships. Those from a data science background may be tempted to use more complex machine learning techniques like Random Forest or Neural Networks which are normally suitable for handling non-linear relationships. However in our experience the loss of interpretability you get from these methods defeats the entire purpose of MMM: to learn what marketing channels are driving sales.

Bayesian models built in PyMC or Stan allow you to incorporate prior knowledge and domain expertise into the models, so as to protect against implausible results. This is particularly important if you're planning to automatically update your model, as it can provide guardrails against deviating too far from reality. In addition, when automating your model it can run in the background, taking care of any concerns around the time it takes to run a model. Simple linear regression-based techniques tend to be quicker to run, so are well suited for analysts building a simple static model on their local computer (although at the cost of flexibility and accuracy).

Once the model has been selected, feature selection becomes an important step in building a custom marketing mix model. This is the process of transforming raw data into features that can be used in the model, and deciding what goes in. This can greatly impact the performance of the model, and it's important to be strategic in selecting which features to include and how to transform them. For models such as Recast, very little custom feature selection is done: only when deemed necessary for an individual client's situation. As mentioned earlier, there is a danger of including too many variables and ending up with a less generalizable model. As renowned physicist John Von Neumann was known to say "with four parameters I can fit an elephant, and with five I can make him wiggle his trunk".

Hyperparameter tuning, the process of finding the best set of hyperparameters for a model, is another important step in building a custom marketing mix model. These are variables that relate to how the model is built, rather than specifically related to the data ingested by the model. Different settings in the hyper parameters can lead to radically different results, so it's important to try many combinations to determine what works in terms of improving model accuracy and plausibility. If done manually in a grid search this can be time-consuming, but it is important to achieve optimal model performance, and there are more automated techniques like evolutionary algorithms that can help.

Cross-validation is a technique for assessing the performance of a model by dividing the data into training and testing sets. This allows for an unbiased estimate of the model's performance and helps to prevent overfitting.This measures the model's ability to predict future data that it hasn't seen yet, by holding back some of the data from the model when building it. We then have multiple error metrics, such as Root Mean Squared Error, or Mean Absolute Percentage Error, which can help us compare the performance of different versions of our model. It's important to note that the methodology that works in MMM is making the holdout group "future" data, i.e. leaving 30 days off the end. That isn't the way most cross-validation methods work in common statistical and machine learning packages. Traditional econometricians often make the far more grave mistake of having no holdout group at all, and testing accuracy on data the model has already seen: watch out for that one!

Understanding how the model is making predictions and how different features are contributing to the model is also important. This can be done by analyzing the model's coefficients, and interpreting the plausibility of the model in terms of how well it agrees with your current understanding of what's driving performance. For example if the model suggests that 90% of sales come from one small channel, it's likely something went wrong. For more subtle plausi-

bility issues you can increase confidence by calibrating the model based on the results of other marketing attribution methods, for example lift tests or checkout survey results. Often good use of data visualization techniques can help give intuition to the users of your model around what it's recommending.

One other consideration is the programming language you'll use, typically a choice between Python and R. Analysts from a statistics background typically prefer R for manipulating and drawing inferences from data. Whereas Python is typically favored by those with a data science or engineering background, given its greater flexibility in terms of building wider products compared to R. At the time of writing, Python was used by 40% of software developers compared to 5% who used R, according to Stack Overflow.

Building a custom marketing mix model can be a complex process, but with careful consideration of these key points, it can be a powerful tool for understanding the impact of marketing efforts on business outcomes.

3.4: Project timeline and key milestones

An MMM project requires careful planning and execution in order to be successful. In our experience, an MMM project with an external vendor typically takes 8-14 weeks from start to finish. This assumes a motivated internal team, using an open-source MMM library (rather than building their own), and working with a modern brand. Legacy enterprise companies working with traditional econometrics consultancies should expect a longer timeline of 12-24 weeks (or beyond). Below is a timeline of the key milestones and tasks necessary to complete an MMM project if you outsource to a vendor or build in-house.

STEP 1:
Establish project goals and determine scope [1-2 weeks]

The first step of an MMM project is to define the objectives and key business questions that the study should answer. This involves understanding the goals of the project and outlining the scope of the study, which will help determine how the MMM will be designed. This step typically takes 1-2 weeks.

STEP 2:
Gather and clean data [2-4 weeks]

Data collection is an essential part of the MMM process. Time-series data for sales, media, non-media marketing, and macroeconomic factors must be acquired and appropriately prepared for the MMM. Inaccurate or poor quality data can lead to inaccurate or poor quality results, so it is important to ensure data accuracy. This process usually takes 2-4 weeks.

STEP 3:
Modeling and validation [4-6 weeks]

Once the data is collected and cleaned, the modeling process can begin. This can be an iterative process, in which the models are constantly re-run and refined. It is important to go back and find data for any important variables that were omitted. Depending on the scope and complexity, this step typically takes 4-6 weeks.

STEP 4:
Analysis and recommendations [1-2 weeks]

The next step is to analyze the data and generate actionable recommendations based on the original business questions. There are many different outputs and metrics that can be used to analyze the results. Generally, it takes 1-2 weeks to analyze the data and make recommendations.

At Recast we have automated a lot of the above process over the past 4 years, including building our own proprietary Bayesian model. We have data connectors built for the major ad platforms, and can ingest data from your data warehouse. We have automated pipelines in place for cleaning and modeling the data, and have built all the necessary charts and tools for displaying the model results, and taking action from its recommendations. We also have robust monitoring in place to ensure the model remains accurate and plausible as it continues to update automatically, so you can rely on it for decision-making. This grants us an accelerated timeline for onboarding, and we aim to get our clients up and running within 4 weeks.

WORKING
WITH RECAST
[4 weeks]

3.5: Red flags to watch out for when evaluating if your model can be relied upon for decision making

When validating if your MMM is accurate enough to rely on for decision making, there are a range of techniques that can be used, including parameter recovery, cross-validation, and holdout sampling. Each of these techniques can help to ensure that your model is accurate and reliable, but it's important to be aware of certain red flags that may indicate that your model is not accurate enough to rely on for decision making.

One way to spot red flags is to use parameter recovery to test the validity of your modeling algorithm. This refers to the ability of your model to accurately recover the parameters that were used to generate the data. You should simulate several plausible marketing scenarios to generate realistic datasets, then run your model against them. If your model is not able to accurately recover the parameters you used to generate the data, it may indicate that the model is not accurate enough to rely on for decision making.

Another red flag to watch out for is a high error rate in out of sample testing, i.e. on predicting sales for time periods the model hasn't seen yet. This involves dividing your data into two or more sets, and then using one set to train the model and the other set to test the model (typically the last 30 days or final 15% of the data). If the model performs poorly on the test set, it may indicate that the model is not accurate enough to rely on for decision making and won't work well in making allocation decisions for future marketing budgets.

It's also important to check your model against the recommendations from other attribution methods, as well as calibrating it against the results of incrementality tests. This will help to ensure that your model is providing accurate and reliable results, and that it is aligned with the recommendations from other channels. Of course this must be done judiciously, as the job of MMM is to tell you independently where your other methods might be wrong. When your MMM is the only attribution method that disagrees, that can be a red flag.

If you have a model you suspect of being inaccurate or unreliable, there are steps you can take to improve it. These include reviewing the data used to build the model, checking for outliers or missing data, and using different modeling techniques to see if they provide more accurate results. Additionally, you can seek the help of a professional or consulting firm to help you identify and resolve any issues with your model, or explore different statistical techniques or libraries for building the model.

4. COLLABORATING WITH **YOUR TEAM OR CLIENT**

4.1: Involve all relevant stakeholders in the modeling process

MMM projects require input and collaboration from a wide range of stakeholders, including marketing, finance, and business leaders. Typically that would include marketing leadership, representatives from both brand and performance teams, as well as offline and digital. The finance team is crucial to involve, as they sign off on the budget allocations the model will ultimately recommend.

To ensure the success of the project, it is essential to involve all relevant stakeholders in the modeling process and to ensure that they have a clear understanding of the goals and objectives of the project. This can help to ensure that the model is aligned with business needs and that the insights and recommendations are actionable and supported by the wider organization.

One way to involve all relevant stakeholders in the modeling process is to establish a cross-functional team that includes representatives from different departments and functions within the organization. This team should be responsible for defining the goals and objectives of the project, identifying the data and resources that will be needed, and creating a plan for how the model will be developed and deployed.

Another important step is to establish clear communication channels between the cross-functional team and the wider organization. This can include regular meetings and updates, as well as a dedicated portal or platform where stakeholders can access project information and provide feedback. It's important to gather and address each team's concerns and requirements throughout the project, so it isn't unexpectedly rejected in the final stages.

It is also important to involve relevant stakeholders in the testing and validation of the model. This can help to ensure that the model is accurate and reliable and that the insights and recommendations generated by the model are actionable and relevant to the business. If the wider team has participated in interrogating the model, they're more likely to trust its recommendations, and will know where its blind spots are, and how to avoid them.

Ultimately, involving all relevant stakeholders in the modeling process and ensuring that they have a clear understanding of the goals and objectives of the project is critical for ensuring the success of MMM projects. By working together and aligning on the project's goal, the organization can ensure the model is actionable and supported by the wider organization.

4.2: Ensure that everyone is aligned and working towards common goals

Collaboration is essential for the success of an MMM project, but it's important to ensure that everyone is aligned and working towards common goals. This helps to ensure that the project is delivered on time and on budget and that the insights and recommendations generated by the model are relevant and valuable.

One way to ensure alignment is to establish clear roles and responsibilities for team members. This can include assigning a project manager to oversee the project, designating team leads for different functions or departments, and establishing a clear chain of communication between team members.

Regular communication and updates are also important for alignment. This can include regular team meetings, status updates, and project reviews. These can help to ensure that everyone is on the same page and that any issues or concerns are addressed in a timely manner.

When working with external stakeholders, alignment is particularly important. It's essential to establish clear goals and objectives for the project, to understand how your vendor's business needs and priorities relate to your own, in order to ensure that the project is delivered on time and on budget. This can be achieved by setting up regular communication channels with the vendor, such as weekly check-ins, and by involving the vendor in key project milestones such as presentations to leadership.

It's also important to be aware of situations where the results of the model may be politically sensitive or have important implications for key stakeholders. In such cases, it's essential to involve these stakeholders in the modeling process, to ensure that they are aware of the potential implications of the model, and to work with them to ensure that the model is aligned with their needs and priorities.

Ensuring alignment and working towards common goals is a continuous effort throughout the project, it's important to have regular check-ins and communication to ensure that everyone is on the same page and working towards the project's goal, which ultimately leads to a successful MMM project.

4.3: Presenting your model to the wider business and stakeholders

Once your MMM model is complete, it's important to communicate the insights and recommendations to the wider business and stakeholders. This is critical for ensuring that the model is used to inform decision-making and drive business value.

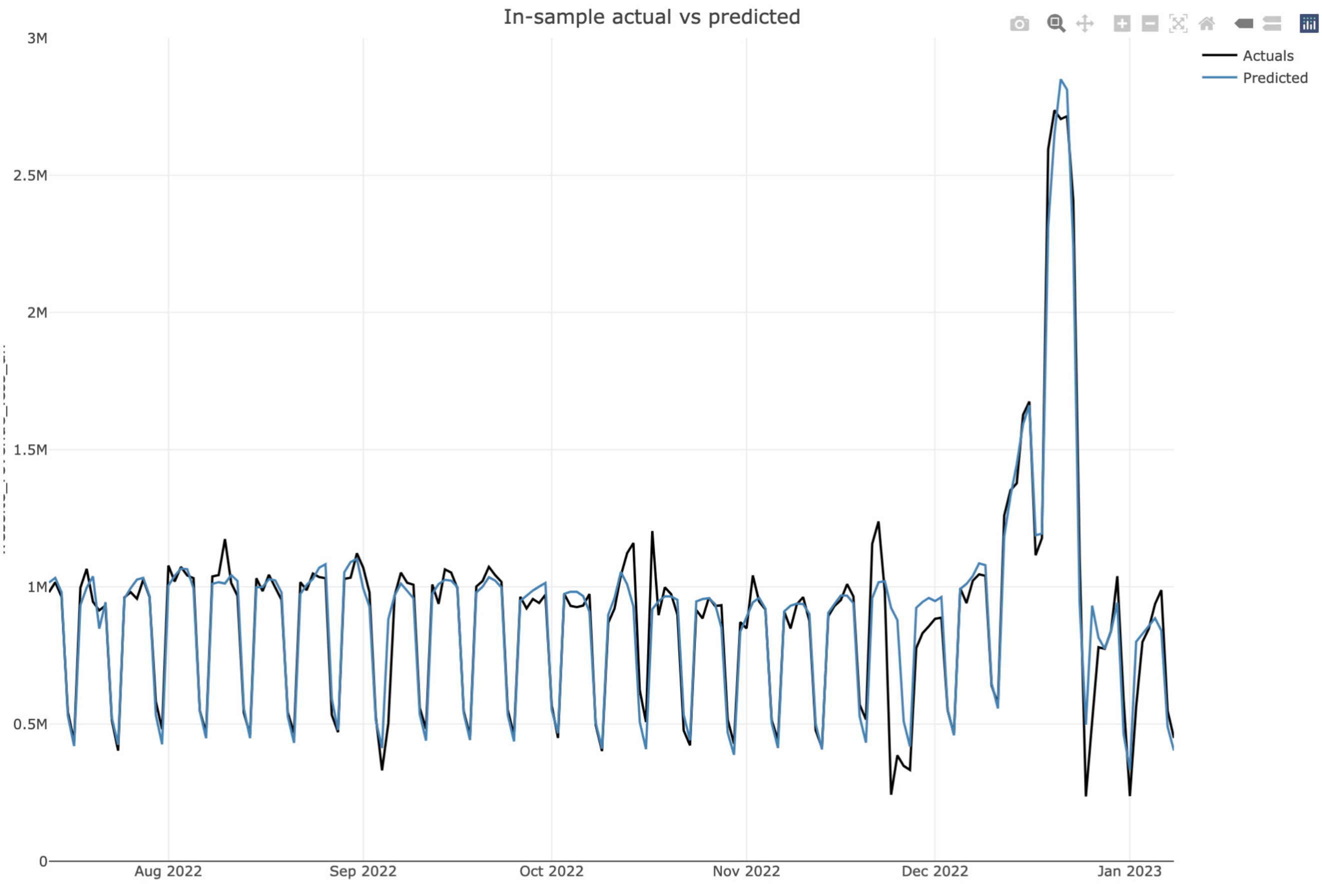
Presenting the results of the model to key decision-makers and other stakeholders in a clear and engaging way is essential. It's important to consider the audience and tailor the presentation to their needs and interests. This may involve highlighting the key findings of the model and how they align with the business's goals and objectives, as well as providing actionable recommendations for how the insights can be used to drive growth and improve performance.

Data visualization is an important aspect of presenting the model's results. It's important to choose the appropriate charts and graphs that help communicate the key insights of the model in a clear and concise way. For example, if you want to show the contribution of each marketing channel to overall sales, a bar chart or waterfall chart might be appropriate. If you want to show how performance has changed over time, a line chart might be more appropriate. Let's dive into a few examples of key charts, with examples.

It's also important to be prepared to answer questions and address any concerns that may arise during the presentation. This can include providing additional detail on the methodology used to build the model, addressing any limitations of the model, and discussing how the insights and recommendations can be implemented in practice.

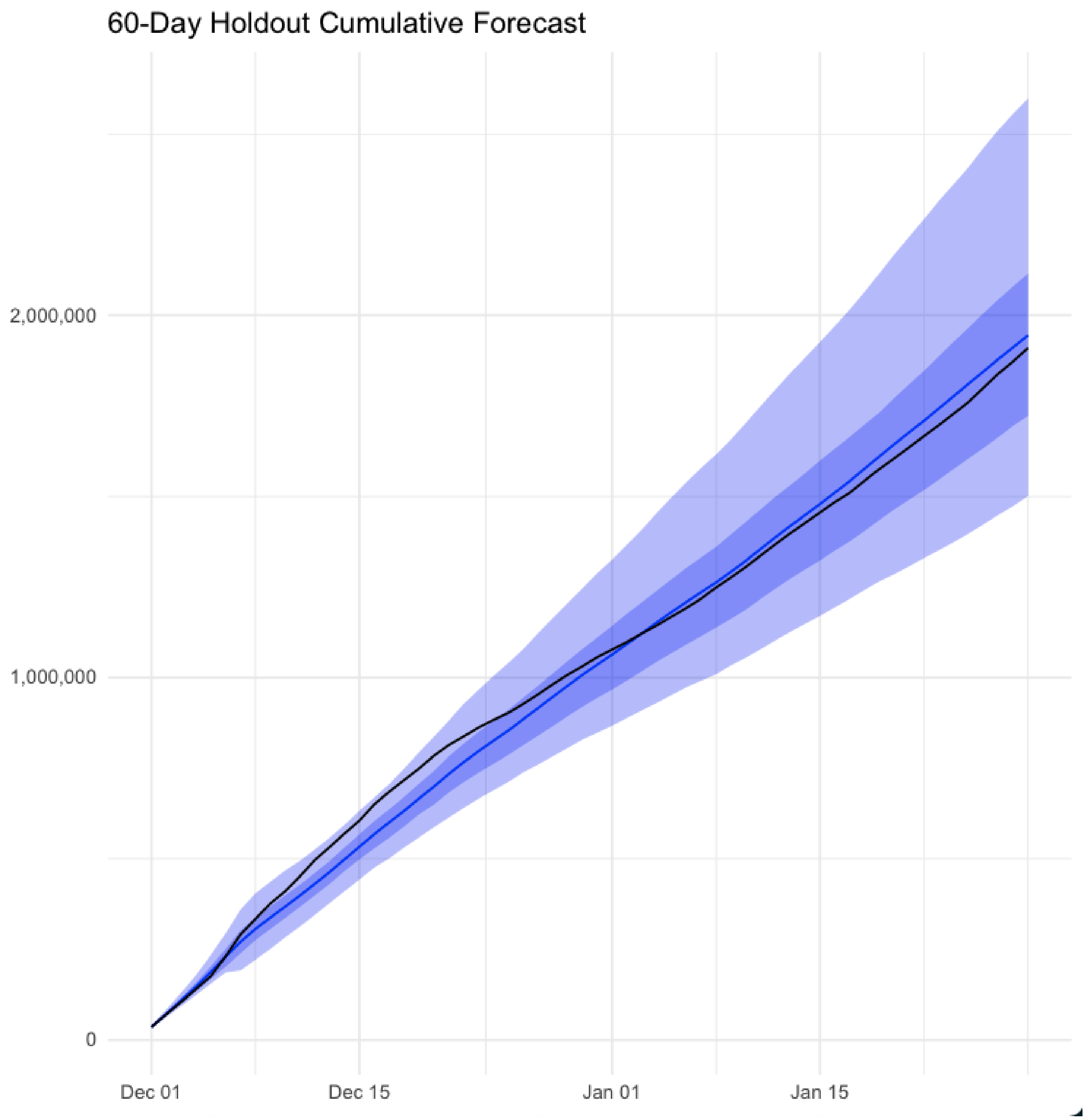
When presenting the MMM model, it's important to remember that the goal is not only to communicate the results but also to get buy-in from the stakeholders. To achieve this, it's critical to present the results in a way that is easy to understand, relevant, and actionable for the audience. By doing so, the model's results can be used to inform decision-making and drive business value.

4.3.1: In-Sample Actual vs Predicted



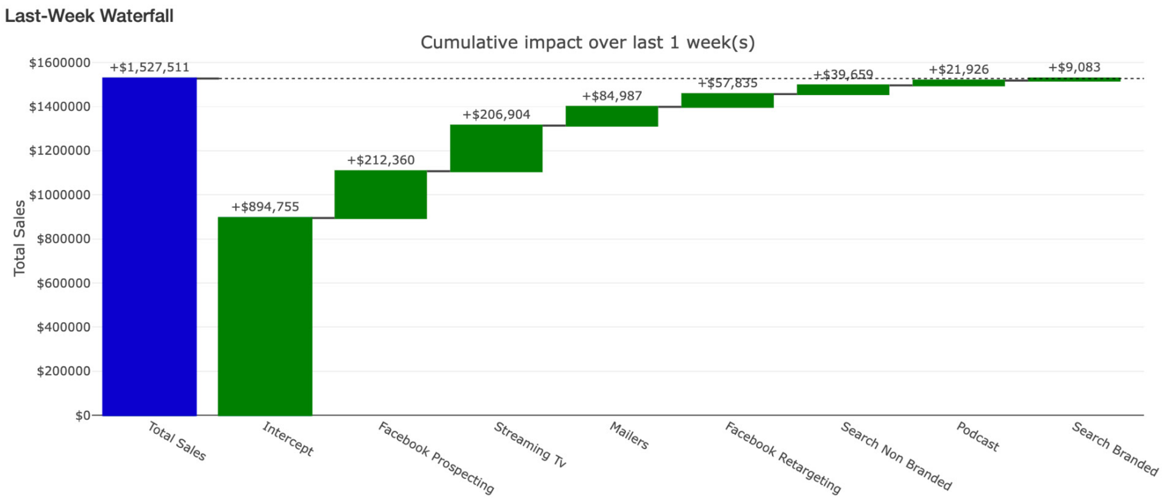
This type of chart is usually the first thing any modeler looks at, because it tells you how the model is doing in terms of accuracy. Visually it's easy to see, and rather pleasing, that the actual numbers line up well with the model. However to really make this chart sing, incorporate out of sample data too: how well does the model perform once it's past its training data, and has had to predict the holdout data? When automating MMM it's important to show the user what was predicted and what the actual data ended up being on a rolling basis, as that will either point you to model drift – when accuracy is degrading for some reason – or prove to them that everything is a'ok.

4.3.2: Out-of-Sample Actual vs Predicted



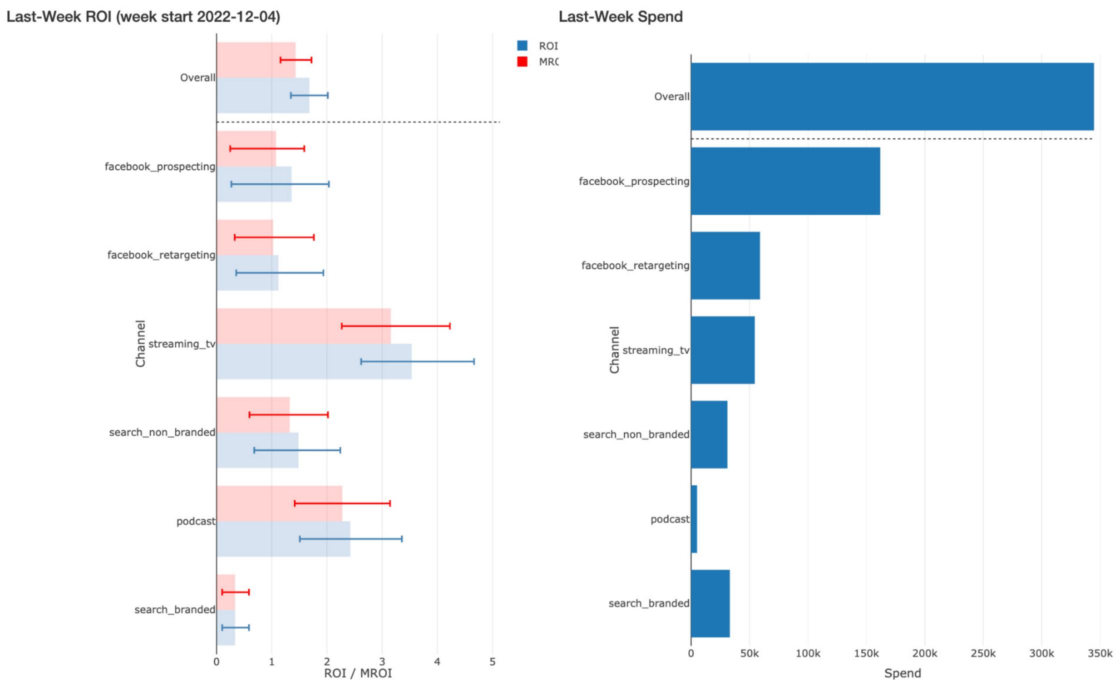
This chart shows how well the model predicts on data it has never seen before. The blue cones are the uncertainty in the model's predictions on data it hasn't seen before: what we're looking for here is that the model is "well calibrated" in that the actuals fall within the predicted along the lines of what's predicted: so the actuals fall within the 50% confidence interval 50% of the time.

4.3.3: Waterfall Decomposition



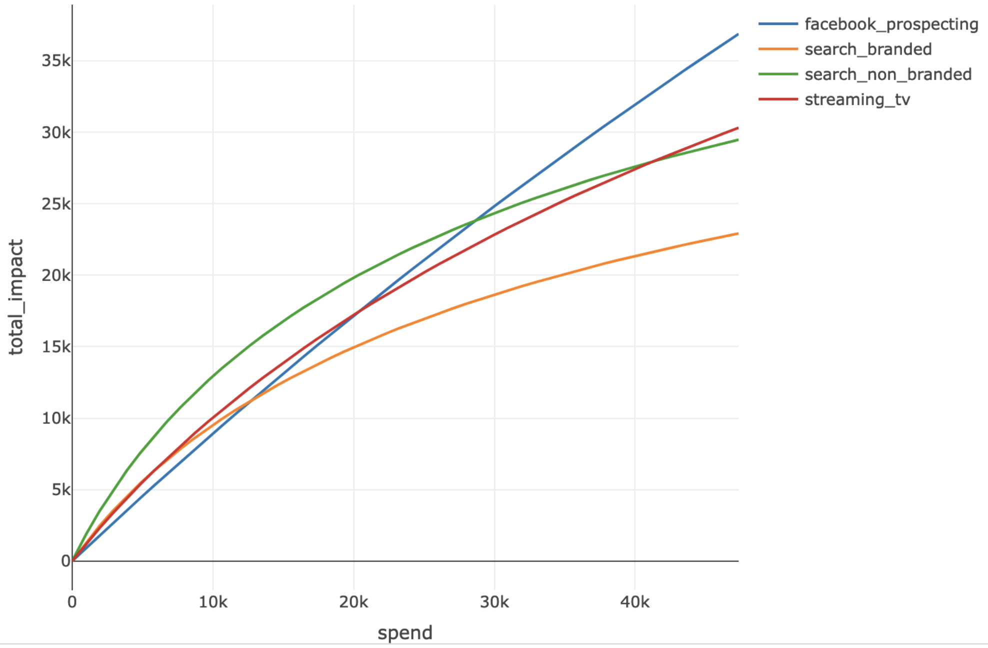
Once you trust the model, it's important to dig into what it's saying about your marketing mix. The waterfall chart shows how much each channel contributed to sales. Variables can be negative or positive, so for example if you model seasonality, inventory issues, or pandemic lockdowns, these would show as having a negative contribution. The thing to look for here is plausibility: does it look like a variable you would expect to be unimportant is getting a disproportionate share of sales? Or is a channel you think is important not getting enough credit? The model might still be correct (in which case that's a great insight) but it's worthy of investigation if something looks off.

4.3.4: Spend Levels and Effectiveness



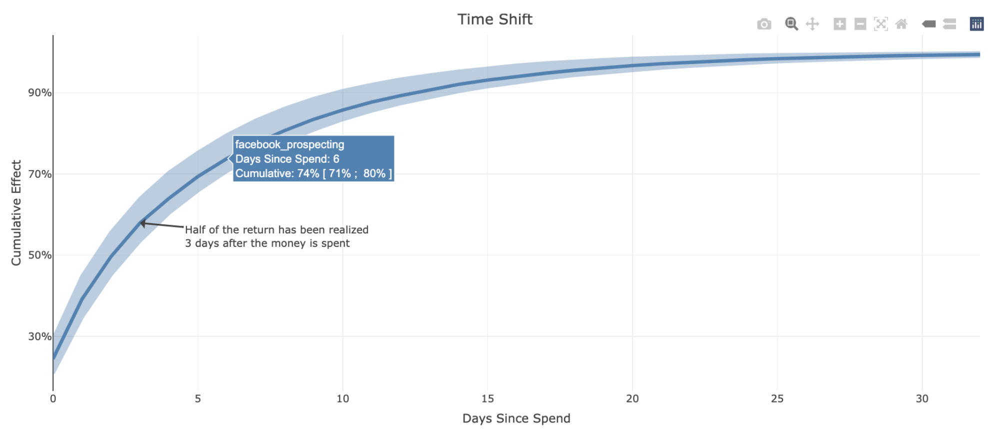
This chart shows you how each of your channels are performing and how much spend is being allocated to the channel. This is the primary view that will tell you if you need to adjust your marketing budget if you're allocating too much budget to under-performing channels.

4.3.5: Response Curves



If you've gotten this far, it's because the model is accurate and plausible. That means it's time to start taking action. The response curves are the number 1 most actionable chart to look at, because they tell you how different channels perform at different spend levels. You can optimize your budgets by choosing a point on the curve for each channel, accounting for diminishing returns. For example one channel might have a steep curve, meaning only a small amount of additional spend will yield great results, and another channel might have a flat curve, meaning there's not much room to increase volume without seriously hurting performance. Budget optimizers are simply finding the point on the curve where across all your channels you're at the point of highest efficiency, for the amount you want to spend.

4.3.6: Time-shift Curves



Now the important work of optimizing the budget is done, one final thing that's useful to look at is the time-shift curves. It's useful strategically to know how long the lagged effect of contribution to sales takes for each channel. The time-shift curves tell you how long it will take for you to realize the benefits from your marketing spend. It might take longer for TV to generate its return than for spend on search channels, for example.

4.4: Handling objections and dealing with skepticism regarding the credibility of your model's insights and recommendations

It's common for MMM projects to encounter objections or skepticism, particularly if the insights or recommendations are unexpected or challenging. It's important to be prepared to address these objections and to provide clear, evidence-based explanations for the results of your model.

There are two ways we like to validate our models here at Recast:

1. Through "back-testing" and looking at holdout predictive accuracy
2. Via an incrementality test

Back-tests have the benefits of being easy to run (if you're not using Robyn), simple to interpret, and can be run at any time. Incrementality tests are great ways to validate the model but they can be operationally complex and time-consuming to run.

Getting the same answer from multiple sources does the most in our experience to quell any uncertainty and dismiss any politically driven objections.

Another way to handle objections and skepticism is to be transparent and thorough in your methodology and to provide detailed information about the data and assumptions that were used to build the model. This can help to build trust and credibility in the model and its results. Get on the same page about how accurate the decision you're making needs to be, and realistic about if any alternative methods exist that can be relied on more than your existing model.

An approach we've also found effective is to invest in data visualization tools or other means to help explain your findings intuitively to a non-technical audience. Data visualization can be a powerful way to communicate the insights and recommendations of your model in a clear, concise, and easily understandable way. This can help to build support and buy-in for your recommendations, even if they are unexpected or challenging.

It's also important to be prepared to address any specific concerns or objections that may be raised during the presentation of your model's results. This can include discussing the limitations of your model, providing additional data or evidence to support your findings, and being open to feedback and suggestions for how to improve the model or its implementation.

In situations where skepticism persists, it can be helpful to gather feedback, incorporate them back into your model, and then test your updated model's results with a small group of stakeholders before presenting to the larger audience. This can help to identify any potential issues and address them before they become a roadblock to the acceptance of your model's results.

Ultimately, handling objections and dealing with skepticism requires a combination of transparency, preparedness, and effective communication. By being transparent about your methodology, data, and assumptions, providing clear evidence-based explanations, and using visualization tools, you can build support and buy-in for your model's insights and recommendations.

5. INTEGRATING MARKETING MIX MODELING **INTO YOUR DECISION-MAKING PROCESS**

5.1: Setting up the necessary infrastructure to update your model on a regular basis automatically

Traditional econometrics would only be done at most quarterly, and sometimes only annually, because of the great cost incurred, and expertise required to build a model. This is too slow for the pace of modern marketing, where you can't afford to wait until the end of the annual planning cycle to make budget optimization decisions.

In order to fully leverage the benefits of your MMM, it is essential to ensure that your model is kept up-to-date with the most recent data and business conditions. This means setting up the necessary infrastructure to automatically update your model on a regular basis. This requirement changes the way you build the model, as well as the ongoing resources needed to keep the model running accurately.

To begin, it is important to consider the frequency of your data updates. For example, if your business operates in a rapidly changing industry, you may want to consider updating your model on a weekly or even daily basis in some cases. On the other hand, if your business operates in a more stable industry, a monthly update may be sufficient. Each new model update is a point in time when the model might break, so more frequent updates tend to require an exponentially more robust model, with more mature monitoring in place to detect issues.

The complexity of your marketing mix is another important factor to consider. If your model is simple and straightforward, with only a handful of channels that rarely change, it may be relatively easy to set up automated processes for refreshing it. However, if your model is complex and involves multiple variables, with new channels coming and going as they are tested and either scaled or discarded, it may be more challenging to set up automated processes. In this case, it will certainly be necessary to work with a data scientist or software vendor to ensure that your model is properly maintained.

Another important factor to consider is the resources required to maintain your model. This includes both the technical resources needed to set up and maintain automated processes, as well as the personnel resources needed to monitor the model over time. For example, if you have a dedicated data team, they may be able to handle the majority of the maintenance work. However, if your business does not have a dedicated data team, it may be necessary to outsource this work to a third-party provider, or update less frequently.

5.2: Use your model to inform your marketing strategy and budget allocation

Using your MMM to inform your marketing strategy and budget allocation is a powerful way to achieve better results for your business, and translate your modeling effort into action. By understanding the drivers of your key performance indicators (KPIs) through simulating their impact on sales via your model, you can make more informed decisions about how to allocate your marketing resources.

When you're happy with the accuracy and plausibility of your model, you can use it for forecasting the impact of different marketing scenarios. For example, you can use your model to estimate the potential return on investment (ROI) of shifting the allocation of budget from one channel to another. This can be done by inputting different budget scenarios into your model and analyzing the projected impact on your KPIs. This allows you to make data-driven decisions about how to allocate your marketing resources in a way that will have the greatest impact on your business.

Another way to use your MMM model to inform your marketing strategy is by identifying opportunities for optimization. For example, by understanding the drivers of your KPIs, you can identify areas where you are over-investing or under-investing in your marketing efforts. This allows you to make adjustments to your marketing strategy in order to achieve better results. By identifying these areas, you can make changes to your marketing mix, such as increasing budget allocation on certain channels or campaigns, which lead to more efficient use of your resources and better results.

You can also use the model to understand the impact of different channels, campaigns and messages on the business. For instance, you can use the model to understand which channels are driving the most conversions, and how many sales you'd get if you stopped advertising entirely. This information can help you to decide which channels to invest in, which campaigns to run and how to communicate to your target audience.

In addition, it is important to keep in mind that MMM is an iterative process. As you make changes to your marketing strategy, it's essential to update your model regularly to reflect the most recent data and business conditions. This will help to ensure that your model is always providing accurate and up-to-date insights to inform your marketing strategy and budget allocation.

5.3: Put the marketing team in control by providing a simulator for forecasting and scenario planning

One underrated way to make MMMs more actionable is to build a simulator that empowers marketing teams to adjust inputs and get forecasts from the model.

Simulators enable non-technical business users to explore different marketing scenarios without needing the development or data team, and lets them build an intuition of the impact on KPIs. By providing marketing teams with a user-friendly interface for running simulations, you can put them in control of the forecasting process and help them to make more informed decisions about their marketing strategy and budget allocation.

When building a simulator for your business, it is important to consider factors such as user experience, data integration, and modeling flexibility. User experience is important because it will determine how easy it is for your marketing team to use the simulator. A user-friendly interface with intuitive navigation and clear instructions will make it easier for your team to run simulations and make decisions based on the results.

Data integration is another important factor to consider. Your simulator should be able to integrate seamlessly with your existing data sources, such as your marketing automation platform, CRM, and data warehouse. This will ensure that the simulator has access to the most up-to-date data and that the results are accurate. If your simulator does not have the latest version of the model's findings, it quickly gets abandoned.

Additionally, it is important to consider the type of simulations that the simulator can run. For example, if your business operates in a rapidly changing industry, you may want to build a simulator that runs real-time simulations based on market trends, which can help your marketing team to quickly adapt to changing market conditions. On the other hand, if your business operates in a more stable industry, a simulator that offers marketers more flexibility in inputs to build longer-term simulations may be more appropriate.

5.4: Building confidence in your model's recommendations by running incrementality tests

Building confidence in your model's recommendations is essential, especially when it comes to recommendations that may be considered politically sensitive or economically risky. One way to do this is by running incrementality tests.

Incrementality tests, such as lift testing or geo-market testing, can help to validate the results of your model and improve the confidence of your team in its recommendations. Lift testing, for example, involves comparing the performance of a test group that was exposed to a specific marketing campaign or tactic, to a control group that was not exposed. This allows you to measure the incremental impact of the campaign or tactic on your KPIs, and to determine whether or not the model's recommendations are accurate.

Another type of incrementality test is geo-market testing. This involves testing the model's recommendations in a specific geographic market or region, and comparing the results to other geographic markets or regions. This can help to validate the model's recommendations and to determine whether or not they are applicable to other markets or regions. It's also important to note that no attribution method is perfect and sufficient, thus it's important to actively look for ways in which your predominant attribution method is provably wrong, when compared to other attribution methods and basic logic (i.e. your model tells you most of your sales were driven by one small channel).

Remember that the goal of marketing mix modeling is to offer an alternative opinion to your other attribution methods. It's supposed to disagree in some ways, otherwise it wouldn't be worth building! What you need to watch out for is times when the model is suggesting something extremely surprising or unlikely compared to what your other methods reported: these areas are worth investigating because you'll either find a way to improve your model, or record your model's first big win if it proves to be correct!

6. SEEKING **OUTSIDE** **EXPERTISE**

6.1: Determining whether it makes sense to build vs buy

When it comes to implementing Marketing Mix Modeling (MMM) within your organization, one of the key decisions to make is whether to build or buy. MMM projects can vary in size and complexity, and it may not always make sense to build your own model in-house.

When determining whether to build or buy, it is important to consider factors such as the expertise and resources available within your organization, the complexity of your marketing mix, and the data and infrastructure required. For example, if your organization has a dedicated data team with experience in advanced analytics, it may make sense to build your own model in-house. On the other hand, if your organization lacks the necessary expertise and resources, it may make more sense to buy an off-the-shelf MMM package or to seek the guidance of a freelance professional or consulting firm.

This is the type of project where external expertise can be invaluable, because it differs in objective from common data science objectives. Typically in data science you have a variable you're trying to predict, and a lot of data you can use to make the prediction. The overriding is to improve the accuracy of a model, so that you can trust its recommendations. This is important in Marketing Mix Modeling also, but the key difference is that MMM is useless if it also doesn't reveal something about the underlying structure of what drove sales.It is better to have a model that makes less accurate predictions but is correct about which marketing channels drove more or less sales than to make accurate predictions but get the relative performance estimates wrong! This dual objective means the project has to be approached completely differently to how most data projects are handled.

Another important factor to consider is the complexity of your marketing mix. If your marketing mix is relatively simple and straightforward, it may be relatively easy to build your own model in-house. However, if your marketing mix is complex and involves multiple variables, it may be more challenging to build your own model and it may make more sense to buy an off-the-shelf package or seek outside expertise. This is particularly important if you have a significant marketing budget, because every percentage point of error might mean tens of thousands, or even millions of dollars in wasted advertising spend.

Additionally, the data and infrastructure required to build and maintain an MMM model should also be considered. Building a model in-house will require a significant investment in data infrastructure, including data warehousing and data cleaning. If your organization lacks the necessary data infrastructure, or it needs a cleanup, you may need to address that first before attempting a modeling project. Outside vendors can help in this case, as they may have built all of the necessary connectors and can host a marketing data warehouse for you, helping you skip this time-consuming and resource-intensive step.

6.2: Seeking the guidance of a freelance professional or consulting firm for further model accuracy and credibility

Seeking the guidance of a freelance professional or consulting firm for further model accuracy and credibility can be an effective way to enhance your Marketing Mix Modeling efforts, particularly if you don't have the necessary in-house resources or if you are looking to improve the accuracy and credibility of your model.

When seeking outside expertise, it's important to carefully evaluate the experience and credentials of the individual or firm. This includes looking at their track record of successfully implementing MMM projects, as well as their expertise in the specific areas of your project such as the industry or the data size. It is also important to ensure that they align with your goals and objectives, and that they understand the specific needs and requirements of your business.

Another important factor to consider when engaging a freelance professional or consulting firm is cost. It's important to have a clear understanding of the costs involved, including hourly rates or project fees, as well as any additional expenses such as travel or data costs. It's important to evaluate whether the costs align with your budget and whether the value provided by the freelancer or consulting firm justifies the investment.

In addition to cost, it's also important to consider project scope and timeline when engaging a freelance professional or consulting firm. It's important to have a clear understanding of the scope of the project and the specific deliverables that will be provided, as well as the timeline for completing the project. This will help to ensure that the project stays on track and that it is completed on time and within budget.

Finally you should consider the incentives of the firm building your model. Are you confident that they will provide an unbiased model, even if it tells you something that you aren't going to like? To help align incentives it is important that senior leadership and finance have a say in commissioning the model, rather than leaving it entirely to the marketing team to grade their own homework. Even as the leader of the marketing team, you will be in a far more secure position with executive buy-in, and find it easier to get budgets approved.

The worst case scenario you should avoid is having multiple marketing teams each build their own model: MMM is a holistic practice and needs to account for the entire marketing mix. In scenarios where there are multiple models we find that human bias creeps in: for example the model built by the vendor working for the brand team (of course) shows that brand advertising is driving lots of revenue, whereas the one built by the digital marketing team (unsurprisingly) shows that money should be reallocated from TV to digital.

6.3: Evaluating external technology vendors and onboarding effectively to ensure a smooth transition

If you decide to buy an off-the-shelf MMM package, it's important to carefully evaluate your options and to choose a vendor that meets your needs. This includes evaluating different MMM vendors and their offerings, and comparing features and pricing.

When evaluating MMM vendors, it's important to consider factors such as pricing, features, and customer support. Pricing is an important consideration, as different vendors may offer different pricing models, such as subscription-based or a cost-per-model update, as well as setup fees. It's important to evaluate whether the pricing aligns with your budget and whether the value provided by the vendor justifies the investment.

Features are another important consideration when evaluating MMM vendors. Different vendors may offer different features, such as advanced modeling capabilities or real-time reporting. It's important to evaluate whether the features offered by the vendor align with your specific needs and requirements, and whether they will provide value to your business.

Check whether the vendor has worked with similar businesses, both in terms of industries and company size. They should be able to point to several logos of companies from your industry that you recognize and respect. In addition, at the end of the sales process, be sure to ask for a reference from an existing client, before you sign on the dotted line. This can help you make the final decision as well as give you a candid view of what to avoid, as well as what you can do in order to make the relationship a success.

Customer support is also an important factor to consider when evaluating MMM vendors. It's important to ensure that the vendor offers adequate customer support, including training and technical support, to ensure that your team is properly trained and supported to use the new technology. If you require enterprise level support, a self-serve solution is unlikely to be the best fit, as they will potentially struggle to deal with the increased complexity and data security requirements of a more mature business.

Once you have selected a vendor, it's also important to ensure that you have a smooth onboarding process and that your team is properly trained and supported to use the new technology. This includes providing training and support for your team, as well as ensuring that the vendor's technology integrates seamlessly with your existing systems and processes. Ensure that you're comfortable with the in-platform data visualizations you saw in the product demo, and be up front with any advanced or custom requirements you're likely to have.

7. GATHERING THE RIGHT DATA

7.1: Types of data needed for marketing mix modeling and how much of it is needed for a robust statistical model

Marketing mix data includes information on marketing activities such as advertising, promotions, and pricing. This data can be collected from a variety of sources, including internal marketing reports, third-party data providers, and social media analytics. It is important to ensure that the data is accurate and complete, as missing data can lead to inaccurate predictions and suboptimal marketing decisions.

To make the data collection process more efficient, it's highly recommended to plan to set up a long-living marketing data warehouse from the beginning. That way everything is collected in one place in the right format, so that modeling can happen as many times as you like after. This is a key first step to automating MMM, and making sure your model receives regular weekly updates so that you can get up-to-date recommendations in real time. Creating a centralized location for all of your data will make it easier to do modeling and analysis, because the data will already be cleaned, standardized, and prepared in the right format. Additionally, having a marketing data warehouse will make it easier to access data and perform other types of analyses in the future, not just MMM, saving time and resources.

Sales data includes metrics such as revenue, units sold, and customer types. This data can be collected from internal sales reports, point-of-sale systems, and customer relationship management systems. It's important to ensure that the data is accurate, complete, and consistently reported across all regions and business units.

External data sources can include data on consumer trends, competitive activity, and other factors that may impact your marketing efforts. However, it's worth noting that including these alternative factors may not always be necessary. For example Recast's model allows for time-varying coefficients, which allow performance to move up or down with seasonality. If you control for seasonality instead of measuring it, your model may tell you to increase spend at precisely the wrong time, so be careful with traditional modeling approaches.

In order to build a robust and reliable statistical model, it's important to have at least 6 months of data, and as much as 3 years, depending on the context of the model. Two years or more is ideal because that allows you to identify seasonal patterns.

The more years worth of data you have, the better the model will be at understanding seasonality, because it'll have multiple years to compare to tease out the underlying trend. Having a larger amount of historical data will (all things being equal), give your model more to work with in determining the impact of marketing campaigns. Even if the model is less noisy or more relevant with a shorter time series, it's still helpful to understand these cutoff points in the modeling process.

7.2: Collecting and cleaning data from various sources

When operationalizing marketing mix modeling (MMM), it's essential to collect and clean data from various sources in order to build a robust and reliable statistical model. MMM data can come from a variety of sources, including internal databases, 3rd-party data providers, and advertising/marketing platforms.

Collecting data from various sources can be a significant effort, and it's important to ensure that your data is accurate, complete, and consistent. This may involve removing duplicates, correcting errors, and standardizing data from different sources. Data cleaning and preparation can be a time-consuming and resource-intensive task, so it's important to allocate sufficient resources to this task.

There are several steps involved in cleaning data for marketing mix modeling (MMM) or any other type of data analysis:

1. ***Inspection:*** The first step is to inspect the data and get a general understanding of its structure, format, and content. This includes looking for missing data, outliers, and unusual values.
2. ***Formatting:*** The next step is to format the data so that it is consistent and ready for analysis. This may involve standardizing column names, converting data types, and removing duplicates.
3. ***Data Quality Check:*** Checking the quality of the data by verifying the accuracy, completeness and consistency of the data. You should make sure that the data in the warehouse are consistent with other sources (e.g., in your financial reporting, your Shopify account, and individual platform reporting tools).
4. ***Data Transformation:*** Transform the data to meet the requirements of the analysis. This may include aggregating data, creating new variables, or removing unnecessary columns.
5. ***Data Imputation:*** Handling missing data by replacing missing values with estimates based on the available data.
6. ***Data Validation:*** Verify the integrity of the data by cross-checking it with other data sources or by using statistical tests.
7. ***Data Export:*** Export the cleaned data in a format that can be easily used for analysis, such as a CSV file or Data Warehouse.

It's important to note that these steps may not always be necessary, and the specific steps used will depend on the data and the analysis being performed.

Collecting and cleaning data from various sources is an essential and time consuming part of the process. It's important to ensure that your data is accurate, complete, and consistent, and to remove any duplicates or errors. Data cleaning and preparation can be a significant effort, so it's important to allocate sufficient resources to this task. Our recommendation is to set up a long-living marketing data warehouse that collects all of the useful data for the business, not just for MMM.

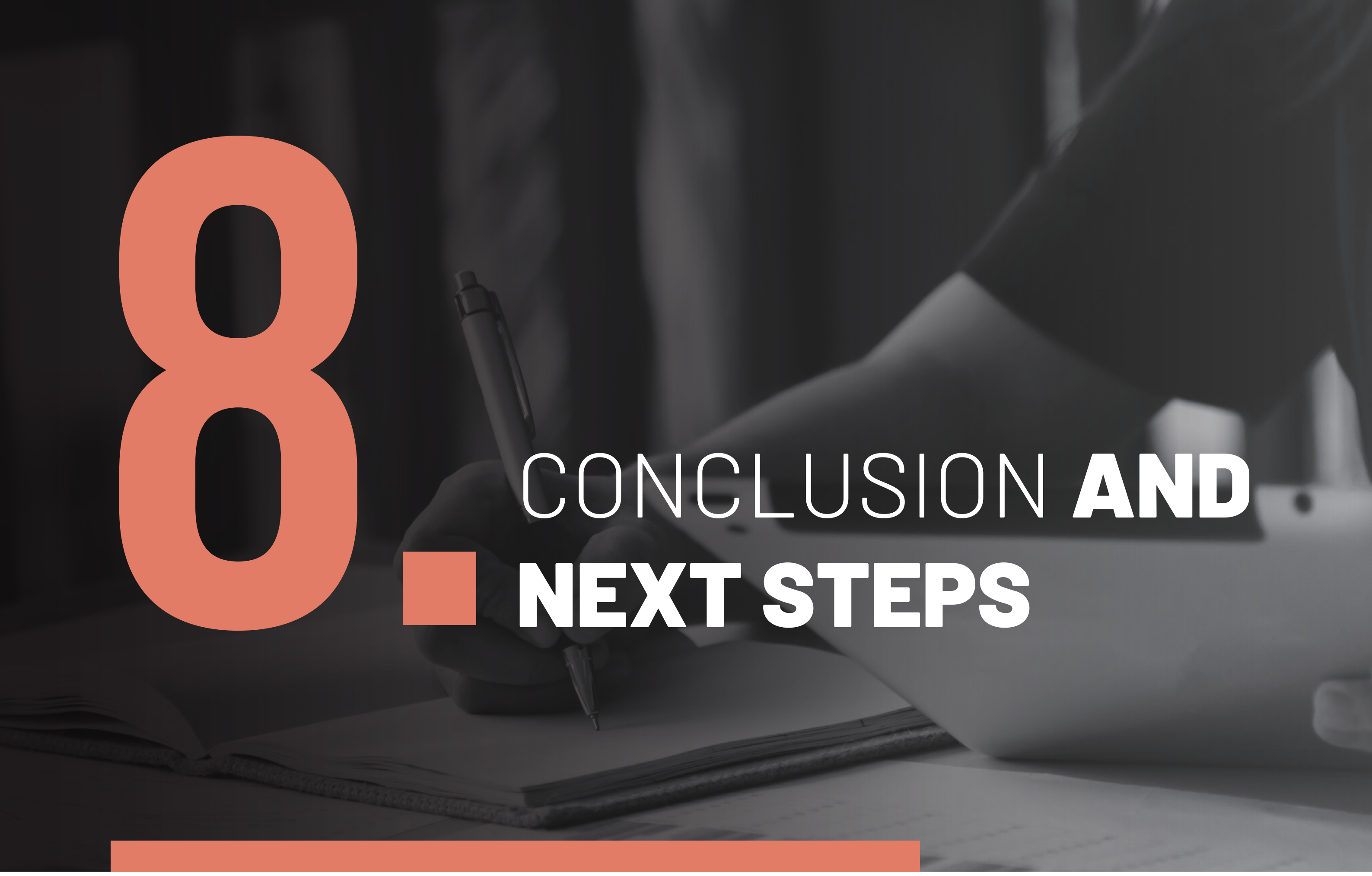
7.3: Considering non-obvious data sources, such as social media data, 3rd-party competitive data, or consumer trends

Marketing mix modeling (MMM) can benefit from a range of data sources beyond the traditional marketing mix and sales data. For example, a finance product or travel business might benefit from incorporating major fluctuations in the exchange rate, because they may affect user behavior and therefore impact sales. Similarly, very seasonal businesses may stand to benefit from incorporating Google search trends data to act as a proxy for seasonality in their industry. Additionally, most businesses should consider their strategy for accounting for the impact of COVID-19 in their models.

Social media data, 3rd-party competitive data, and consumer trend data can all provide valuable insights into the performance of your marketing efforts. For example, social media data can provide information on the engagement and reach of your social media campaigns, while 3rd-party competitive data can provide information on the activities of your competitors. If a competitor suddenly starts spending significant amounts on TV, or runs a large promotion, that may impact your sales greater than anything you did in marketing. Consumer trend data can provide insights into the preferences and behaviors of your target audience, as well as economic data such as unemployment, GDP growth, and inflation.

When considering non-obvious data sources, it's important to consider the availability, quality, and relevance of these data sources as well as how they impact your model's inferences. Additionally, it's important to ensure that these data sources align with your goals and objectives. Keep in mind, controlling for more factors isn't always better! Recast's model is extremely intentional with every variable we include, because each comes at a cost in terms of complexity and noise: including one external factor may "push out" the impact of an important marketing campaign, simply because they're correlated. For us, this part is handled effectively by our time-varying coefficients, which let performance flex up and down with demand.

Considering non-obvious data sources, such as social media data, 3rd-party competitive data, or consumer and economic trends, can provide valuable insights into the performance of your marketing efforts. It's important to consider the availability, quality, and relevance of these data sources as well as how they impact your model's inferences, and be intentional with your strategy for including them (or not). Additionally, it's important to ensure that these data sources align with your goals and objectives. It's also important to keep in mind that controlling for more factors isn't always better, and it's important to find the balance between controlling for more factors and overfitting the model.



8. CONCLUSION AND NEXT STEPS

8.1: Recap of main points and takeaways

In conclusion, it is clear that marketing mix modeling (MMM) is a powerful tool for optimizing marketing budgets, driving better business outcomes, and maximizing ROI. It is a privacy-friendly and channel-agnostic alternative to other marketing measurement methods, providing an unbiased way to measure the effectiveness of marketing efforts regardless of the data source or channel. With the emergence of new privacy laws and regulations, MMM has become increasingly important for understanding the impact of individual marketing channels, as well as how they interact.

To ensure success with MMM, marketers need to consider budget, data quality, expertise, and features when deciding on a solution. There are many options: Bayesian and Frequentist models open-sourced by tech giants such as Meta, Google, and Uber have advantages and drawbacks, and should be carefully weighed against the project's goals and resources. Careful validation of both a model's accuracy and plausibility is key to building a model that's actionable, and can be relied on for important decision-making.

It is important to the project's success to create a cross-functional team to ensure that the model aligns with business objectives, and that results are presented in a clear, engaging way to stakeholders. Additionally, it is important to carefully evaluate vendors and understand their pricing, features, customer support, and references to ensure the model is the best fit for the project and that the data used to build the model is accurate and reliable. An understanding of the resources and expertise needed, as well as the importance of aligning KPIs with business goals, are also essential for making informed decisions and maximizing ROI.

KEY LEARNINGS

- MMM is a privacy-friendly and channel-agnostic alternative to other marketing measurement methods.
- Different modeling approaches have benefits and drawbacks and should be carefully considered for each project.
- Building a custom MMM requires careful consideration of the model type, marketing complexity, resourcing, and the data available.
- Evaluate vendors carefully, considering pricing, features, customer support, and references.
- Use the model's insights to build a simulator too, to inform decision-making and budget allocation for better results.

Overall, MMM is a powerful tool for optimizing resources, making data-driven decisions, and predicting future performance. It provides companies with a compliant and ethical way to measure the effectiveness of their marketing efforts, and is an important tool for maximizing ROI and understanding the impact of individual marketing tactics. As MMM continues to be reinvented for the modern era, understanding how to operationalize MMM within your brand will be an essential skill.

If you wish to learn more about MMM and marketing measurement, we send an email newsletter once per week with the best articles we've read on the topic, including articles published on our popular blog.

If you'd like to see a Recast product demo, we would love to talk!

BOOK A DEMO