2025

market mix modelling landscape

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contents

chapter 1

introduction to the iab australia ad effectiveness council

This report, produced by the IAB Australia Ad Effectiveness Council in collaboration with leading vendors, provides a comprehensive overview of the Market Mix Modelling vendor landscape in Australia.

The IAB Australia Ad Effectiveness Council undertakes various activities to provide guidance to the industry on the best methods to assess the impact of marketing activities along with insight and inspiration to help marketers optimise their digital advertising investment.

The Council includes representatives from media owners, data agencies, media agencies, research companies, tech vendors and advertisers.

The contents of this guidance paper are not necessarily reflective of individual company policies, rather it is a collaborative effort of Market Mix Modelling vendors and the members of the council to provide greater understanding to the market.

Yasmin Sanders (Council Chair) | Samba TV
Tim Hull |Amazon Ads
Casey Greig | Audience Group
Michelle Thompson | Azira
Stephen Kyefulumya | Carsales
Andrew Macdonald | Dentsu
Trisia Wiecek |DoubleVerify
Andrew Rudd | Experian
Justin Taylor Nel | Gain Theory
Amir Jangodaz | Google
John Nguyen | IAS
Michael Serratore | Innovid
Rory Burger | iProspect
Andreea Chirila | Kantar
Peter Madani | Lifesight
Felicity Wainright |LoopMe
Aimy Le | Meta
Ian Garland | Milton Data
Sheetal Nand |Microsoft
Will Marks |Mutinex
Craig Johnson |Netflix
Stephen Warren | News Corp
Kirsten Riolo | Nielsen
Mark Griffiths | On Device Research
Mark Titley | Paramount
Dave Goodfellow | Pinterest
Jordan Taylor-Bartels | Prophet
Duran Bradley | REA Group
Jonathan Henshaw | Ryvalmedia
Ashley Spinks |Seven West Media
Louise Hutley | Stackadapt
Ezio Fernandez | Smartly
Jade Watson | WPP Media
Rahila Nadir | Yahoo
Natalie Stanbury | IAB Australia

chapter 2

executive summary

Media fragmentation and the increasing number of marketing options available have driven marketers to look for measurement solutions that capture the impact of full cross-media activities. Combined multi-channel approaches drive higher ROI, so it's important for marketers to understand the holistic impact of their media investments.

IAB industry engagements have shown that with reduced signals and changes to privacy legislation, advertisers and agencies have increased their usage of measurement techniques such as experimentation and Market Mix Modelling. Market Mix Modelling is not a new technique but has experienced a revival and evolution in recent years. *Outcome-based measurement provided by Market Mix Modelling ties media performance to the metrics that are crucial to a business' growth.* It enables marketers to assess the performance of their media investments with clearly defined financial related metrics while accounting for external influences such as pricing, promotions, competition, and economic conditions.

The evolution in Market Mix Modelling has been made possible by the increased power of cloud computing, increasing the speed of insights delivery. Market Mix Modelling can work with more granular data than in the past, taking advantage of more sophisticated modelling techniques driven by machine learning. These advancements have resolved some of the common complaints of Market Mix Modelling, like timeliness and providing the capability of drilling down into more granular drivers of performance such as creative, format and geography.

Market Mix Modelling requires resources, careful analytic design, robust implementation, model validation and expertise to interpret the results and apply the learnings to future plans. IAB Australia's Ad Effectiveness Council has collaborated on this *'Market Mix Modelling Landscape Report' to provide marketers, ad agencies and media owners with information for greater understanding and transparency on the different types of vendors, products and methodologies available in market.*

The vendor landscape in Australia is diverse, the report profiles twelve active vendors, outlining their methodologies, validation practices, data requirements, refresh cadences, and decision-support capabilities. This information was collected from vendors by the IAB using a standardised written questionnaire and we sincerely thank the following vendors for their contribution: *Analytic Edge, Analytic Partners, Annalect, Circana (formerly Nielsen MMM), Gain Theory, Google, Kantar, Lifesight, Meta, Mutinex, Prophet and Recast.*

These vendors employ a range of modelling techniques, from classical econometric models to modern Bayesian and machine learning approaches. *It is essential for marketers seeking the right partner for their business needs to understand the differences in offerings available in market and conduct a thorough RFP to research and compare MMM vendors based on specific needs and criteria.*

Common challenges identified across the landscape include isolating the effects of multiple concurrent media channels, validating model accuracy, ensuring causal relationships are correctly identified and keeping models current with shifts in consumer behaviour and media dynamics. Each participating vendor provides information on how they address these issues and highlight how they overcome these challenges through model calibration and validation.

The report also presents a structured checklist to guide marketers through the key considerations for MMM implementation. It emphasises the importance of strategic clarity, comprehensive data readiness, cross-functional stakeholder alignment, model validation and informed vendor selection. Effective use of MMM requires accurate and granular input data, including media activity, pricing, promotional events, and external variables. Data systems must be equipped for routine and automated data delivery to maintain and update the models. Furthermore, MMM should not be used in isolation. Instead, it should function as part of a broader measurement framework, working in tandem with attribution models, experimentation, and platform-specific analytics. *MMM is not a one-off exercise but a process of continuous refinement.* Models must be regularly updated to reflect changes in consumer behaviour, media effectiveness, and business dynamics.

Industry perspectives collected for this paper reinforce that when implemented thoughtfully, MMM enables marketers to optimise their investment, enhance strategic decision-making, and demonstrate the value of marketing in driving business growth.

"Since we began our MMM modelling in early 2023, our focus areas continue to shift alongside our modelling maturity. At the start, it's very much about establishing baselines, validating marketing's incremental impact on business growth and gaining high level media channel insights. Today, our focus has evolved to understanding where we have opportunities to push further in under-invested channels, controlled experimentation to inform media investment portfolio optimisation at more granular geographic levels, validating predicted vs actual outcomes, and gaining a deeper understanding of creative performance across various channels and formats."

- Angela Greenwood Chief Marketing Officer at Youi Insurance

"Given MMM isolates the true drivers of the chosen business KPIs, MMM ensures that marketing is not held solely accountable for outcomes influenced by forces beyond its control. I found this clarity essential during annual budgeting cycles, as it doesn't just acknowledge market factors, it quantifies the impact which I have found leads to fairer whole of business OPEX allocation. Oftentimes, without an MMM, Marketers are on the hook for the whole increase in Revenue YoY, without any acknowledgment that typically Marketing is only responsible on a causative basis for about 30-40% of business KPIs (significant variance by vertical exists). "

- Liam Loan-Lack, Chief Customer Officer at Keystart

"MMM is vital within a comprehensive measurement framework, enabling marketers to navigate data-driven decision-making effectively. Its ability to link media investments to business outcomes is greatly enhanced when combined with other tools that provide deeper consumer insights and improve channel effectiveness. By adopting an integrated approach, marketers can align strategies with evolving business goals, ensuring every dollar spent drives sustainable growth."

- Lillian Zrim, Head of Research at PHD

"Seven's engagement in MMM was driven by a need for more strategic media planning, more precise allocation of resources and spend, and a deeper understanding of media effectiveness. We're using the insights from this model to help us prioritise the most effective combinations of media channels and investments to drive efficient, high-value audience viewership uplift. MMM has enabled us to tackle several longstanding business challenges including understanding the value of owned media, modelling for viewership rather than sales and being able to quantify the contribution of social content. "

- Ashley Spinks, Head of Research and Effectiveness at Seven Network

"MMM is a powerful tool and one we are committed to as an agency. It can help mitigate ongoing challenges in signal loss, privacy legislation and evolving consumer behaviours. MMM's resurgence is a good thing. But if we want it to stick, we need to move beyond the hype. Advertisers don't just need more models. They need more clarity, more context, and more confidence in the decisions they make. Realising that MMM is one of multiple layers to measurement, we also ensure that it is surrounded by the appropriate testing roadmap to validate key hypotheses and budgeting decisions that come out of MMM."

- Andy Macdonald, National Head of Digital at Carat

"MMM is a powerful tool for measuring how various marketing investments contribute to business outcomes. The Trade Desk's built-in measurement tools support accurate and actionable modelling by helping advertisers feed data that better captures the unique specifications of programmatic buying, into their MMM models. The quality of your MMM is only as good as the data it's built on, which is why The Trade Desk has developed feed integrations with major MMM vendors globally to provide advertisers with an optimal way to get the data needed to power models and ensure accurate campaign data enters these feeds."

- Bella Spragg, Director Data Partnerships ANZ at The Trade Desk

"MMM offers the potential to transform marketing measurement, but realising this promise requires vigilance on several fronts—granular measurement across the media mix, high quality data flows, rigorous calibration, methodological scrutiny, and transparent partnership. By embracing these principles, advertisers can cut through complexity and chart a path to smarter, more effective cross channel media investment."

- Dave Goodfellow, Head of Measurement Solutions, APAC at Pinterest

chapter 3

marketers' checklist

Market Mix Modelling is a powerful tool for optimising your marketing efforts, but it can be complex to implement. This checklist is designed by the IAB Ad Effectiveness Council to guide marketers through the essential steps and considerations when implementing Market Mix Modelling:

Strategic Foundations

- Clearly articulate the primary objectives of your marketing and advertising efforts and how these align to business goals.
- Identify well-defined business questions.

Measurement Framework

- Review your current measurement tools in relation to your objectives, understand how your framework addresses short- vs long-term objectives; media delivery, performance and brand objectives; cross-platform measurement; the impact of ad creative.
- Pinpoint specific limitations or pain points in your current measurement approach.
- Identify gaps and limitations in your existing measurement tool kit that MMM could address.
- Recognise MMM as one tool in a broader measurement framework and how you will complement and combine with other techniques such as experiments and attribution.

Data Readiness

- Evaluate your current data collection and management practices.
- Ensure you have the necessary data infrastructure and resources in place to support MMM implementation.
- Secure accurate, comprehensive data at the most granular level possible across MMM inputs including sales, revenue, ad exposure, ad expenditure, other marketing and promotional data, pricing, product, brand measurement, creative testing, customer data.

- Set up routinised, automated data collection, QA procedures and delivery processes, to ensure timely updates of data provided to your vendor to maintain the model.
- Identify any data quality or integration challenges that need to be addressed.
- Evaluate the privacy implications of data collection and usage for input data required.
- Understand the external factors (such as economic, environmental and social conditions, competitive actions, and seasonality) that are important to incorporate into your model.

Stakeholder Alignment

- Identify and involve key stakeholders from relevant business areas including marketing, finance, analytics, IT.
- Communicate the benefits and potential impact of MMM to secure buy-in and support.
- Assign a project champion to manage timelines, cross-functional alignment, and decisions.
- Educate teams on how to interpret and act on MMM outputs to drive internal adoption.

Vendor & Model Selection

- Conduct an RFP to research and compare MMM vendors based on your specific needs and criteria.
- Request demonstrations, case studies and references to assess the capabilities and track record of potential partners.
- Consider factors such as validation, transparency on models, data granularity and timeframe required, reporting capabilities, customer support, cost.
- Ensure vendors are equipped for supporting change management and internal training (if required).
- Understand how the vendors model handles the common challenges of MMM such as isolating channel effects, distinguishing between channel spend-driven sales and sales-driven channel spend increases, seasonality and trends, outliers and changes in consumer behaviour.
- Understand the model assumptions and limitations.
- Assess vendors capabilities to support your required cadence (eg daily, weekly, monthly etc).
- Evaluate the source of data used to include external factors into your model such as economic, environmental and social conditions, competitive actions, and seasonality.

Compare and test models

- Your RFP should assess validation protocols for prospective MMM providers.
- Models vary vendor to vendor so it's essential to rigorously assess how viable each prospective MMM is for your business and test for accuracy, stability and robustness.
- Compare margin of error results from out of sample testing across each prospective MMM.

Model Implementation & Validation

- Ensure your vendor has a validation framework that includes a range of statistical measures to evaluate model accuracy and reliability such as out of sample or holdout testing and statistical diagnostics (R^2, MAPE, etc.).
- Validate incrementality by using experimental lift test to calibrate the model.
- Incorporate post-deployment monitoring to check for model drift and update as needed.

Actionability & Integration

- Translate model findings into executable actions that can drive business decisions
- Use MMM results for:
  - Tactical and strategic planning
  - Budget allocation and media optimization
  - Scenario testing and ROI simulation
- Integrate MMM insights into business processes and planning cycles.
- Set realistic expectations about what MMM can and cannot answer; manage internal understanding accordingly.

chapter 4

market mix modelling vendor landscape

background on participating vendors

Analytic Edge

Analytic Edge provides technology-enabled analytics solutions for marketing and sales effectiveness. The founders' vision was to "imagine a future where marketing analytics is simple, fast and accessible to all."

Analytic Edge has offices in 17 countries working across various industry verticals. Development and delivery teams are based in India with around 175 data scientists and technologists. Since launching an Australian office in 2021, Analytic Edge has now built a local Australian client base.

Analytic Edge is nominated for the Forrester Wave and Gartner Magic Quadrant report for 2025, results are due to be published soon.

Analytic Edge's proprietary platform, Demand Drivers™ is a cloud-based MMM platform designed for continuous marketing effectiveness measurement. It supports both linear and non-linear multivariate Bayesian and partial least squares regression models. The platform supports both manual and auto-modelling to reduce response times and focus more on higher level business and marketing insights and story-telling, as well as dramatically reducing project timelines for model builds and updates.

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Analytic Partners

Analytic Partners was founded in 2000 in the US, and established in Australia in 2006, with a core focus on commercial measurement and optimisation. Analytic Partners operate in over 55 markets, with offices in Melbourne and Sydney. Analytic Partners mission is to identify growth opportunities aligned to our client's key business questions with commercial analytics.

Analytic Partners was named a Leader in the 2023 ForresterWave™: Marketing Measurement and Optimization, Q3 2023 report and named Leader in the 2024 Gartner® Magic Quadrant™ for Marketing Mix Modelling Solutions. Analytic Partners have validated client results, for example from commissioned Forrester Consulting Total Economic Impact™ study.

GPSE powered by ROI Genome is Analytic Partners proprietary MMM platform that uses advanced statistical methods, machine learning, data mining techniques, and predictive modelling for explicit hypothesis testing.

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annalect

Annalect is Omnicom Media Group's data, technology, and analytics division, delivering data-driven marketing solutions to leading brands. In Australia, Annalect partners with clients to deliver advanced analytics, including bespoke Market Mix Models. We combine deep media knowledge with statistical and data science expertise to drive marketing effectiveness. Positioned at the intersection of technology and strategy, our mission is to empower better business decisions through actionable insights

Annalect's MMM solution is built on a multi-level hierarchical Bayesian framework, designed with the flexibility to adapt to diverse business needs. It scales seamlessly from single-market to multi-region advertisers, enabling robust measurement for simple to complex portfolios.

Beyond short term returns, the model supports measurement of long-term impact of marketing, empowering marketers to maximize overall ROI and improve allocation decisions. Its adaptable structure ensures insights remain actionable in dynamic market environments.

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Circana.

(formerly Nielsen MMM)

Circana is a leader in providing technology, AI, and data to fast-moving consumer packaged goods companies, durables manufacturers, and retailers seeking to optimise their businesses. Circana's predictive analytics and technology empower clients to measure their market share, understand the underlying consumer behavior driving it, and accelerate their growth. Circana's Liquid Data® technology platform is powered by an expansive, high-quality data set, and intelligent algorithms trained on six decades of domain expertise. With Circana, clients can take immediate action to future-proof and evolve their growth strategies amid an increasingly complex, fast-paced, and ever-changing economy.

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GAIN THEORY

Gain Theory is a global marketing effectiveness and foresight consultancy, recognized as a Leader in the 2023 Forrester Wave™: Marketing Measurement and Optimization, Q3 2023 Report. With over 50 years of marketing effectiveness experience, we fuse deep expertise and 'next generation' solutions with AI to empower brands to make smarter, data-informed investment decisions that accelerate growth.

We provide a prescriptive, not just descriptive, view of marketing and business performance, offering actionable insights that are both broad and deep. Our unique, globally scalable solutions enable continuous experimentation and improvement, empowering brands to make decisions with confidence. This allows our clients to activate recommendations for immediate impact and long-term, unmatched competitive advantage, transforming marketing into a sustainable engine for growth.

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Meridian

Google's mission is to organise the world's information and make it universally accessible and useful. Google Ads Measurement enables marketers to understand the effectiveness of their campaigns and make data-driven decisions to improve their performance.

Meridian is Google's open-source Marketing Mix Model launched in January 2025. Meridian employs a Bayesian causal inference framework through a single-equation regression model.

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KANTAR

Kantar is a marketing data and analytics company, helping clients optimise marketing investments through our advanced Market Mix Modelling platform, LIFT ROI. Having been running MMMs for more than 30 years, we offer MMM capability built through in-house innovation and strengthened by the strategic acquisition of Bayesian pioneers Blackwood Seven in 2022.

Our solutions combine proprietary technology with deep domain expertise. Our mission is to unlock the value of marketing and shape brand success through evidence-based decision-making.
Kantar's LIFT ROI platform employs machine learning-based Bayesian hierarchical modelling.

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lifesight

Lifesight was founded in 2017 to help marketers make better decisions that drive growth and profitability.

Our Unified Marketing Measurement Platform empowers e-commerce and omnichannel brands to move beyond outdated touch-based attribution. By combining Causal MMM, Incrementality Testing, and Causal Attribution, we solve the flaws of traditional measurement while addressing today's privacy challenges.

With automated test deployment, real-time planning, budget optimisation, and dynamic dashboards, marketers can seamlessly plan, measure, and act directly from Lifesight.

To ensure success, we pair our platform with Managed Services in Data Implementation, Marketing Science, and Customer Success—enabling brands to optimize spend, forecast accurately, and prove true marketing ROI with confidence.

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Robyn

Meta's mission is to build the future of human connection and the technology that makes it possible. Advertisers can leverage Meta's vast user base and tools to create personalised and engaging ad experiences that can reach billions of people worldwide.

Robyn is an experimental, AI/ML-powered and open-source MMM package from Meta Open Source that pioneers gradient-free multi-objective optimisation in MMM. Robyn's mission is to democratise modelling know-how, inspire industry innovation and contribute to the open-source marketing science community.

Note: Robyn is not an official Meta product nor vendor, where Meta does not build clients' MMMs directly.

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MUTINEX

Founded in 2018, Mutinex is a SaaS platform that turns messy marketing data into weekly, decision-ready ROI. Our tri-stack—DataOS (automated ingestion), GrowthOS (Bayesian MMM engine) and MAITE (AI co-pilot)—delivers first models in ≤ 90 days and monthly refreshes or faster thereafter.

By combining transparent code with embedded marketing-science partners, Mutinex focuses on delivering the rigour of consulting at the speed of SaaS.

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prophet

Prophet, established in 2020, is an Australian predictive intelligence platform designed to enhance real-time, data-informed marketing decision-making. Initially created to address inefficiencies in traditional market mix modelling, Prophet employs sophisticated statistical methodologies including Bayesian inference, ARIMA, and Structural Equation Modelling (SEM). The platform integrates across various data streams, enabling dynamic and timely decision-making. Prophet's primary objective is to enable precise, measurable marketing strategies that significantly enhance efficiency and business growth.

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Website

RECAST

Recast is fast and accurate incrementality measurement, comprising Recast's Causal MMM and Recast GeoLift. Founded in 2020 by Michael Kaminsky and Tom Vladeck, Recast leverages a fully Bayesian, time-series-based MMM. The platform's current out-of-sample forecast accuracy is a leading 94.4% across clients.

Recast continuously updates with new daily data every week, dynamically captures fluctuations in marketing performance, calibrates with lift tests, and provides in-platform validation tools. Recast is purpose-built for teams that want to engage in Incrementality Systems of planning, experimentation, validation, and marketing optimisation in a single, unified platform. Recast openly publishes all model documentation and forecast accuracy, and leverages in-house PhD-led research to deliver precise, data-driven insights.

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chapter 4

market mix modelling vendor landscape

methodology and models

Market Mix Models inform how marketing inputs translate into sales return on investment using *econometric techniques*. Market Mix Modelling (MMM) is a statistical analysis of aggregate sales, advertising and marketing data, and data on other factors outside a marketer's control, that *quantifies the impact of different marketing channels and tactics (the marketing mix) on business or financial outcomes over time such as sales.* MMM is a form of econometrics which predicts how all marketing activity (including all advertising activity on TV, print, out of home, online video, social media, and search) translates into outcomes.

MMM can be used to answer a range of business questions from strategic budget allocation decisions to marketing contribution insights for the marketing team and to more granular tactical media and advertising decisions for media planners and creatives. MMM econometric models also take a range of other variables into account that might affect sales such as the weather, pricing and overall economic conditions.

Under the hood, MMM has traditionally used the principle of *linear regression* a statistical technique to understand how media channels have performed in the past by analysing the relationship between a dependent variable (like sales or market share) and multiple independent variables (like advertising spend, price, distribution, etc.). It helps determine how changes in these independent variables impact the dependent variable, allowing for budget optimisation and performance insights. An *Ordinary Least Squares (OLS) model* used by some vendors highlighted in our paper is similar to ordinary multivariate linear regression.

Today, there is a greater variety of Marketing Mix Models in market using hybrid, combinations of techniques from traditional regression analysis to newer Bayesian methods, time series analysis, and machine learning. A *Bayesian model* is a statistical framework that combines prior knowledge with new evidence to make inferences or predictions. Bayesian regression runs millions of simulations and returns a probability that a specific set of outcomes is possible.

Some MMM vendors build models from scratch, tailored to a specific brand and business. Other vendors, use generalised models that are not specific to a brand or business and take broader market dynamics into account. It is common for marketers to use an external vendor partner for MMM as it can be challenging to build valid and robust models without clear guidance, however there are *open-source MMM* tools available that can be a cost-effective and flexible choice.

There's an important place for new technology and techniques as they have evolved marketing evaluation to help us deal with lower media budgets, smaller sample size and allow faster and more granular insights, however *in any modelling solution the limitations need to be well understood.*

You should expect your MMM vendor to have a validation framework that includes a range of statistical measures and tests to evaluate model accuracy and reliability. The vendors participating in this paper have outlined their approaches and combination of tests they conduct to help their clients understand robustness, stability and accuracy in results. For example, multiple vendors have mentioned the practice of 'hold-out testing' (out-of-sample testing) where a portion of data is withheld from the model during training and development and then used to evaluate the model's performance on previously unseen data.

MMM often incorporates the concept of *incrementality*, sometimes referred to as "incremental analysis". Incrementality is often used to establish causal relationships, it identifies the impact delivered above what would have occurred without the marketing activity and plays a crucial role in understanding the true impact of marketing activities and optimising marketing strategies. Capturing true causal relationships is complex and requires specific techniques to test for causality within MMM to provide estimates of the incremental value of each marketing channel. Combining MMM with controlled experiments (such as geo sales lift experiments) can also be used to identify incrementality and calibrate models.

MMM is not "set and forget." Models need to be continually validated to drive impact, and regular updates are necessary due to changing consumer behaviour and media environments.

Our participating vendors have also provided brief information on some of the key questions you will want to understand about your model

- How does your modelling approach solve for *isolating which channel had an effect* when there are multiple channels running at the same time?
- How does your modelling approach solve for *understanding if the channel spend itself caused sales to rise*, as opposed to a sales period causing the marketer to increase channel spend?
- How does your model handle *seasonality and trends*?
- How does your model deal with *outliers*?
- How does your model handle *changes in consumer behaviour*?

The choice of methodology depends on factors like the complexity of the business, the amount and type of data available, the level of detail required in the analysis and the budget available for MMM.

"MMM is not a 'one-size fits all' methodology. The specific methods used, underlying assumptions, and the volume or types of data used can vary significantly from business to business and vendor to vendor. Some opt for traditional linear or multivariate regression models and the make-up of each can vary significantly from one to the next—some opting for Bayesian or Frequentist frameworks, and many offer ensemble approaches that combine multiple modelling strategies. The key inputs, data weighting, and even optimisation objectives can vary just as much.

As an advertiser, you should probe vendors and partners deeply—ask how the models are constructed, which variables consume the greatest weight, what time lags are considered, how external factors are controlled, and what validation exercises have been performed. The best MMM application is one that closely aligns with your business context and reflects the actual consumer behaviors you want to measure."

- Dave Goodfellow, Head of Measurement Solutions, APAC at Pinterest

Participating Market Mix Modelling vendors have provided a description of their product including an outline of methodology, the type of statistical model used, how models are calibrated and updated and approaches for solving the common challenges of Market Mix Modelling (isolating channel effects, causality, seasonality, outliers and changes in consumer behaviour).

Analytic Edge

Methodology:

Analytic Edge's proprietary platform, Demand Drivers™ is a cloud-based Marketing Mix Modelling (MMM) platform designed for continuous marketing effectiveness measurement. The underlying modelling algorithm is a hybrid of the classical OLS, time-series multivariate regression framework and a quadratic programming-based optimisation. You can set and change prior coefficients by setting empirical priors or contribution ranges at the variable level, based on either Analytic Edge benchmarks or geo-lift experiments or test and learn studies. The platform supports log-linear modelling using the volume-due-to-removal method to account for Jensen's inequality to decompose log-linear models. The platform supports pooled dimensional modelling. Full-funnel or Nested (network or causal inference) models are currently supported as a 2-step process. Running nested models simultaneously as a single-step process is part of the platform roadmap.

Analytic Edge can also capture the short and long-term impact of media tactics to capture the overall impact of upper-funnel focused media, i.e., brand awareness campaign types vs. conversion or performance focused campaign types.

Model calibration and refreshing:

The platform supports model builds at different periodicities, i.e., daily, weekly, or monthly, depending on the business domain and the granularity at which data is available. The model periodicity defines the refresh cadence, i.e., daily models can be refreshed weekly, weekly models can be refreshed quarterly, etc. Models are calibrated through the model actualisation process, where the model is tested on out of sample data. If the model fit stats for the delta period degrade beyond pre-defined acceptability thresholds, we first check with the business to identify any potential extraneous reasons for the model fit stats to degrade. If none are provided, we propose splitting certain variables and recalibrating the model, assuming the elasticities for these variables may have changed. Typically, this is not warranted for at least 6-9 months for a weekly model.

The platform has in-built functionality to apply typical MMM transformations to the predictor variables (such as AdStock, Gamma, Log, Lag, Saturation curves, etc.) to capture lagged media impact as well as the non-linear behaviour of media accounting for the diminishing returns on media execution).

The changing effect of media over time can be captured by incorporating time- varying coefficients.

Model validation:

Analytic Edge evaluate model accuracy and reliability using both face and statistical validity criteria.
Face Validity Criteria include:

- Variable transformations based on mental models and adhering to best practices
- Correct signs on coefficients ensuring intuitive impact directionality
- Variable elasticities within reasonable ranges
- Variable interactions and competitive effects within reasonable ranges
- Variable contributions within reasonable ranges
- Changes vs. year ago due to model errors within reasonable ranges
- Minimal use of dummy variables and trend terms

Statistical Validity criteria include:

- Low MAPEs
- High R-squared
- Alignment of predicted to actual, no odd jumps or 0s in predicted volume
- High confidence in coefficients either via reliance on Priors or via high t-stats, Variance Inflation Factor < 10
- Forecast accuracy

How does your modelling approach solve for isolating which channel had an effect when there are multiple channels running at the same time?

If there is sufficient media execution across each tactic being measured, i.e. a minimum of 8-10 weeks of execution across the entire modelling duration, and if the media execution across each tactic exhibits variation, i.e., unequal impressions, clicks per week, the underlying modelling methodology can accurately isolate the impact of concurrently executed media tactics.

How does your modelling approach solve for understanding if the channel spend itself caused sales to rise, as opposed to a sales period causing the marketer to increase channel spend?

The platform allows you to include event flags like sales days, Black Friday, etc., as base drivers of the KPI. The model construct allows you to isolate the impact of the event on the KPI and the incrementality driven by media executed on the sales days. This way we avoid the pitfall of misattributing the impact of media.

How does your model handle seasonality and trends?

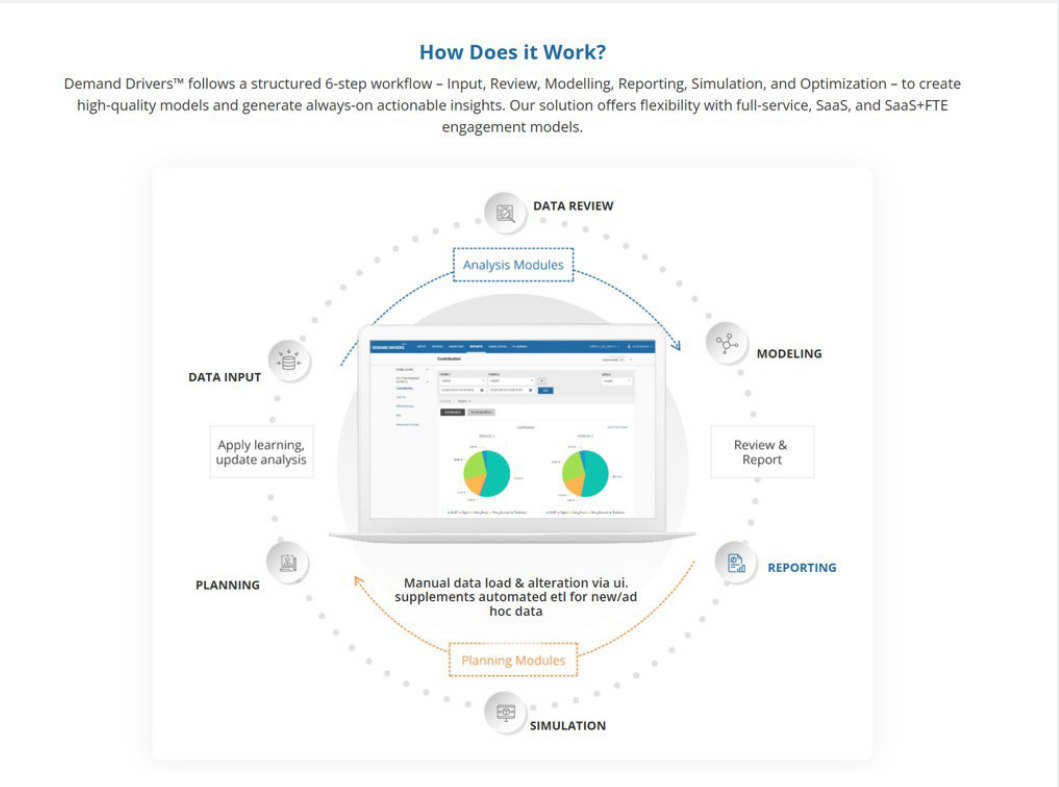
The platform uses in-built machine learning time-series techniques like the Meta open-source package Prophet for example, to automatically capture seasonality and trends from the KPI data. These are then tested as independent drivers in the model to ascertain if they are critical explanatory drivers.

How does your model deal with outliers?

Assuming the outliers are not data errors, but actual execution anomalies, media saturation transformations ensure that unusual peaks are truncated to avoid inflating the impact of such outliers on the KPI. If the outliers are data errors, these are typically captured as part of the comprehensive data review process prior to commencing the modelling process.

How does your model handle changes in consumer behaviour?

If the changes in consumer behaviour can be captured through time series data, it can be tested as an independent driver in the model. Typically, brand health trackers capture variations in awareness, affinity and love/loyalty scores, although these metrics exhibit gradual variation, i.e., quarterly.



Source; Analytic Edge

Analytic Partners

Methodology:

Commercial Analytics, powered by GPS-Enterprise, our proprietary technology platform, helps organisations optimise business performance by enabling data-driven decisions that drive efficiency, profitability and business growth. It involves using advanced statistical methods, machine learning, data mining techniques, and predictive modelling to extract meaningful patterns and trends from large datasets related to sales, marketing, customer behaviour, operations, finance, product, strategic pricing and other areas of a business. When adopted broadly, commercial analytics enables businesses to allocate resources more effectively, offset macroeconomic headwinds, fend off competitive pressures and identify levers to drive sustainable growth.

Because our technique utilises modellers explicit hypothesis testing, rather than being driven by priors like a Bayesian model, there are less explicit assumptions in the approach - these are tested with actual data. We assume that marketing has an impact, but test that across channels and across time frames and geographies.

Model calibration and refreshing:

Models are calibrated and updated for right time decisioning.

Model calibration and refreshing:

Analytic Partners has opened themselves up to external validation. Firstly, through interviews and 3rd party analyst interrogation through Forrester and Gartner where Analytic Partners has consistently been named a global leader by both, as well as through pitting our models and modellers against others in events such as the i-com Hackathons where we have entered and won twice.

The individual models are validated through multiple validation steps which are communicated through our engagements to ensure accuracy of insights blending technology and human intervention. We share model inputs and fits statistics and intelligence benchmarks from ROI Genome, all available within GPS-E.

We also include in-sample and hold out tests which are enhanced by Agile Learning, our control test approach that allows for a different tests and data sets to further validate the models and enable clients to reduce the contamination common in experiments.

How does your modelling approach solve for isolating which channel had an effect when there are multiple channels running at the same time?

Commercial Analytics provides insight into how marketing performs by channel and within channels (i.e. by campaign, objective, geography, etc.) We follow a process that combines business insights along with tactical treatment (ie SEM, data transformations and/or ridge regression) to mitigate correlation among channels.

How does your modelling approach solve for understanding if the channel spend itself caused sales to rise, as opposed to a sales period causing the marketer to increase channel spend?

Incrementality modelling is core to 100% of our client engagements. Our Commercial Analytics ensures marketing results are incremental and not due to changes in consumer demand, distribution, relative pricing, competitive activity, weather, store openings or other exogenous factors. Our approach to non-marketing factors is as rigorous as our approach to media.

How does your model handle seasonality and trends?

Our models are fully customised for the dynamics of the client's business, incorporating relevant brand, operational, and exogenous drivers, and available data specific to the modelled brands, markets, and sales channels. This includes seasonality and weather at a geographic level rather than just using a national level.

How does your model deal with outliers?

Our comprehensive, guided data management capability, ADAPTA checks for data anomalies and outliers through prebuilt scripts and workflows which quickly identifies and summarises outliers and other areas to validate. These are shared as part of technical reviews and vetted by customers.

How does your model handle changes in consumer behaviour?

Macroeconomic and regional specific consumer shifts are incorporated into our models down to the customer segment level when needed. Understanding changes in consumer demand is integral to the Commercial Analytic approach.

Annalect

Methodology:

Annalect's MMM solution is built using a multi-level hierarchical Bayesian framework, designed for large, multi-region advertisers. The model decomposes marketing impact across geographic, temporal, and channel dimensions, enabling granular attribution of performance. It quantifies the short- and long-term effect of marketing activities while accounting for external and internal variables such as pricing, seasonality, and competitor activity.

The model accommodates diminishing returns, media saturation, and delayed effects using flexible adstock and decay structures. Assumptions are made explicit and transparent to clients, with a focus on interpretability. Limitations include dependency on quality of historical data and difficulty attributing impact in low-variance environments. The model is typically designed to complement other measurement tools such as digital attribution.

Model calibration and refreshing:

Calibration is performed using historical data, with model priors informed by industry benchmarks and past campaign performance. Our models are refreshed monthly, quarterly, or bi-annually depending on client needs, business cycles, and media investment cadence.

Each refresh integrates the latest data inputs and business updates, including channel shifts, competitive dynamics, and new product launches. As part of the calibration process, we generate and provide media response curves, which form the basis for scenario planning and budget optimisation. This helps clients visualise diminishing returns and informs more efficient allocation of future spend. The process is transparent and collaborative, ensuring results remain accurate, credible, and aligned to business goals.

Model validation:

Annalect applies a rigorous validation framework to ensure the credibility, robustness, and stability of its MMM models. This includes both in-sample and out-of-sample testing to assess model accuracy, as well as cross-validation where applicable. We evaluate fit metrics such as R-squared, Mean Absolute Percentage Error (MAPE), and lift accuracy, and we benchmark model outputs against known business events and actual outcomes to ensure practical reliability. We also review the stability of model coefficients over time and between geographies to verify consistency in variable importance and media effects. Scenario testing is conducted with clients to validate the realism of response curves and business recommendations.

How does your modelling approach solve for isolating which channel had an effect when there are multiple channels running at the same time?
We use a hierarchical model that leverages temporal, geographic, and media variance to disentangle channel effects, even when campaigns run concurrently.

How does your modelling approach solve for understanding if the channel spend itself caused sales to rise, as opposed to a sales period causing the marketer to increase channel spend?
We apply lag structures, external controls, and incorporate leading indicators to mitigate endogeneity, helping isolate true media impact from reverse causality.

Beyond that, we also apply practical understanding of the media ecosystem and consumer behaviour to structure models appropriately. We incorporate nested models to isolate certain channels where demand drives higher spend and redistribute attribution value to factors which drive demand rather than those that capture it.

How does your model handle seasonality and trends?
To account for seasonality and long-term trends in our MMM model, we incorporate a combination of external and internal variables that influence baseline performance over time.
Specifically:

- Seasonality is captured through:
  - Public holidays and key calendar events that may drive spikes or dips in consumer behaviour.
- Macro and market trends are modelled using:
  - External trends metrics, such as Cash rate, CPI (Consumer Price Index), and CCI (Consumer Confidence Index) – which reflect broader economic conditions that may influence purchasing behaviour.
  - Internal trends metrics, such as brand consideration – which help separate baseline growth or decline from media-driven effects.

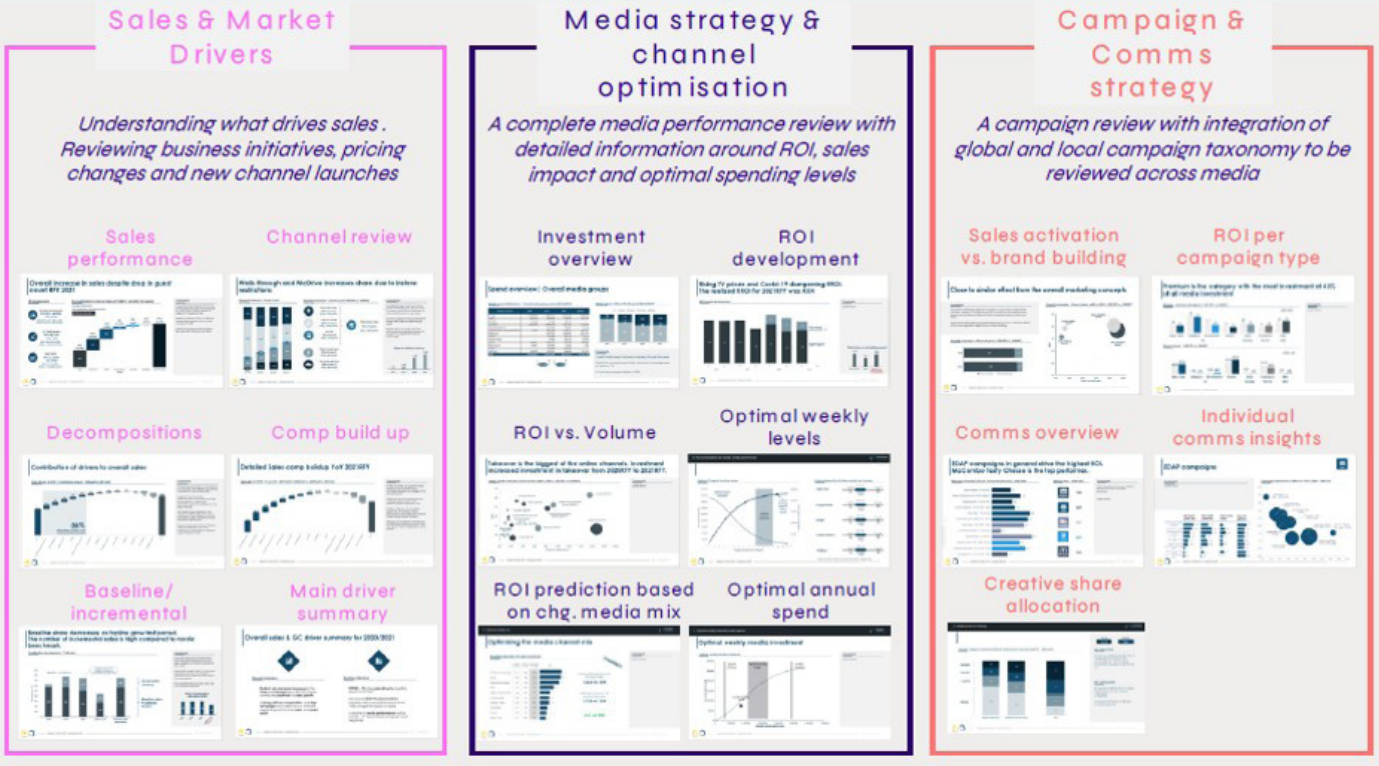
Together, these inputs allow the model to adjust for underlying fluctuations in demand that are not directly attributable to media, improving the accuracy of media ROI estimation.

How does your model deal with outliers?

We apply data scaling techniques as part of preprocessing, which helps reduce the influence of extreme values. Outliers are further identified using statistical diagnostics and validated with business context. We also run sensitivity tests to ensure model stability under various input scenarios.

How does your model handle changes in consumer behaviour?

Our models are refreshed frequently to account for shifts in consumer behaviour, and we include variables like economic indicators, competitor actions, and CRM signals where available.



Source; Annalect

Circana (formerly Nielsen MMM)

Methodology:

Circana (formerly Nielsen MMM) use econometric methods with both time series and cross-sectional variation, which, when combined with significant non-marketing variables, minimize selection bias to estimate the true causal effect of marketing. Our model form is a pooled multivariate (multiplicative) regression, including Bayesian techniques, to develop marketing mix models, where regression lines up a key performance indicator representing some level of the customer conversion funnel, whether top of funnel (e.g. awareness, consideration, purchase intent, etc), mid-funnel (e.g. leads or site visits) or bottom funnel (sales) with all paid, earned and owned media, promotions, CRM, Operational factors and external drivers (e.g., weather, economy, seasonality, Covid, etc.) and mathematically ascribes a lift factor to each of these drivers. These lift factors (aka "coefficients" or "elasticities") will define how much sales change as a result of change in each individual driver.

Using the coefficients along with values of the driver variables the model can calculate the contribution of each driver, the amount and percentage of sales that are incremental "due to" each non-marketing and marketing driver. This includes an understanding of what drives your base sales through non-media drivers.

Models will be built at the lowest level of granularity possible, in some cases location level but always with a target to have sub-national data. We firmly believe, based on investigation and rigorous testing, that granular inputs results in the best quality models. Granular level models maximize variability and also observations per coefficient, both of which provide the power to counteract the adverse effects of multicollinearity. Unless multicollinearity is present (where marketing tactics move completely or close to completely in lockstep with one another), Circana will be able to get a read on the incremental impact of each marketing investment across your media execution landscape.

As part of Circana's commitment to meeting the evolving needs of the marketplace we are excited to be transforming our Marketing Mix solution to include AI/ML principles. Our methodological transformation will position us to maintain the analytic rigor for which we are known while delivering unprecedented speed to insights while maintaining the depth of insights critical to addressing our partners needs.

Model calibration and refreshing:

A single recommendation on the update frequency of a Marketing Mix assessment would be inappropriate without an understanding of and deference to the insights needed across your annual marketing cycle. Generally speaking, models need to be updated when business dynamics have changed sufficiently so that the previous models do not completely reflect current conditions. Changing conditions could include new messaging, new tactics, new product, and dramatic shift in competitive/industry conditions, as examples. Typical Marketing Mix update cadence can vary anywhere from annual to quarterly. Circana (formerly Nielsen MMM) has a significant cohort of advertiser partners that leverage Marketing Mix insights as part of their annual media planning cycle to establish strategic spending levels across media tactics. That said, we have advertiser partners with insight needs that dictate a more frequent cadence. Needs associated with more frequent updates typically fall in one of two categories; either there is a need to understand the specific performance of new, unique campaigns executed in a specific period of time (updating effectiveness and ROI measurement) or in support of business reporting cycles (decomposition of sales performance to provide common understanding of drivers of growth/decline). In the latter instance we recommend bi-annual or quarterly model recalibrations which are essentially an update of the initial annual full model engagement.

Model validation:

Circana (formerly Nielsen MMM) ensures that models are robust and predictive via a rigorous model fit protocol. Model selection is primarily based on holdout testing. This is because, we believe, model performance against data the model has not seen is the very best indicator of the ability to make models predictive. Circana applies formal validations to all models, including but not limited to, standard fit diagnostics such as R2, mean absolute percent error (MAPE), and Durbin-Watson, ranked error terms based on magnitude, observations per variable and multicollinearity diagnostics.

Holdout testing:

- Models validated based on fit and predictive power in holdout samples
- In-sample R2 alone not a reliable indicator of model quality - perfect fit possible with random numbers
- Good holdout sample fit is a requirement for model's ability to predict future sales

Additional diagnostics:

- Standard fit diagnostics such as R2 and mean absolute percent error (MAPE)
- Checks for multicollinearity (e.g., Variance Inflation Factor)
- Time-series plots of actual, predicted, and residual values
- Use of theory and reasonableness of driver coefficients, media decay rates, and return on investment measures.

Specific diagnostics we do produce with their cut off values are:

- MAPE - Holdout (10% of sample) no more than 50% greater than in Sample.
- R-Sq - Greater than 90%
- Durbin Watson - Between 1.5 and 2.5
- Ratio of observations to coefficients (no less than 10 with 30-70 preferred)
- Fit Charts - Visualization
- VIF - Less than 5

The Circana (formerly Nielsen MMM) process is not a "black box" and we are transparent in terms of model methodology, model diagnostics and discussing results. We can provide any model statistics or details on your specific functional form that you may request. The only thing that we cannot share is our source code.

How does your modelling approach solve for isolating which channel had an effect when there are multiple channels running at the same time?

Circana's Market Mix Modelling approach (formerly Nielsen MMM) uses several statistical techniques to isolate the effects of multiple marketing channels running simultaneously. Some common approaches used to address this challenge:

- ***Multivariate Regression Analysis:*** This is a core technique in MMM that allows for the simultaneous estimation of multiple variables' effects on sales or other KPIs. It helps in parsing out the individual contributions of different marketing channels.
- ***Time-lagged Variables:*** By incorporating lagged variables, the model can account for the fact that marketing efforts may have delayed effects on sales, helping to distinguish between channels with immediate versus longer-term impacts.

- ***Interaction Terms:*** These are included to capture how different channels might work together, either amplifying or diminishing each other's effects.
- ***Adstock Modeling:*** This technique accounts for the diminishing returns of advertising over time, which can help differentiate between channels with different decay rates.
- ***Bayesian Techniques:*** These can be used to incorporate prior knowledge about the effectiveness of different channels, helping to produce more stable estimates when data is limited.

How does your modelling approach solve for understanding if the channel spend itself caused sales to rise, as opposed to a sales period causing the marketer to increase channel spend?

Circana's Market Mix Modelling approach (formerly Nielsen MMM) addresses this challenge of causality versus correlation through several sophisticated techniques:

- ***Time-lagged analysis***: Circana models incorporate time lags between marketing activities and their effects on sales. This helps distinguish between immediate sales lifts and delayed impacts of marketing spend.
- ***Base vs. incremental separation:*** The models separate base sales (what would have happened without marketing) from incremental sales attributed to marketing activities. This helps isolate the true impact of marketing spend.
- ***Control for external factors:*** the approach accounts for various external variables like seasonality, competitor actions, economic indicators, and other market forces that could influence sales independently of marketing spend.
- ***Historical data analysis***: By analysing long-term historical data, the models can identify patterns and relationships between marketing spend and sales across different time periods and conditions.
- ***Granular data examination:*** Circana looks at data at a very granular level (e.g., weekly or daily) to better understand the precise timing of marketing activities and sales changes.
- ***Econometric techniques:*** Advanced statistical methods are used to establish causal relationships and control for endogeneity (the possibility that sales expectations influence marketing spend decisions).

- ***Holdout testing:*** When possible, Circana may use holdout tests or experiments where marketing spend is intentionally varied in certain areas or time periods to directly measure its impact.
- ***Cross-channel effects:*** The models account for how different marketing channels interact and influence each other, providing a more holistic view of marketing impact.
- ***Diminishing returns analysis:*** By examining how the effectiveness of spend changes at different levels, the models can identify when increased spend is driven by sales versus when it's driving sales.
- ***Bayesian inference:*** This statistical approach allows for the incorporation of prior knowledge and uncertainty, which can help in distinguishing between correlation and causation.

By combining these techniques, Circana's MMM approach (formerly Nielsen MMM) aims to provide a robust understanding of the causal relationship between marketing spend and sales, rather than just identifying correlations. However, it's important to note that while these methods significantly improve the ability to determine causality, absolute certainty is challenging in complex market environments.

How does your model handle seasonality and trends?

Circana's preferred approach (formerly Nielsen MMM) is to use category sales to create a seasonal index to control for seasonal trends along with holiday dummy variables. When category sales are not available, we would use Fourier Series terms as an alternative.

How does your model deal with outliers?

Circana (formerly Nielsen MMM) has an extensive list of automated data checks that include outlier identification, missing data, misaligned data, wrong format, etc. In addition, our experienced consultants review all data based on their experience to ensure all streams are robust given our knowledge of the industry. Finally, we have a data review session with the client and agency partners to collectively sign off on data quality.

If data is missing or imperfect, we will try to find a substitutable proxy data stream. If not feasible, Circana will help put a data collection plan in place to ensure that the correct data is available during the next model update.

How does your model handle changes in consumer behaviour?

Circana (formerly Nielsen MMM) custom builds all models. Circana has an R&D team with dedicated resources and has established best practices for all clients in order to properly isolate the impact of changing consumer behaviours. To maintain model precision in a constantly changing time, we account for multiple impacts to avoid model bias. The best example of this was during the COVID pandemic. Some factors accounted for include:

- The impact of reduced footfall due to lock downs and resulting channel shifting
- Shifts in Media Consumption Behaviour & Competitive Intensity / Swings in CPM & CPP
- Declining Consumer Confidence / Increased Unemployment
- New campaigns/promotions that were created post the start of Covid
- Structural breaks in campaign/pricing/promotion performance pre and post the start of Covid
- A "New Normal" in the Mid to Long Term

Using our patented methodology, we will identify response curves for each marketing tactic using effective frequency, marketing vehicle penetration rate, and half-life parameters for each vehicle and campaign in scope. We directly estimate the response curves within the modelling process, rather than afterwards. This results in better fit and better forecasting. We empirically test both C and S-shaped curves and select appropriate curves using a combination of model fit and plausibility based on known penetration of the media employed. The way that we parameterize our response curves is directly tied to consumer behaviour.

Gain Theory

Methodology:

Gain Theory delivers comprehensive solutions that provide short, mid, and long-term impact across all business drivers. Our methodology is built on a foundation of advanced analytics, proprietary technology, and deep industry expertise, ensuring our clients can unlock growth and impact through optimized marketing and broader business investments.

Gain Theory's Marketing Mix Modeling (MMM) captures direct and indirect impacts on sales and complex interactions. Our proprietary analytic platform, Rova, leverages machine learning and AI techniques to drive speed and enhance insights. For most brands, we employ a Bayesian statistical methodology for MMM, which offers improved model quality and greater speed to insight. Bayesian approaches effectively utilize prior information related to the model and explanatory factors, which is especially important when data is sparse or when dealing with new market conditions.

Gain Theory's MMM offer features several powerful extensions:

- Integrated Marketing Response: A nested modeling framework that analyzes marketing impact across the full consumer funnel, from equity to conversion.
- Unobserved Component Modeling: Assesses how marketing impacts have driven longer-term KPIs, beyond immediate sales.
- Gain Theory's AdModel™: Enables measurement and recommendations of media in the common media currency used by media planners (reach and frequency), facilitating seamless integration with media planning processes.
- Gain Theory's Sensor™: A granular modeling approach that provides MTA-like results without the need for user-level or PII data, offering detailed tactical insights while respecting privacy.

These extensions can be fully unified, enabling measurement and optimization capabilities for both granular tactical and holistic strategic objectives, across short-, medium-, and long-term horizons.
Model limitations include the reliance on historical data, potential for multicollinearity, and the inability to capture real-time effects without continuous updates. We mitigate these limitations through continuous monitoring, foresight projections, robust validation techniques, and a collaborative and transparent approach with our clients.

Gain Theory's broader HiFusion framework integrates our advanced Marketing Mix Modeling (MMM) with other powerful techniques like testing, war gaming, and scenario planning. This holistic approach allows us to not only answer "What Happened?" (Hindsight) and "Why Did It Happen?" (Insight) but also to predict "What Will Happen Next?" and guide "What Should Happen Next?" (Foresight), providing a complete decision-making ecosystem for our clients.

Model calibration and refreshing:

At Gain Theory, models can be refreshed as often as clients require, with options for annual, bi-annual, quarterly, monthly, and even weekly updates. Our recommended model cadence is tailored to the client's decision-making timelines, their capacity to implement changes, and the stability of the markets in which they operate.

Our model update methodology typically involves updating all data sets within existing models as well as including data for any new events or activities. The model is now extended to include all of the new periods which the model is now trained over, and new activities and/events are tested and included in the models where found to be significant.

At all stages we follow a rigorous validation process that includes

- ***Data QA Assessment:*** We have a dedicated data team that performs an initial QA to ensure data meets expectations, followed by the application of customized business and QA rules.
- ***Client Validation:*** We verify the processed data with the client team and/or respective data providers.
- ***Statistical Techniques:*** We apply statistical techniques and vast historical business experience to validate the data.
- ***Stress Testing***: Models are developed in accordance with client objectives and stress-tested to ensure they represent real world consumer behaviour and predictability. Part of this stress testing includes using hold-out samples for validation.

This multi-faceted approach ensures that our models are accurate, reliable, and aligned with our clients' business objectives.

Model validation:

Gain Theory uses a rigorous, multi-faceted approach to verify and validate its MMM and attribution models, ensuring accuracy, reliability, and actionability. This process includes three key steps:

1. ***Statistical Diagnostics:*** A Bayesian approach underpins model validation, with diagnostics grouped into four categories:

    - Model Convergence: Ensures the Bayesian model converges to stable solutions (e.g., R-hat, Trace-plots, outlier analysis).
    - Comparison of prior and posterior distributions to ensure that "cohort effects" are dealt with appropriately – eg where we shift state of nature from low to high back to low price inflation we might see multi-modal distributions on price elasticities.
    - Variable Inference: Confirms sensible variable relationships and assesses sensitivity to priors (e.g., High Density Intervals, Prior sensitivity).
    - In-Sample Fit: Evaluates how well the model explains historical data without overfitting (e.g., Bayesian R^2, Residual Analysis).
    - Out-of-Sample Prediction: Tests the model's ability to generalize to unseen data (e.g., Leave-One-Out Cross Validation, K-fold testing).
2. ***External Validation:*** Outputs are compared to external research and broader industry benchmarks. For example, last-click attribution results can be cross-referenced with performance and brand media impacts for alignment.
3. ***Business-Sense Inferences:*** Model outputs are evaluated against expectations derived from stakeholder engagement and analytics expertise. Key factors influencing sales—such as large promotions and seasonal peaks—are expected to outweigh brand media within a given week. If model inferences contradict these expectations, further investigation and stress testing are conducted.

Throughout this iterative process, models are adjusted and re-evaluated until robust results are achieved. Gain Theory emphasizes transparency, collaborating closely with clients to ensure they understand model assumptions, limitations, and biases. Workshops with client data science teams are also offered to facilitate evaluation and understanding.

How does your modelling approach solve for isolating which channel had an effect when there are multiple channels running at the same time

- ***Induce / maximise variation in the data:*** For example, first differences, YTYD, regional share of national can all help mitigate multicollinearity
- ***Bayesian Modelling:*** Flexible and agile, addressing media fragmentation and multicollinearity.
- ***Nested Modelling:*** Measures direct and indirect marketing effects on sales.
- ***AdModel:*** Incorporates reach and frequency data for cross-channel analysis.

How does your modelling approach solve for isolating which channel had an effect when there are multiple channels running at the same time?

Gain Theory disentangles causality from correlation in marketing spend and sales using:

- ***Lagged Variables:*** Assessing past spend's impact on current sales.
- ***Instrumental Variables:*** Isolating causal effects by addressing endogeneity.
- ***Granger Causality Testing:*** Identifying predictive relationships between spend and sales.
- ***Expert Insights:*** Leveraging business context to refine models.

How does your model handle seasonality and trends?

Gain Theory's models capture seasonality and trends to analyse sales drivers using:

- ***Application of a year-to-year transformations to strip out seasonality.***
  Fourier transformation: Harmonic Regression for seasonal cycles with sine and cosine.
- ***Decomposition:*** Separating datasets into trends and seasonal indices.
- ***Moving Baselines:*** Assessing short-, mid-, and long-term explanatory variables.

How does your model deal with outliers?

Gain Theory ensures model accuracy by addressing outliers through:

- ***Data Validation:*** Identifying errors, missing values, and unusual patterns.
- ***Statistical Checks:*** Detecting outliers using distribution analysis.
- ***Expert Review:*** Flagging anomalies linked to real-world events.
- ***Robust Regression:*** Using techniques less sensitive to outliers, like Huber regression.

This ensures reliable insights.

How does your model handle changes in consumer behaviour?

Gain Theory's models adapt to evolving consumer behaviour through:

- ***Time Sets:*** Splitting data into cohorts when stationarity is violated.
- ***Time-Varying Parameters:*** Capturing shifts in price elasticity and ad effects.
- ***Regular Updates:*** Ensuring accuracy.

This dynamic approach preserves model integrity and reflects market changes.

Source; Gain Theory

Google Meridian

Methodology:

Meridian, Google's open-source MMM, employs a Bayesian causal inference framework through a single-equation regression model to estimate the impact of marketing activities (paid media, organic media, and non-media treatments) on key performance indicators.

Meridian is a hierarchical model which enables more efficient data modelling, reducing error in estimates (Sun, et al. 2017). Meridian allows for both national level and Geo-level modelling depending on advertiser's need. Geo-level data is the most commonly used hierarchical level modelled in Meridian.

Meridian's regression model incorporates non-linear transformations like Adstock for lagged media effects and the Hill function for saturation. Meridian uses full joint posterior inference, estimating Adstock and Hill parameters simultaneously with other model parameters (including trend and seasonality).

Confounding variables are key in causal inference, and Meridian identifies Google organic query volume (GQV) as an important confounding variable for paid search ads. Meridian recommends including GQV as a control variable to account for the correlation between inherent demand and ad spend.

A strength of the Bayesian approach is its ability to incorporate prior knowledge about media performance (Zhang, et al. 2024). Meridian offers ROI as a parameter within the model, enabling the direct setting of priors based on evidence from incrementality experiments – the gold standard for causal measurement – industry benchmarks, previous analyses, and domain expertise.

Meridian also offers the option to model video channel effects using reach and frequency data (instead of impressions), yielding optimal frequency as an output and linking outcomes to planning (Zhang, et al. 2023).

Model calibration and refreshing:

Meridian makes model calibration simple by using Bayesian inference and offering ROI as a model parameter. Since ROI is a model parameter, a prior can be set directly on ROI, allowing one to incorporate prior knowledge into the model. Prior knowledge can be derived from incrementality experiments, industry experience, previous analyses, or domain expertise. ROI based priors are the default for Meridian.

However, Meridian offers alternative ways to incorporate priors to provide further flexibility to the modeler:

- Channel contribution priors
- mROI priors
- Regression coefficient priors

Meridian can be updated and refreshed on a frequency that aligns with a business' available data and decision-making timeline, with quarterly refreshes being most common. As one refines their model over time, consider adjusting priors as your understanding of media effectiveness evolves.

Model validation:

Meridian assesses the accuracy and reliability of its models through several key methods. First, it is necessary for the model to converge. This is evaluated using the Gelman-Rubin (R-hat) statistic. Goodness-of-fit is examined by reporting metrics like R-squared, MAPE, and wMAPE using both in-sample and out-of-sample data. Users should also consider the reasonableness of the model outputs. For example, users should confirm that ROI inference is reasonable and that the baseline doesn't have a high probability of negative baseline.

Meridian is open-source and published alongside comprehensive technical documentation, so consultants, modelers, and auditors are able to review and validate Meridian. As one example, Google has launched a global Meridian Partner Program of agencies and 3P vendors who are trained & certified experts in Meridian methods. All of these independent partners can help marketers understand, validate, and deploy Meridian.

How does your modelling approach solve for isolating which channel had an effect when there are multiple channels running at the same time?

Meridian is a causal inference analysis based on observational data, where multiple channels often run concurrently. Regression isolates the effect of variables and thus estimates each channel's effect. With careful consideration of assumptions, control variables, and experiment-based priors, the effects can be interpreted as joint causal effects.

How does your modelling approach solve for understanding if the channel spend itself caused sales to rise, as opposed to a sales period causing the marketer to increase channel spend?

Meridian is a causal framework that directly addresses this challenge. It requires identifying and including confounding variables that influence both the decision to increase ad spend and sales. With careful consideration of assumptions, control variables, and experiment-based priors, the effects can be interpreted as the causal effect of the channel spend on sales, not the reverse.

How does your model handle seasonality and trends?

Meridian models seasonality and trends with time-varying intercepts (using "knots"). Meridian estimates time-varying intercepts concurrently with all other parameters, ensuring trend and seasonality are properly accounted for in the causal inference of treatments. Users can tune both knot count and location, thereby balancing the bias-variance trade-off (more knots reduce bias but increase variance).

How does your model deal with outliers?

Meridian utilizes priors to probabilistically guide the range of possible outcomes. This balances existing knowledge with observed data, mitigating outlier influence. These priors act as a regularization mechanism, preventing models from overfitting to noisy data, improving generalizability, and limiting extreme or unrealistic outcomes.

How does your model handle changes in consumer behaviour?

Changes in consumer behaviour can affect inference if they are confounding variables. Confounding variables are accounted for in Meridian as control variables. Google Query Volume is one important confounder for search ads. Changes in consumer behaviour that cannot be measured with control variables are subsumed into trend and seasonality effects.

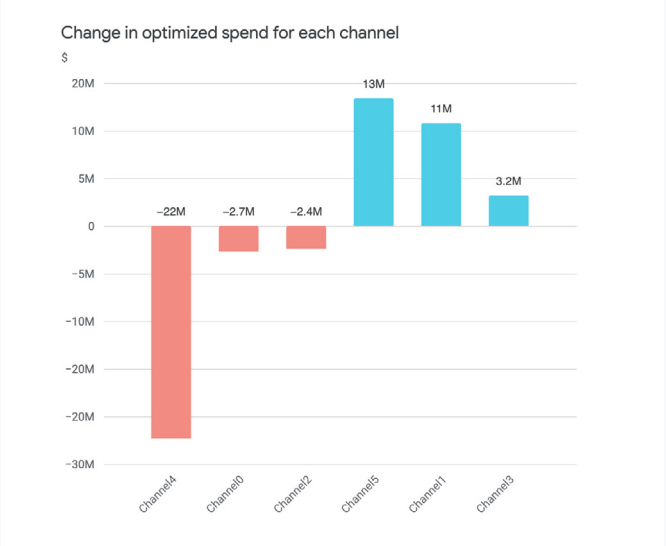


Image courtesy of Google

Kantar

Methodology:

Kantar's LIFT ROI platform employs machine learning-based Bayesian hierarchical modelling to develop a modern, scientifically grounded approach to Marketing Mix Modelling. This approach complements classical mechanistic modelling by reflecting the real-world interactions observed across media, marketing, business activities, and external factors.

The platform uses the No-U-Turn Sampler (NUTS), a variant of the Hamiltonian Monte Carlo algorithm, which is particularly effective for Bayesian inference in hierarchical models. This enables stable, scalable estimation across large, complex datasets.

Once the model is fitted, LIFT ROI supports budget optimisation by identifying the media investment allocation that maximizes return. This is achieved using Adaptive Moment Estimation (ADAM), a form of stochastic gradient descent known for rapid and reliable convergence to optimal solutions.

The model provides granular insights across digital, offline, and owned channels, and integrates non-media drivers such as pricing, promotions, distribution, competitive dynamics, and macroeconomic trends. It supports full-funnel measurement and impact assessment across short-, medium-, and long-term horizons.

Scenario planning and simulations are fully supported, and the platform can generate specific media recommendations by channel, publisher, and campaign type—including daily or weekly spend levels. Business rules and constraints can be applied to reflect operational realities.

Model assumptions include diminishing returns, lagged effects, and the separation of media and base trends. Limitations relate to the quality and granularity of historical data, and reduced precision when modelling new or rare activities.

However, there are limitations to the model. It may not fully capture sudden changes in consumer behaviour or external factors (ie that are not already in the model) that significantly impact sales. Additionally, the accuracy of the model depends on the quality and completeness of the input data. The framework requires two years-worth of data across all input variables. Despite these limitations, the Kantar LIFT ROI MMM product provides valuable insights and helps optimise marketing strategies for better business outcomes.

Model calibration and refreshing:

The frequency of analysis is determined by the cadence of model updates and refits.

Model updates involve adding new time-period data to the existing structure without altering the model's variables or adding new media channels or publishers. These are used to keep the model current and track emerging trends.

Model refits involve re-estimating parameters to reflect real-world dynamics such as changes in media effectiveness or consumer behaviour. Refits may include new publishers or business variables but typically retain the same model structure. These updates ensure the model adapts to changing conditions and maintains predictive accuracy.

Kantar's LIFT ROI platform is particularly well-suited to frequent updates and refits. Built on Bayesian methods, our models are inherently ideal for continuous refitting. They can efficiently incorporate new data while preserving prior learnings, ensuring model stability and sensitivity over time.

We typically recommend monthly data updates paired with quarterly refits, or more frequent cycles (e.g., weekly updates with monthly refits) depending on business decision-making cadence and data availability. The platform supports automated data ingestion and version control, enabling fast recalibration and reliable performance over time.

Model validation:

We automatically generate a comprehensive Model Diagnostics Report each time a new model is released, or an existing model is updated or refitted. This report provides full transparency into model structure, performance, and diagnostic outputs, helping clients assess credibility, robustness, stability, and accuracy of results. Where available, we calibrate to independent incrementality experiments to further align Bayesian priors with caudal ground-truth.

We use a combination of classical and Bayesian validation techniques:

Model Fit & Accuracy:

We assess in-sample fit using R-squared, MAPE (Mean Absolute Percentage Error), MAE (Mean Absolute Error), and residual correlation. For out-of-sample validation, we use hold-out testing with R-squared and MAPE to evaluate predictive performance on unseen data. ROI inspection, including Max ROI Ratio (actual vs. theoretical maximum ROI), provides a reality check on result plausibility.

Effect Attribution & Business Relevance:
We assess the split between direct effects and synergies to ensure the model reflects true media interactions, not just statistical artefacts. These insights improve stakeholder trust in tactical and strategic recommendations.

Bayesian-Specific Diagnostics:
To ensure statistical stability, we conduct MCMC convergence tests such as Gelman-Rubin (R-hat), Geweke diagnostics, Bayes R-squared (model explanatory power), Effective Sample Size (ESS), and inspection of trace plots. These tests confirm the reliability of parameter estimates and the overall robustness of model inference.

Clients are supported with clear interpretations of all diagnostics. Where needed, results can be reviewed with independent experts or third-party auditors to provide an added layer of validation and assurance.

How does your modelling approach solve for isolating which channel had an effect when there are multiple channels running at the same time?
One of the many benefits of Bayesian methodology, is the ability to account for synergies between channels. The algorithm is set up to read data in small batches, and therefore the weekly / daily movement of each channel is examined, disentangled, and measured independently, avoiding channel conflict issues.

How does your modelling approach solve for understanding if the channel spend itself caused sales to rise, as opposed to a sales period causing the marketer to increase channel spend?
Our modelling accounts for many variables outside of marketing investment, which helps to account for non-marketing-driven changes. This includes holidays, market trends, seasonality, macroeconomic etc. So for example, we can disentangle the impacts of Christmas marketing from the seasonal effects of Christmas.

How does your model handle seasonality and trends?
Our solution includes seasonality / holiday / macro factors as inputs, which very often accounts for a lot of the non-marketing factors. Where available we also build in Brand, which often accounts for changes in trends, or we work with our customers to identify any overall market / industry / category consumer trends that exist.

How does your model deal with outliers?
LIFT ROI utilises the Interquartile Range (IQR) to detect outliers, identifying data points that significantly deviate from the central range and isolating anomalies for robust analysis. Integrated with holiday data, it distinguishes between genuine anomalies and holiday effects, ensuring heightened accuracy and superior analytical outcomes. Empowering streamlined data-driven decisions continuously.

How does your model handle changes in consumer behaviour?

Our MMM models include the following data: creative effects, sponsorship data, competitors (media, pricing, promos), PR, organic social activities, CRM / DM, organic and direct website traffic, market trends, technical distribution, industry factors, brand data when relevant and available. This comprehensive approach ensures that changes in consumer behaviour are robustly accounted for and lead to well-rounded, actionable insights.

Lifesight

Methodology:

At Lifesight, our Marketing Mix Modeling combines structural causal modeling, regression-based machine learning, and ensemble forecasting—blending the rigor of causal inference with the power of modern ML. This approach unifies robust inference with accurate forecasting, enabling brands to measure and optimize the true impact of their marketing investments.

We begin by mapping variable relationships into a Causal Graph (e.g., how top-funnel activity influences bottom-funnel outcomes) and validate these assumptions using causal discovery techniques. Guided by this structure, we run multi-level nested regression models to infer true incrementality.

To address multicollinearity among highly correlated channels, we apply ridge regression, ensuring stable and interpretable coefficients. Adstock transformations capture lagged and carryover effects, while Hill functions model nonlinear saturation—reflecting real-world diminishing returns, where doubling spend does not double impact. This enables us to disentangle overlapping campaigns and capture how marketing actually drives results over time. Lifesight also adopts a bootstrapping technique to recover stable coefficients from a pool of highly converged models - this guarantees recovery of coefficients within a certain confidence interval.

We then combine the inference from the machine learning model to adjust forecasts generated by an ensemble forecasting technique - we call this incrementality adjusted forecasting.

All input data is categorized into four groups:

- Paid Marketing: Media with direct spend (e.g., TV, social, search).
- Contextual Variables: External factors like GDP, weather etc.
- Organic Variables: Non-paid efforts such as organic impressions.
- Halo Variables: If some spend variable is indirectly affecting the KPI (like Amazon spend driving D2C revenue)

Our models support a wide range of KPIs—revenue, installs, leads, and more—and are calibrated with experimental data, post purchase survey and market research insights, when available, to enhance causal validity.

Common assumptions include consistent data quality, stable baseline trends, and that modelled relationships reflect real world media effects. Limitations include sensitivity to input data quality and the need for regular refreshes to maintain accuracy.

At Lifesight, we believe measurement is a continuous process—refined through new data ingestion, data and model refresh, drift monitoring, calibration with experimentation and model retraining. We support weekly model refresh and also offer seamless measurement orchestration between causal models, experiments and causal attribution.

Model Calibration and Refresh:

Model refresh: Model refresh is the process of ingesting new data to the model to check the robustness of model coefficients and validate the accuracy of prediction. If the new data diverges from the model's expectation, we need to calibrate or re-build the model. Refresh cadence is user-defined. If daily models are created, a weekly refresh cadence is recommended. If weekly models are created, a monthly refresh cadence is recommended.

Calibration: The source of calibration can be any form of incrementality testing done on or off the Lifesight platform. The iROAS or iCPA from these tests is used to calibrate an existing model or when creating a new model

1. Holistic Calibration: Hyper-parameters are picked to minimize the distance between MMM-inferred incrementality and the actual Causal incrementality obtained from the experiment. This acts similar to setting a prior and retraining the model. This method is used when the calibration period is outside of the model's training window or if the calibration is based on "Go Dark" experiments, when the spend for the period of testing for the whole platform is zero. It is also used for new channels (or channels that have zero or near-zero contribution in the model)

2. Contextual Calibration: This is the recommended approach to calibration (wherever possible). In this approach, Lifesight's calibration function minimises the distance between MMM-inferred incrementality and the actual Causal incrementality for the specific period of testing. This method is used when the calibration period is within the training period of the model.

Model validation:
Lifesight uses bootstrapping to introduce confidence intervals for iROAS and iCPA metrics by:

- Finding Optimal Models: Lifesight calculates optimal models, identifying models that strike the best balance between accuracy and generalisability.

- Clustering Models: Using clustering techniques such as K-means, Lifesight identifies groups of models with similar hyperparameters. This ensures that each cluster represents a set of models with comparable behavior across channels.

- Bootstrap Sampling: For each cluster of models and for each channel, Lifesight performs bootstrap resampling on the calculated ROIs.

Standard validation metrics include:

- Estimation Error (Predicted vs Actual)

- NRMSE
  > Measures the model's overall error
  > Crucial for assessing model quality

- CIDI (Channel Impact Divergence Index)
  > Quantifies the allocation of effects between different marketing channels
  > Indicates how "radical" the model's recommendations are
  > Lower values suggest more balanced channel impact predictions

Other than that, we also divide the data into training and validation sets. The training data is used to train the model, and the validation data is used to evaluate the model's accuracy. Higher accuracy on the validation set generally indicates a better model for forecasting.

To validate the MMM model, clients can forecast on data not exposed to the model so far and check if the actual and predicted revenue are matching. Clients can also adopt our budget recommendations partially and see if the results are good.

Incrementality Testing (Geography-Based)

Lifesight enables marketers to design and deploy high-power, high-velocity experiments directly within advertising platforms to calibrate MMM. This empowers organisations to build a culture of experimentation and uncover causal insights at scale to improve the accuracy of marketing mix models and overall marketing efficiency.

Our methodology is based on a multi-objective augmented synthetic control framework. This allows for the concurrent execution of robust experiments to measure the incremental lift of specific channels, tactics, audience segments, and creative strategies across a primary KPI and multiple Secondary KPIs.

The process begins with an analysis of historical geo-level KPI data, followed by statistical power analysis. Statistical power is a critical aspect of hypothesis testing—it represents the probability of correctly detecting a true effect between test and control groups. A high power (typically above 80%) reduces the likelihood of false negatives, ensuring that meaningful effects are not overlooked.

Based on this analysis, Lifesight generates:

- A list of recommended test market clusters and their matched synthetic control markets along with estimates for test duration, required additional spend, minimum detectable lift
- Diagnostics for synthetic control balance and potential bias

This approach ensures your experiments are not only statistically valid but also actionable for real-world marketing decisions.

How does your modelling approach solve for isolating which channel has an effect when there are multiple channels running at the same time?

1. We start by incorporating channel interaction assumptions in the causal graph. This helps us understand the right modelling approach for mediator and confounder analyses.
2. We use ridge regression applied at multiple nested levels to address multi-colinearity and isolate channel / tactic effects, modelling sales against channel activity with adstock (time lags) and control variables.
3 We support model calibration with experiment result or informed priors - we also help marketers design and deploy experiments from Lifesight platform making the process seamless

How does your modelling approach solve for understanding if the channel spend itself caused sales to rise, as opposed to a sales period causing the marketer to increase channel spend?

This is a case of demand generation spend being driven by seasonality itself — i.e., marketers decide to scale spend during certain seasons or months. Data alone won't give the model the right context to handle this (one might observe a high correlation between seasonality and top-of-funnel spend), but Lifesight's unique approach first encodes the interaction between variables into a causal DAG, validates the causal graph with observed data and then runs nested models to capture the dependence of top-of-funnel spend on seasonality. This allows the model to separate the true effect of spend from seasonality-driven patterns.

How does your model handle seasonality and trends?

Our MMM automatically extracts trends (cumulative) and seasonal components from time series data. We do additive decomposition of KPI into trend, seasonality, special events/holidays and noise. These, along with holidays, become regressors in our Ridge Regression model. This isolates the incremental impact of marketing, contextual and organic factors by controlling for baseline time-dependent variations.

How does your model deal with outliers?

During our data preparation process, we systematically handle outliers. We employ anomaly detection algorithms to identify potential anomalies, and critically, we then investigate whether these detected points are explainable by factors within the input data or known business events before deciding on the appropriate treatment. We also normalize the data before feeding them for modelling, ensuring that extreme data points do not have excessive influence on model outcomes.

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How does your model handle changes in consumer behaviour?

Consumer behaviour resets from time to time, and we believe the way it's incorporated into the saturation curve of traditional MMMs is no longer relevant in today's business context. At Lifesight, our budget optimiser assesses media saturation based on specific base periods — for example, to plan for October–December 2025, we analyse how channels and tactics saturated during October–December 2024.

This approach is more relevant than looking at cumulative saturation over the past two or three years. It also allows us to account for changes in user behaviour and how they respond to channels. Most importantly Lifesight offers the entire Incrementality system - which comprises of Structural Causal Modeling based feature selection, Ridge Regression based ML modeling, Ensemble Forecasting based prediction, Easy Design and Deployment of Incrementality experiments, Model Refresh & Validation, Model Calibration, Model Monitoring and Retraining all in one end-to-end Unified Marketing Measurements platform.

Meta Open Source - Robyn

Methodology:

Robyn is an experimental, AI/ML-powered and open-source MMM package from Meta Open Source. Being open-source, Robyn was created to democratise high quality measurement to all advertisers, irrespective of their research budgets.

Robyn's mission is to democratise modelling know-how, inspire industry innovation and contribute to the open-source marketing science community. It's designed to reduce human bias in the modelling process, improve automation and scalability. This is enabled through various techniques like:

- Multi-objective evolutionary algorithm with hyperparameter optimisation via Nevergrad - this means Robyn is optimised towards not only the statistical fit only, but on multiple objectives functions (more details in later sections). The gradient-free evolutionary algorithm provides a powerful and flexible framework that facilitates fast convergence of this novel optimization approach.
- Time-series decomposition for trend & season via Prophet, another Meta open-source package - Prophet can calculate any underlying trends or seasonality that may exist, where no additional data will be required (more details in later sections).
- Ridge regression for model fitting - Ridge regression is a statistical technique that helps to deal with multicollinearity, a common occurrence in MMMs where independent variables are highly correlated with each other (more details in later sections).

While Robyn is available to anyone to download and use, it is recommended for users to have some coding, statistical or MMM experience to get the maximum value - similar to as if you were building an MMM in-house. Alternatively, the benefit of paying for a 3rd party vendor is that they have the skills and expertise to confidently build suitable MMMs for your brand and help turn the insights into actionable recommendations.

Ultimately at Meta, we support all brands who run MMMs no matter how they are run, as we believe MMMs play an important role in anyone's measurement framework.

Model calibration and refreshing:

Calibration: A recent Meta whitepaper about Measurement 360 found that advertisers are moving beyond a single source of truth (e.g. attribution models) to a suite of trusted tools and methods to capture a more complete picture of performance. Robyn has an in-built calibration feature to ensure the incorporation of causal knowledge into the model. Meta believes this is an essential step in MMM, where an Analytic Edge whitepaper "The Value of Calibrating MMM with Lift Experiments" found that uncalibrated models show 25% average difference to the ground truth. To calibrate models produced by Robyn, it is encouraged to run Randomised Control Trial (RCT) experiments, such as Meta's Conversion Lift or Google's Conversion Lift, as they are the gold standard for measuring incrementality. Assuming these are available for an advertiser, the study results can be inputted into Robyn's calibration feature, where Robyn will add an additional objective function towards closer prediction to the actual uplift from the experiment.

Model Updates: Conventionally the model refresh cycle of MMM is bi-annual or even longer, where the time delay leads to limited actionability of MMM insights. Robyn's model refresh feature aims to solve this challenge and enables model refresh and reporting as frequently as the data allows and at the end user's discretion. It also enables MMM to be a continuous reporting tool for actionable and timely decision-making that could feed your reporting or BI tools. Robyn's model refresh feature builds on top of the selected initial model, where it selects hyperparameters from a smaller range and reduces the time taken to refresh the model. However, if there have been significant changes to the advertiser's marketing or business activities, it is recommended to not use this feature and re-build the model again.

Model Validation: Being open-source, the end user is responsible for validating the accuracy and reliability of the Robyn models. It is recommended for Robyn users to have historical MMM experience to be able to correctly validate the accuracy and reliability of the models.

To assist with this, Robyn uses Nevergrad, Meta's gradient-free optimisation platform for multi-objective evolutionary algorithms for hyperparameter optimisation. In layman's terms, Robyn aims to optimise and improve models based on multiple objectives or goals:

Prediction error: Formally known as Normalised Root Mean Square Error (NRMSE), this is a relatively standard approach to validate a model's accuracy. Robyn uses time-series validation to minimise the model's prediction error by splitting the input datasets into a train/validation/test periods:

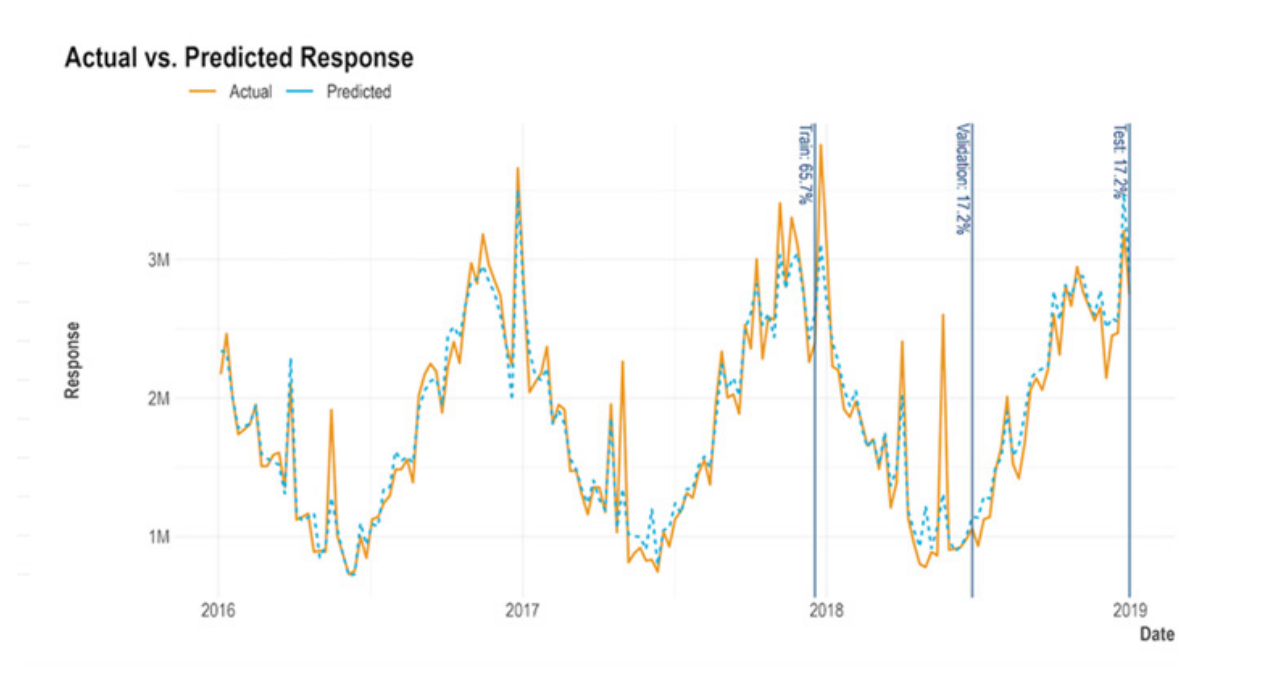


Image courtesy of Meta

In the example above, the model is built only using data from the train period (i.e. from 2016-2018). The model is then validated for its accuracy by comparing the actual vs. predicted sales on the validation period (i.e. first half of 2018). The test period (i.e. second half of 2018) is also used to assess the out-of-sample prediction error.

Business error : formally known as the Decomposition Root Sum of Squared Distance (DECOMP.RSSD), this represents the difference between share of spend and share of effect for paid media variables. If a model is produced whereby a media channel accounts for a small proportion of total media spend but has a significant contribution to sales (or vice versa), this will be picked up in this metric. While we would never expect every modelled channel to have a 1:1 relationship between share of spend and share of sales, this metric is in place to pick up models with significant outliers that don't match expectations and helps narrow down the models for final selection.

The inclusion of Business Error is a key feature of Robyn to sense check model results for its believability from a business perspective. While more emphasis should be placed on the Prediction Error when building models, having a multi-objective approach means that the business error is an additional metric to help with model selection.

Calibration error: Formally known as Mean Absolute Percentage Error (MAPE.LIFT), this is activated when Robyn models are being calibrated with experiments. In the situation that calibration is occurring, Robyn will minimise the difference between the model's predicted effect and the causal effect that has been inputted during calibration.

How does your modelling approach solve for isolating which channel had an effect when there are multiple channels running at the same time?

MMMs often encounter difficulty in isolating a channel's impact when there is multiple running at the same time (aka multicollinearity). Robyn uses Ridge regression, a technique which adds a penalty to the loss function that has the effect of reducing overfitting in test set as well as ensuring the optimal solution despite multicollinearity. This in turn helps the model find the perfect balance between all the channels.

How does your modelling approach solve for understanding if the channel spend itself caused sales to rise, as opposed to a sales period causing the marketer to increase channel spend?

The circular causality between marketing and sales is among the biggest challenges in ads measurement. There are two ways that Robyn attempts to solve for this:

- We believe the ultimate solution is to calibrate MMM through randomised experiments and thus induce true causality (see earlier section for more details);
- This is also mitigated by Prophet, a popular time-series forecast package by Meta Open Source (not connected to the MMM vendor Prophet featured in this paper). From the dependent variable data, Prophet can calculate any underlying trends and seasonality that may exist (where no additional data will be required to collect and include) and thus reduces over-attributing to marketing channels.

How does your model handle seasonality and trends?

As mentioned above, Robyn can provide trend, season, as well as holiday and weekday data via Prophet. Prophet will calculate these trends from the dependent variable data, where no additional data is required to be collected and it can automatically be incorporated into modelling.

How does your model deal with outliers?

Being open-source, it is the end user's responsibility to check input data for any potential outliers. Meta recommends doing thorough checks and validating it with other stakeholders before proceeding with modelling.

For potential model outliers, Robyn includes Nevergrad, an evolutionary algorithm that learns and improves the model as more iterations are run. The premise of an evolutionary algorithm is that of natural selection - that is, you may have a set of iterations where some combinations of coefficients that will be explored by the model will survive and proliferate, while outliers will die off and not contribute to the gene pool of further generations.

The chart below shows every model run - as the iterations increase and dots become darker, they converge towards a more accurate (i.e. lower NRMSE) model that makes more business sense (lower DECOMP.RSSD). Outlier models like in the far right will die off and aren't considered in later iterations and the model's learning.

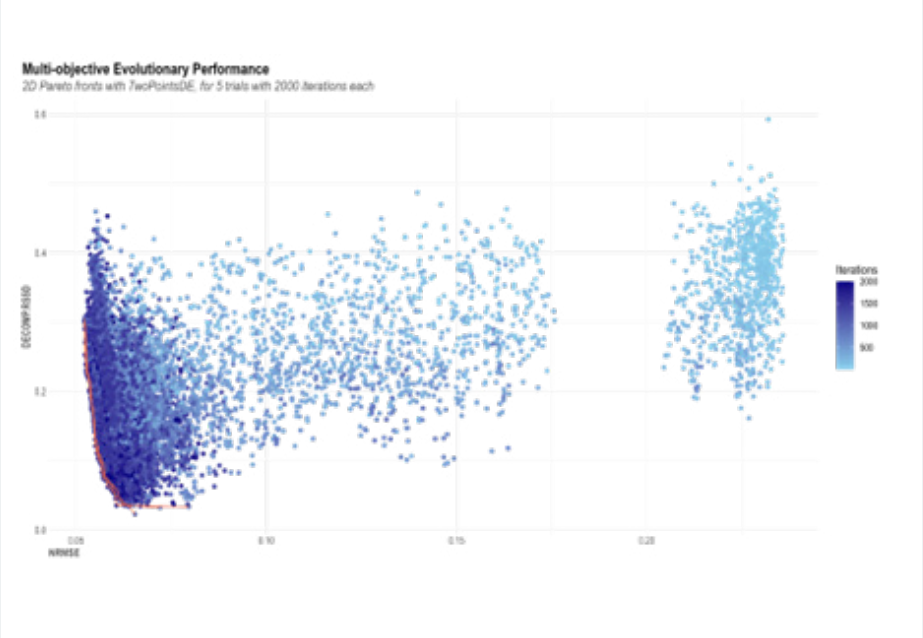


Image courtesy of Meta

How does your model handle changes in consumer behaviour?

Robyn's model refresh feature can adapt to changes in baseline and media behaviour by exploring new periods. However, it's recommended to create a new model for significant changes.
Alternatively, adding context variables (e.g., COVID-19) or using Prophet can help capture trend changes in KPIs.

Mutinex

Methodology:

Mutinex delivers insights with a proprietary generalised priors and time-varying MMM using a Bayesian Hierarchical model at its core. The Mutinex approach goes beyond media mix modelling and models the entire market mix. Measuring the impact of pricing, socio-economic events and trends as well as competitive factors to build a data representation of a company.

Rather than assuming static media performance, we incorporate time-varying parameters to reflect how ad stock and outcomes evolve with creative execution or shifts in market conditions. Time lag analysis helps identify when marketing efforts mature, allowing us to decompose sales into baseline performance, pricing and promotions, owned media, external drivers, and marketing/media contributions.

To further refine ROI insights, the model uses nonlinear submodels to isolate the roles of creative, format, publisher, and geography within each channel. Our solution is designed for continuous use.

Model trust is a core tenet of our offering. We have invested substantially in measuring the accuracy and rationality of our insights and our underlying model architecture. We proactively share this information with customers.

We aren't just a measurement tool, we are a decisions tool, a planning tool and an execution tool. Understanding when the model might be wrong or a bit off is critical when making decisions and planning. Understanding uncertainty and margins of error help our customers make better decisions. We don't hide this information.

Model calibration and refreshing:

Mutinex uses Markov Chain Monte Carlo (MCMC) simulation to calibrate the model, with robust validation techniques assessing both predictive accuracy and model reliability. This includes holdout tests and metrics such as R-hats and MAPE to evaluate model performance over time.

We conduct counterfactual analyses to estimate media incrementality at granular levels—including creative, format, publisher, and geography. Influence curves and diagnostic metrics ensure results adhere to key marketing principles, reducing risk of misattribution and increasing confidence in model outputs.

The model is typically refreshed monthly due to data constraints and lags, although some customers opt for different refresh rates depending on data availability. Our Bayesian updating framework naturally incorporates new data over time, meaning prior insights are updated in light of emerging evidence. This continuous refinement allows customers to keep pace with evolving market conditions and consumer behaviours.

We consistently monitor model stability and accuracy with our suite of governance metrics and refine/adjust when we see things are going off track. Should model stability, hold-outs or governance fail we automatically trigger re-training of the entire model spec with a new range of stability, hold-out, in-sample and co-linearity tests applied.

Model validation:

At Mutinex, model validation is central to ensuring trust in our outputs. Our primary approach involves a rigorous holdout validation process—where a portion of historical data is intentionally excluded from model training to test the model's predictive accuracy on unseen outcomes. This simulates real-world conditions and builds confidence in the model's forecasting capabilities.

In addition to holdout tests, we apply a suite of statistical diagnostics—including R-hat convergence statistics and Mean Absolute Percentage Error (MAPE)—to evaluate estimation stability and precision. These metrics enable us to assess how well the model reproduces observed outcomes and identify areas for potential improvement.

We welcome third-party review and collaboration with independent consultants should customers wish to gain additional assurance. Our transparent validation approach has been successfully reviewed across multiple industries, helping customers build internal confidence and alignment around MMM findings. We share the code for our testing protocols to third parties so our approaches can be validated properly and robustly.

How does your modelling approach solve for isolating which channel had an effect when there are multiple channels running at the same time?

Our unified Bayesian framework estimates the effect of all marketing channels concurrently, while accounting for uncertainty. To isolate the impact of individual channels, we conduct rigorous counterfactual analyses—simulating what sales would have looked like in the absence of a given channel.

Example: When Channels X and Y are active simultaneously, we model the hypothetical outcome had only Channel X run. If observed sales exceed this prediction, the model attributes incremental value to Channel Y.

How does your modelling approach solve for understanding if the channel spend itself caused sales to rise, as opposed to a sales period causing the marketer to increase channel spend?

To assess causality, our model evaluates how sales would have behaved under different marketing spend levels using counterfactual scenarios. If sales increase during a period of high media investment—and the model shows that lower spend would have resulted in lower sales—it provides strong evidence that the marketing activity drove the observed uplift, rather than being a response to it.
Iterative simulations focus the model onto the scenarios of highest confidence.

How does your model handle seasonality and trends?

Rather than relying on abstract mathematical decompositions (e.g. Fourier transformations), our model incorporates real-world seasonal drivers such as weather and annual events. This reduces misattribution and improves model interpretability. In parallel, our library of over one million macroeconomic signals captures both short- and long-term market trends, allowing us to accurately separate media impact from broader economic effects.

How does your model deal with outliers?

Our Bayesian model structure inherently accommodates uncertainty and applies regularisation through prior distributions. This reduces the influence of anomalous data. For example, if a sales spike occurs alongside a media spike, but the magnitude of change is statistically improbable, the model adjusts attribution accordingly and discounts the outlier.

How does your model handle changes in consumer behaviour?

All media effects are modelled as time-varying, enabling the model to capture evolving performance over different periods. This allows customers to compare the impact of campaigns across time, geographies, or contexts.

Additionally, over 1,000 external sources—including macroeconomic and behavioural data—are incorporated to isolate media impact from broader changes in consumer behaviour. This collates to over 360,000 data points that sit in our external MMM.

Many brands underestimate the importance of embedding MMM into regular decision-making cycles. MMM delivers the greatest value when used continuously—to inform budgeting, planning, and optimisation—not just as a one-off analysis. We find it is very important the brands be bought into making decisions leveraging data before they decide to buy MMM.

Prophet

Methodology:

Prophet's Market Mix Modelling (MMM) integrates advanced statistical techniques, notably Bayesian inference, ARIMA, and SEM. The model incorporates diverse data sources, including media, organisational, commercial, macroeconomic, and behavioural datasets. This comprehensive integration supports robust scenario analysis and forecasting capabilities.

Core assumptions include:

1. Marketing activities and outcomes are causally linked and measurable.
2. Historical data is obtainable, stable and reliable.
3. Variability in media spending allows for impact detection.
4. External factors, such as economic cycles or seasonal trends, can be statistically managed.

While Prophet's predictive algorithms enhance forecasting precision, accuracy is contingent upon data quality and availability. Unexpected external events or shifts in consumer behaviour may affect model performance, underscoring the need for ongoing calibration.

Model calibration and refreshing:

Prophet continuously calibrates and updates its models using live data integrations from multiple systems (over 590+ APIs from online, offline and organisational), including CRM and financial operations. Initial calibration incorporates historical data analysis to inform baseline models. Subsequently, real-time data feeds into the platform, employing machine learning for continuous improvement.

Calibration is validated through methods such as backtesting and cross-validation, ensuring model predictions align with actual outcomes. Automatic adjustments respond to campaign launches, external market shifts, and organisational changes. Regular monitoring and strategic reviews (weekly, monthly, quarterly) ensure sustained accuracy and relevancy.

Model validation:

Prophet employs a comprehensive validation approach combining statistical testing, real-world experimentation, and client collaboration:

1. ***Statistical Testing:*** Initial model assessments include diagnostics such as R-squared, Mean Absolute Percentage Error (MAPE), confidence intervals, and residual analyses. These tests evaluate model fit, predictive accuracy, and variability to ensure robustness.
2. ***Cross-validation:*** Prophet utilises cross-validation to rigorously test model performance against unseen data, mitigating risks of overfitting and ensuring model stability.
3. ***Backtesting:*** Historical data comparisons allow clients to retrospectively assess how accurately the model would have predicted past outcomes, enhancing trust and validating predictive capabilities.
4. ***In-market Experimentation:*** Real-world experiments such as controlled holdout tests isolate specific variables, providing empirical evidence of causality and the model's predictive accuracy.
5. ***Model Interpretability:*** Prophet's no-code interface provides clients with visualisation tools to understand and interrogate model outputs and drivers, supporting greater transparency and usability.
6. ***Independent Audits:*** Prophet actively supports independent third-party validation, providing full transparency of methodologies, data inputs, and assumptions, thus enabling external verification and confidence in results.
7. ***Client Collaboration:*** Regular validation meetings (quarterly) with clients review model performance, identify anomalies, and align outputs with evolving business needs and market conditions.

How does your modelling approach solve for isolating which channel had an effect when there are multiple channels running at the same time?

Prophet exploits the fact that there will be variation in spends per channel across time and location. Prophet applies advanced Bayesian inference and Structural Equation Modelling (SEM) to effectively attribute unique channel impacts. These statistical methods enable the disentanglement of channel-specific effects, even during simultaneous multi-channel campaigns, ensuring accurate attribution.

How does your modelling approach solve for understanding if the channel spend itself caused sales to rise, as opposed to a sales period causing the marketer to increase channel spend?

Prophet explicitly integrates the potential for confounding in our structural equation models. We account for both macroeconomic factors leading to greater sales, and upper funnel activity creating brand equity that lower funnel activity exploits.

Prophet leverages time-series modelling, lag analyses, and channel decomposition to rigorously separate causation from mere correlation. By evaluating spend timing relative to sales outcomes, Prophet identifies whether media spend drives results or responds to existing demand trends.

How does your model handle seasonality and trends?

Prophet employs ARIMA and time-series decomposition techniques to systematically manage seasonality and long-term trends. This approach isolates the underlying baseline performance, distinguishing the impact of marketing from cyclical and growth-related patterns.

How does your model deal with outliers?

Outliers are managed through statistical anomaly detection and robust regression techniques. Sudden, significant deviations due to external events or data errors are flagged, down-weighted, or excluded appropriately, ensuring stable, unbiased insights. Events leading to genuine spikes are integrated into our structural equation models.

How does your model handle changes in consumer behaviour?

Prophet continuously ingests real-time data and external behavioural signals, allowing dynamic model adjustments via machine learning. This enables rapid adaptation to changing consumer trends, ensuring ongoing model relevance and accuracy.

Recast

Methodology:

Recast uses a Bayesian hierarchical time-series modelling approach for Marketing Mix Modelling (MMM), setting it apart from traditional static methods. Unlike standard approaches to media mix models, which assume static relationships between marketing inputs and outcomes, Recast's model is fully dynamic, allowing for continuous learning and adaptation as marketing performance changes over time.

Key aspects of Recast's modelling approach include:

- ***Dynamic Time Series:*** The model estimates how marketing performance changes over time instead of assuming static performance.
- ***Experimental Calibration:*** The model is designed to be used in conjunction with an experimentation program in a virtuous cycle of hypothesis testing and model calibration.
- ***Testable predictions:*** Recast is designed to be explicitly testable so that organizations can build confidence through experimentation.
- ***Uncertainty quantification:*** Provides calibrated uncertainty intervals around predictions, allowing for more informed decision-making.

This advanced modelling framework enables Recast to offer real-time, continuously improving MMM insights that adapt to evolving market conditions and media investments.

Recast's underlying MMM powers a platform that includes a range of insights dashboards and reports alongside a complete suite of forecasting, optimization, and goal-tracking tools. Recast's Causal MMM is also complemented by Recast GeoLift, a platform for designing and analysing geographic-based lift tests.

Model calibration and refreshing:

Recast's models are designed to be calibrated with experimental data. Because of the underlying time-series nature of the model, Recast is able to calibrate the model with multiple experiments for the same channel conducted at different points in time.

Recast is designed to do a full parameter re-estimation and re-training on-demand, and most Recast customers set up a weekly refresh cadence.

Model validation:

Recast ensures the accuracy and reliability of its models through rigorous backtesting and post-model validation techniques. Out-of-Sample (OOS) forecast accuracy checks are exposed in the Recast app with every refresh so clients and their third-party consultants can build trust in their models over time.
The core model validation checks Recast employs are:

1. ***Parameter recovery:*** After initial model configuration, parameter recovery checks serve as an internal validity check. Parameter recovery exercises answer the question "If we simulate data where we know the true correct answer, can the model as it is currently configured identify that answer and give it back to us?"

2. ***Stability and robustness checks:*** Next, the stability loops exercise validates the robustness of a model's results. During this exercise, Recast runs the same model configuration on different subsets of the data to check how much results change when the underlying data is varied slightly. This set of tests ensures that the model's output is not overly sensitive to small changes in data, a huge problem for many MMMs.

3. ***Out-of-sample forecast accuracy:*** Out-of-sample forecast accuracy checks show how well the model can predict a KPI of interest on data that it hasn't seen before. This step helps validate the model's output, provides evidence that true causal signals have been identified, and allows clients to start building trust in their model's forecasting ability.

External validation with experiments and quasi-experiments: Internal validation metrics–like R-squared and MAPE–can be misleading in the context of MMM. Recast employs external validation methods like geographic holdout tests, on/off experiments and budget shifts to allow clients to build confidence in their models' robustness in the face of real-world changes

How does your modelling approach solve for isolating which channel had an effect when there are multiple channels running at the same time?

Recast exploits day-to-day variation in marketing activity in order to differentiate between the effects of multiple channels running at the same time.

To the extent that effects are not able to be estimated precisely due to high correlation, Recast will surface that to the brand and can recommend ways to generate more signal for the model.

How does your modelling approach solve for understanding if the channel spend itself caused sales to rise, as opposed to a sales period causing the marketer to increase channel spend?

Recast explicitly models the causal relationship between marketing channel activity and sales using probabilistic inference. These inferences are designed to be explicitly testable using experiments and quasi-experiments outside of the model itself.

How does your model handle seasonality and trends?

Seasonality and trends are handled naturally by Recast's time series model without any specific inputs. Longer term factors such as economic factors are often incorporated as contextual variables in Recast models.

How does your model deal with outliers?

Recast's Bayesian, hierarchical structure ensures that extreme data points do not unduly influence results while still allowing the model to learn from meaningful variations. There is no explicit handling of outliers required.

How does your model handle changes in consumer behaviour?

Recast's model is designed to dynamically adapt to changes in consumer behaviour in ways that traditional MMMs cannot by re-estimating the model frequently and the use of time-varying parameters.

chapter 4

market mix modelling vendor landscape

input data

A robust data collection plan for MMM is very important. The biggest hurdle to timely delivery of insights from MMM is often delivery of accurate, clean data available in the vendors required format. You will have heard the phrase, "garbage in, garbage out", it most certainly applies to MMM where data quality, volume and granularity are critical contributors to the accuracy of your model.

The pain points tend to lie in capturing adequate historical data. All data needs to be time-series data (generally daily or weekly). *Guidelines for the length of historic data required are provided by each vendor on following pages.* Generally, recommendations are for around 2 years of historic weekly data, however if daily data can be used there are options for less historic data requirements.
For MMM to obtain results that are meaningful and actionable, the marketing investment needs to reach a certain scale. While most people agree with this concept, vendors will look at case by case basis and provide guidance on minimum media spend or minimum annual revenue.

Generally, Market Mix Modelling requires historic time-series data at the most granular level possible across internal and external sources, examples below.

Internal data:

- Your dependent variable KPI: e.g. sales, revenue, conversion, active user etc
- Media variables: ad exposure, ad expenditure across all media channel used
- All other marketing and promotional activities
- Pricing data and strategies
- Product data and strategies
- Measures of brand awareness and perceptions of your brand, for example from your brand tracking study
- Creative testing scores
- Customer reviews and sentiment
- Market share data for your brand
- Consumer data, such as demographics, customer segmentation data

External data:

- Market share data and activities for your competitors
- Economic indicators
- Seasonal trends
- Any other external variables that could influence sales

Input data granularity constrains the model granularity. The more granular data the better but you will need to work with your vendor on the granularity they support. For example, media data can be supplied broken down by geography, target audience, creative, campaign, ad placement, ad format, devices, channel, media owner, campaign objective.

A typical question is how to *select the primary metric for media variables*; this is generally either media exposure metrics (e.g. impressions) or media expenditure data. Your vendor may have a preference for their models, however many vendors can support either if one is not viable. For digital media, viewable impressions is generally a good choice to describe actual ad exposure. While reach and frequency is a valid and often used indicator of ad delivery effectiveness, calculating reach and frequency across different campaigns and channels is challenging.

It would be advisable to understand with your vendor up front the responsibility for obtaining, cleaning and validating to ensure data quality. The level of support in these areas varies across vendors.

The participating vendors have highlighted *various ways their clients provide data*, typically via API, flat file (eg excel) or cloud storage service. Some vendors have data partnerships with media owners to obtain campaign data.

"Programmatic enables advertisers to buy media across channels. For MMM to reflect its impact accurately, inputs should reflect how programmatic spend is structured. That's why The Trade Desk's MMM feed helps brands succeed in this environment by offering:

> Automated, no-cost data feeds updated weekly

> Granular inputs that align with how media is actually bought (e.g., by channel, format, and buying model) and provide flexibility to adapt when strategies change

> Templatised data structures that eliminate the need to recategorize raw inputs

This approach makes it easier to analyse programmatic tactics with precision and adapt as measurement practices evolve."

- Bella Spragg, Director Data Partnerships ANZ at The Trade Desk

"We find that data readiness remains a key barrier to adoption. Granular, clean, and timely data is essential, but so is organisational alignment. Successful MMM implementations can require collaboration across marketing, finance, analytics, and IT. Assigning internal champions and investing in education around model interpretation are critical steps toward driving adoption and impact."

- James Morgan, Head of Data & Analytics at dentsu Media ANZ

"Traditional challenges with MMM include the frequency and timeliness of insights generated. As decision-making timeframes shorten, the need for MMM models to deliver timely outputs becomes increasingly important. However, marketers must remain mindful of data input availability and volatility with shorter timeframes; quick reporting timelines may not always provide the full picture and there is a need for robust data governance. Continuous feeding of high-quality data into MMM models is essential, as measurement is never a "set and forget" process."

- Lillian Zrim, Head of Research at PHD

"A fundamental strength of MMM is its ability to disentangle the impact of diverse marketing channels on marketing outcomes. However, modeling often lumps together disparate platforms into broad categories, such as grouping social media platforms under the singular umbrella. This masks the unique ROI and role that each channel plays in the consumer journey, based on the differing shares of investment and impact that each channel provides. We strongly encourage advertisers to ensure their MMM solutions provide granular, channel-level insights. Expect your models and reports to explicitly identify platform-specific ROI, and don't hesitate to push for analysis that separates out investments by media owner in both Traditional and Digital media channels. "

- Dave Goodfellow, Head of Measurement Solutions, APAC at Pinterest

Participating vendors have outlined the specifications for providing advertising and media data for inclusion in models, the key media metric/s used to run their models, the specifications for sales/revenue data required, along with the types and sources of non-media data typically used in models, such as data for other marketing activities and levers, external factors (weather, seasons, economy, competitor activity etc) and where that data is sourced from.

Guidelines for the length and granularity of historic data required and primary media metric used by each vendor is outlined in the table following.

	Historical data guidance	Key/primary media metric
Analytic Edge	For weekly datasets, 2 years of data For monthly datasets, 3 years of data	Exposure metrics like impressions, clicks, GRPs, TARPs
Analytic Partners	Time period varies depending on client but tends to be weekly. Typically, at least 18 months of data, but have done less as the need arises.	Opportunity to see metric such as TARPs, impressions, view, clicks, attention metrics, reach and frequency.
Annalect	Weekly granularity at a minimum, ideally spanning at least 2–3 years.	Impressions and clicks as the core media input.
Circana (formerly Nielsen MMM)	Minimum of 104 weeks.	Typically, Impressions for Digital and Gross Rating Points (GRPs) for Television.
Gain Theory	At least three years of historical data, however can work with as little as 18 months at the lowest granularity available (daily).	Media Ratings (eg Gross Rating Points), Impressions and Clicks, Impression Quality Metrics (eg viewability and ad attention) and Reach and Frequency.
Google Meridian	General recommendation is weekly level granularity, at least two years of data for weekly-level geo models, and at least three years of data for weekly-level national models.	A media exposure metric, such as impressions, clicks, spend, reach & frequency, etc. (impressions are more commonly used).
Kantar	General recommendation is at least two years for daily granularity and three years for weekly granularity.	Impressions, clicks, reach, frequency, and quality measures such as viewability and ad attention.
Lifesight	Daily (recommended) for at least 2 years. Can work with daily for at least 1 year (if 2 years not available) or weekly for at least 2 years.	Media expenditure data. Impressions and clicks are added as supporting variables to the model.
Meta Open Source Robyn	If using weekly data, it is recommended to collect at least two years' worth of historical data. If using daily data, one year's worth of historical data is recommended.	Metrics that reflect how many "eyeballs" have seen or have been exposed to the media e.g. impressions.
Mutinex	Minimum of two years of weekly historical data	Core modelling metric is media spend.
Prophet	Daily-level data spanning at least two years.	Media expenditure data. Other key metrics include impressions and clicks, viewability rates, ad attention and reach and frequency.
Recast	Generally, recommend 27 months of daily data. Can in some circumstances use less data and still be successfully deployed.	Daily media expenditure.

Analytic Edge

Specifications for providing advertising and media data to your company:

The Demand Drivers platform seamlessly supports model building at the daily, weekly, or monthly periodicity. Therefore, depending on the granularity at which media and advertising data is available, we can harmonise the modelling data cube to the desired model periodicity. Typically, for weekly datasets, we recommend using 104 weeks of historical data. For monthly datasets, we would recommend using 36 months of data, or any other additional dimensionality (like region, sub-brand, sales channel, etc.) to generate additional records for each month.

From a media granularity perspective, we require end user exposure metrics like impressions, clicks, GRPs, TARPs, as well as the corresponding cost data. The level of detail we typically support for digital media is campaign objective type, e.g., Meta (Conversion, Reach, Awareness, Outcome Sales), Google (Branded Search, Generic Search, Performance Max, Shopping, YouTube Skippable, non-skippable, 15s vs 30s).

Analytic Edge is flexible with the data ingestion protocols and can automate this process once the access protocols are defined. We can extract the raw data directly from the source, i.e., Meta Business Manager portal, Google MMM data platform once we are authorised by the client, we can write API connectors to the client's data lake, we can process multiple CSV, flat files dropped into a secure FTP site or an S3 bucket to create the harmonised input data cube.

Key media metric/s used to run the model:

We typically use end user exposure metrics like impressions, clicks, GRPs, TARPs etc while modeling the impact of media. However, if such metrics are not easily available, we can use cost as a proxy for media execution. Irrespective of the media metric used in the model, we will still require cost data to generate media sufficiency curves (diminishing returns) as well as to generate the ROI scores.

The impressions or clicks used in the model must be unique, i.e., for YouTube, you cannot use both skippable vs non-skippable and 15s vs 30s splits as there might be overlaps across these cuts.
We have built specific deep dive analyses for Meta, Tik Tok & Google that analyses specific executional attributes such as Reach, Frequency, duration etc.

Any additional metrics such as viewability, ad-attention etc. could be built into secondary stage models or as part of digital media deep-dive analyses as requested.

Other data (non-media data) used in models:

Sales data can either be in the form of volume units or revenue in the local currency. We have experience modelling both sell-in (shipments) as well as sell-out (consumer offtake) data. The periodicity of the KPI data (sales/revenue) dictates the model granularity, i.e., if the KPI data is available weekly, the model cannot be built at the daily periodicity.

Consumer offtake data is typically obtained from Nielsen NIQ once a Third-Party Access Agreement is in place between Nielsen, the client and Analytic Edge. Competitor data may also be obtained from Nielsen. Below the line marketing data such as Feature, Display, Feature & Display, Temporary Price Reduction, as well as Price and Distribution data can also be obtained from Nielsen. The MMM platform calculates drivers such as seasonality, trends using historical KPI data. Temperature and precipitation data can be obtained from sources such as WT360 if the client has a subscription to this service.

Macro data such as Real Private Consumption, Real GDP, Consumer Price Index, Unemployment can be obtained from verified third-party sources such as the Australian Bureau of Statistics (https://www.abs.gov.au)

We could incorporate emissions data into a MMM model. If emissions data was built as a leading KPI, we could then optimise (reduce) carbon emissions in the Simulator. This would just require accurate supply of relevant carbon emissions data. This would be an interesting commission to take on.

There is typically no restriction on client participation, but we have seen that the minimum annual marketing spend for clients conducting an MMM study is AU$100,000.

Analytic Partners

Specifications for providing advertising and media data to your company:
Commercial Analytics includes data supplied by both advertiser and directly through publisher partnerships and other sources to ensure comprehensive and holistic measurement of all business drivers. Data can be connected via APIs or directly uploaded into GPS-E for ease of consolidation and tracking. Analytic Partners maintains a flexible approach to data collection, ingestion, and management centered around our comprehensive, guided data management capability, ADAPTA. ADAPTA ingests, cleanses, transforms, validates, and loads data directly for review, modeling, and insights. We have the ability to run a traditional push approach (the most common approach) where data is automatically ingested once it is made available by the relevant server, or to run a pull approach where the client security posture allows and to extract data by request directly.

Time period varies depending on client, industry and history available, but tends to be weekly. Granularity of analysis and recommendations is reflective of how customers are planning and actioning and can include deeper insights and decisioning at the creative, format and tactic levels.

Key media metric/s used to run the model:
Various media metrics are tested and utilised in the model depending on channel, with a focus on an opportunity to see metric such as TARPs, impressions, view, clicks, attention metrics, reach and frequency.

Other data (non-media data) used in models:
Each model is built with a view to the client's categories, markets and data sets so we do not have rigid specifications as to a standard set of data that clients must conform to. With regards to sales/revenue, we build out models on data clients have and make recommendation for improved data through our initial data scoring process. Numerous non-marketing factors such as seasonality, weather, competitive media, marketing, store openings/closings, economic indicators, mobility data, and other exogenous factors are incorporated directly into the model and potential interactions with all marketing inputs are explored. This includes emissions data to assist clients with optimisations that help clients reduce the carbon footprint of their marketing efforts.

We maintain a flexible approach to data collection and ingestion with the ability to collect directly from advertisers or source the data ourselves via direct access and/or partnerships, with a data bank in excess of 400,000 potential datapoints for modelling.

Annalect

Specifications for providing advertising and media data to your company:
Our MMM models require advertising and media data with weekly granularity at a minimum, ideally spanning at least 2–3 years to ensure sufficient variance and robustness. We support granular inputs across creative, channel, format, and device level where available.

To reflect the breadth of modern media, we encourage the inclusion of data across TV, BVOD, digital display, video, social, search, audio, OOH, and other channels.

Key media metric/s used to run the model:
Our models primarily use impressions and clicks as the core media input, as we focus on modelling the relationship between media exposure and revenue outcomes. Media spend is used as priors for models and for comparative ROI analysis, not as a primary driver.

Other data (non-media data) used in models:
We require weekly or daily sales or revenue data, ideally at a granular level (e.g., region, product category, or channel). Additional non-media inputs may include pricing, promotions, distribution, CRM activity, sponsorships, and macroeconomic factors such as interest rates or inflation.

External datasets such as weather, public holidays, major events, macroeconomics factors and competitor activity can also be integrated. Where clients do not provide this, we source data from publicly available or commercial datasets.

There are no fixed thresholds for client participation, though strong results are more likely where historical media investment and sales data span at least 2/3 years.

Circana (formerly Nielsen MMM)

Specifications for providing advertising and media data to your company:

Each of our Circana (formerly Nielsen MMM) engagements are customised to the needs of a particular partner. A comprehensive determination of which factors we should consider would be part of a discovery conversation that is part of a pre-engagement workshop/kick-off. Circana account for all the Marketing and non-Marketing factors while building models, ensuring that there is no misattribution for marketing.

In terms of paid media, we would comprehensively include all sufficient executions with insights split at granular levels such as:

- Traditional media by campaign, market, potentially by spot length, daypart, origin, language, etc.
- OOH by location, language, etc.
- Direct mail by campaign, type, etc.
- Sponsorships by location, property, campaign, etc.
- Digital by campaign, device type:
  - Search - Branded vs. Non-Branded by keyword group
  - Social - By Publisher (and unique publisher executions)
  - Video - Online vs. Newsfeed by Publisher, Skippable vs. Non-Skippable, Auction vs. Reserve
  - Display - Banner vs. Engagement vs. Newsfeed (Facebook), Auction vs. Reserve or Lightbox vs. Masthead

Below is an example of the data we could use in creation of the models for brands:

- ***Pricing -*** Regular Price, Discounts, Key Price Points
  Promotions - In-Store Displays, Catalogue, Special Events, Email, Direct Mail, Coupons
- ***Paid, Owned and Earned Media -*** TV, Print, Radio, Paid Digital, Video, Mobile, E-Retail, In Store/ Shopper Marketing, PR, OOH, etc
- ***External -*** Competitive Marketing, Weather, Seasonality, Key Holidays, Economic Conditions, Category/ Industry Trend, Regulatory Changes, Covid Factors
- ***Operations and Product -*** # of Locations, # of New/Closed Locations, # of New Competitor Locations, Location Remodels, Product Inventory

Circana (formerly Nielsen MMM) understands that data collection is a large, labour intensive exercise for which resources to accomplish are in short supply. As such we do everything we can to carry as much of the data collection burden process as possible by leveraging the large warehouse of data we have available either through our own assets or through our relationships with walled gardens and others.

Our data collection process is managed by means of data collection templates which are provided to our advertiser partners and, typically, to their agency partners to provide consistency in collection across modelling exercises. We can ingest any data into our model for which sufficient granularity and cadence (ideally by market by week though we can work with less) is available.

Data is submitted through the Circana (formerly Nielsen MMM) Analytics Console (NAC), the design of which emphasises ease of use, accessibility and standard security principles. When a client or partner submits data through the NAC web interface, it is streamed into a Google Drive repository linked to an enterprise service account. Once there, NAC only provides permission to specific folders within Google Drive for those Circana individuals who are involved with the client's project.

Circana has a data cloud that enables cloud to cloud or API connections for data ingestion, harmonization and review powered by the latest advancements from Google Cloud, AWS and Microsoft Fabric Data Factory. Our data cloud enables organizations to orchestrate always on data exchange protocols that enable our customers to have a real time feed of their harmonized data centrally for evaluation and analysis. With our most advanced clients, we rely on a retrieve vs. request data protocol that speeds up the time to models.

Key media metric/s used to run the model:

The key media metric typically used in Circana Marketing Mix models (formerly Nielsen MMM) is Impressions for Digital and Gross Rating Points (GRPs) for Television. Impressions & GRPs are a standard measure of advertising impact in the media industry.

Circana uses these in MMM because:

- They provide a standardised way to measure media exposure across different channels and campaigns.
- They allow for comparison of advertising intensity across different markets or time periods.
- They can be easily related to advertising spend, making it possible to analyse cost-effectiveness.

Circana secondary model deep dive with the examination of more granular media insights, primarily for TV and Digital, than is possible in the main model (e.g. effectiveness by daypart, reach, frequency, target, etc.)

Circana would strongly disagree that a spend-based metric is preferred, and that causal metrics represented by execution (not spend) are superior inputs into the model, understanding that scaling these metrics is advisable to avoid potential bias (which we do). That said, we recognise that execution-based causals are not always available in which case we will use spend as the best available data.

Other data (non-media data) used in models:

In terms of factors that would often be considered as drivers of "base" demand we might include things such as price, promotion, CRM, operational considerations (e.g. sales force activity, significant product changes/enhancements, owned media, etc.), customer reviews/sentiment, brand attributes (e.g. awareness, consideration, purchase intent, etc.) and external factors such as Covid, weather/significant environmental events, economy, seasonality, holidays, competitive media and industry trends.

For any econometrics data like weather, Unemployment rate, Petrol Prices and Consumer Confidence, Circana (formerly Nielsen MMM) leverages publicly available data sources. Additionally, we also have partnerships with publishers like Facebook, TikTok, Pinterest, Snap and Google and we would be able to acquire granular level marketing data for markets globally in a standard format provided by these publishers to use in our MMM study. Circana access the publisher's data centers to pipeline information for MMM's

Circana also has direct access to Australia Grocery Scan Sales data for FMCG brands and a close partnership with YouGov for Brand Health metrics data across many industry verticals.

Gain Theory

Specifications for providing advertising and media data to your company:

To build robust and accurate MMM models, Gain Theory requires detailed advertising and media data. Below are our key specifications:

- ***Granularity:*** We collect data at the lowest granularity available. For digital channels, this includes daily data by postal code, detailing publisher/network, audience targeting, campaign, creative, and ad placement. For traditional media like TV and radio, we seek region-level data broken out by daypart, spot length, and network.
- ***Historical Timeframe:*** Ideally, we require at least three years of historical data to assess long-term impacts. However, we can work with as little as 18 months for standard MMM approaches.
- ***Digital Advertising Variety***: To capture the diversity of digital advertising, data should include details on ad formats (e.g., display, video, native), devices (e.g., desktop, mobile, tablet), and channels (e.g., search, social, display). Information on targeting parameters, creative variations, and other relevant dimensions is also essential.
- ***Data Delivery Specifications:*** We use Gain Theory DataOne (GTD1), our proprietary data management system, to automate data ingestion and processing. GTD1 supports various integration methods, including APIs (with pre-built connectors for common platforms) and custom formats like flat files (e.g., CSV, Excel) shared via cloud storage providers such as S3, SFTP, Azure, or Google Cloud.

We are flexible in accommodating different data formats and delivery methods. Our data team works closely with clients to establish a seamless and efficient integration process tailored to their needs.

Key media metric/s used to run the model:

To build robust and accurate MMM models, Gain Theory requires detailed advertising and media data. Below are our key specifications:

- ***Media Ratings:*** Gross Rating Points against target audiences where available by channel.
- ***Impressions and Clicks:*** To assess reach and engagement across channels.
- ***Impression Quality Metrics:*** Including viewability and ad attention to evaluate exposure quality.
- ***Reach and Frequency:*** Using our proprietary AdModel™ to optimize media plans based on the ideal balance of reach, frequency, and timing.

These measures enable a deeper understanding of media performance, helping us develop more effective marketing strategies for our clients.

Other data (non-media data) used in models:

To build robust MMM models, Gain Theory requires detailed sales/revenue data and a variety of non-media data. Below are our key specifications:

Sales/Revenue Data: We seek granular sales or revenue data, such as weekly or daily metrics by product, region, and sales channel, tailored to client objectives. Common metrics include sales volume, revenue, and profit.

Non-Media Data: We incorporate diverse non-media factors that influence performance, including:

- ***Brand Health Metrics:*** time series brand health and perception metrics for brands.
- ***Marketing Activities:*** Pricing, promotions, trade spend, distribution, in-store activities, and website changes.
- ***External Factors:*** Weather, seasonality, economic indicators (e.g., GDP, unemployment), competitor activity, and events.

Data Sources:

- ***Client-Provided Data:*** Sales data, pricing, promotional calendars, and marketing spend.
- ***Third-Party Providers:*** Syndicated data from providers like Circana (formerly Nielsen MMM) , IRI, weather services, economic sources, competitive intelligence, brand health agencies.

Emissions Data: While not standard, we can leverage GroupM's carbon calculator to incorporate emissions data into scenario planning and optimization tools, assessing the environmental impact of marketing activities.

Our proprietary system, Gain Theory DataOne (GTD1), automates data ingestion and processing, ensuring quality and accuracy across all sources. We work flexibly with clients, imposing no strict participation requirements, to establish seamless integration and deliver actionable insights.

Google Meridian

Specifications for providing advertising and media data to your company:

Meridian is an open-source library, and so data collection is the responsibility of the modeler. Meridian recommends geo-level granular data, when available, in order to take advantage of geo-hierarchical modelling (Sun, et al. 2017). Meridian also supports national models, since geo-level granularity isn't always possible. Meridian doesn't have strict requirements on the amount or history of data needed. Rather, Meridian has general recommendations with an acknowledgement that there are exceptions which can still be modelled successfully with Meridian. General recommendations include weekly level granularity, at least two years of data for weekly-level geo models, and at least three years of data for weekly-level national models.

As one way to represent the nuances of different digital ad types, Meridian enables using reach and frequency data instead of impressions. This allows for a more actionable understanding of advertising impact compared to impressions alone and allows for optimal frequency estimation to maximize channel ROI. Reach and frequency data for YouTube is available in Google's MMM Data Platform.

Meridian supports data loading from Comma Separated Values (CSV) files, Xarray Datasets, or other formats that can be transformed into Pandas DataFrames.

Google media data is available via the MMM Data Platform, which delivers a standard taxonomy with hyper granularity (down to the ad format level for Google campaigns) to enable custom breakouts. Data is available via direct delivery to a cloud instance, refreshed automatically on a monthly or quarterly cadence.

Key media metric/s used to run the model:

To run Meridian, one must provide a media exposure metric. This metric can be a single measure, such as impressions, clicks, spend, reach & frequency, etc. (impressions are more commonly used). Optionally, for a more comprehensive analysis, reach and frequency data can be used instead of a single exposure metric for paid and organic media channels.

Media spend is necessary for paid media channels, but one can optionally model media as organic, for which media spend data is not required.

Other data (non-media data) used in models:

Meridian can model any generic KPI, including but not limited to sales or revenue data. Notably, the data specifications for KPI are similar to those for media data. That is, Meridian doesn't have strict requirements and instead makes general recommendations. Recommendations include geo-level granular data when available, weekly-level granularity, at least two years of data for weekly-level geo models, and at least three years of data for weekly-level national models.

Meridian is designed to estimate the causal impact of intervenable variables. For non-media, this can include variables such as pricing or promotional activities. It is important to include confounding variables in the model, which are those influencing both the treatments (paid media, organic media, non-media treatments) and the KPI. The user should include key confounding variables such as macroeconomics factors and competitive activity. When Meridian is used to model paid search campaigns, query volume data is an important confounding variable to account for the relationship between organic demand and paid search ads.

Kantar

Specifications for providing advertising and media data to your company:
We recommend a historical data range of at least two years for daily granularity and three years for weekly granularity, especially for media and outcome variables. This ensures robust modelling of seasonality, carryover effects, and long-term trends.

Media inputs should be delivered at the publisher or platform level, and where possible, broken down by device, ad format, campaign objective, and creative type. For digital channels—search, display, social, video, and influencer—this allows precise modelling across the marketing funnel. Traditional media (e.g., TV, radio, OOH) is typically captured weekly, with lower-frequency inputs (e.g., sponsorships) interpolated where feasible.

Where available, we also ingest creative and ad testing scores, such as brand lift, recall, attention and/or creative quality metrics. These enrich the model's understanding of qualitative differences in campaign performance and improve accuracy in modelling upper-funnel effects.

Data Delivery: Data can be delivered manually via sFTP (SSH key-based) or via automated API/database integrations. We use Adverity as our ingestion layer to enable secure, automated data transfer into our modelling pipeline.

Data Management & Processing: Our proprietary data platform standardises, cleanses, and validates all incoming media data to ensure consistency and scalability across clients.

Modelling & Visualisation: Our proprietary HamiltonAI engine runs scalable, hierarchical models. Results are made available through an interactive UI, where users can explore drivers and simulate future media investment outcomes.

Key media metric/s used to run the model:
The Kantar LIFT ROI model primarily uses impressions, clicks, reach, frequency, and quality measures such as viewability and ad attention as the key inputs to represent media activity. These metrics offer higher fidelity in capturing campaign exposure and effectiveness. Media spend is only used as a fallback where richer metrics are unavailable—typically in channels like OOH, print, or sponsorships. The model flexibly adapts to available data but prioritises user-level exposure metrics to ensure greater accuracy and relevance in attribution and optimisation.

Other data (non-media data) used in models:

During an initial discovery phase, we work closely with the advertiser to identify all business and market factors believed to impact sales or revenue. Our aim is to include all relevant drivers, not just media, to provide a holistic view of marketing performance.

Sales and Revenue Data: We require transaction-level, store-level, or channel-level data at a weekly or daily level, depending on model cadence. Online and offline sales can be modelled separately or together. Where applicable, we also incorporate lead volume, customer acquisition, conversion, or other commercial KPIs.

Non-Media Drivers typical variables include:

- ***Trade activities:*** in-store promotions, price changes, distribution shifts
- ***Brand activations***: sponsorships, product launches, PR
- ***Brand metrics:*** awareness, consideration, NPS, tracking data
- ***Competitor activity:*** media presence, pricing, launches (where available)
- ***External factors:*** weather, seasonality, holidays, economic indicators

We leverage third-party datasets where needed, including macroeconomic and climate data sources.

Model Requirements & Flexibility: While our Bayesian methodology is well-suited to data-limited environments, and in general, media channels need a small amount of spend that is unique (or inconsistently overlapping) relative to other channels in order to achieve model reliability. There isn't a strict minimum level of spend required, however we assess this feasibility on a case-by-case basis, depending on advertiser size, media mix, and business complexity.

Sustainability Metrics: LIFT ROI can incorporate carbon emissions data linked to media channels or formats, supporting clients in reducing the environmental footprint of their marketing mix.

Lifesight

Specifications for providing advertising and media data to your company:

Input data specifications:

- Data at channel or tactic level (where tactic is user-defined, e.g. Meta TOF, Google Remarketing, Google Brand, etc.)
- Granularity and time-frame
  > Daily (Recommended) for at least 2 years
  > Daily for at least 1 year (if 2 years worth of data is not available)
  > Weekly for at least 2 years
- Lifesight supports additive modelling, thus, data can be split by device type (iOS and Android child models combined into 1 parent model) or geography (multiple region-specific models combined into 1 parent model)
- The incremental results of the model at channel / tactic level are then broken down into campaign, ad set and ad levels (wherever applicable)

Input data delivery specifications:

- Lifesight supports data ingestion through csv files, Google Sheets, custom APIs or a direct integration to a DWH

Ad channel integrations are available to pull in relevant platform metrics such as spend, impressions, clicks, etc. - a complete list of integrations can be found here.

Key media metric/s used to run the model:

The primary input to a model is spend data. Impressions and clicks are added as supporting variables to the model.

Other data (non-media data) used in models:

General format of input data:

- Paid media (spend, impressions, clicks)
  - > Pulled in automatically for integrated channels
- Organic variables (impressions, clicks)
  - > Pulled in automatically for integrated channels
- Contextual variables
  - > Non-paid inputs that influence conversions
  - > These can be Boolean (TRUE / FALSE) or continuous / numeric
  - > e.g. promotions / discounts / product launches, competitor media activity, MAP metrics, seasonal data etc.
- Conversion variable
  - > 1 per model
  - > e.g. revenue, orders, leads, installs, visits, etc.
  - > These can be broken down by type, e.g. iOS revenue, Android revenue etc. which are then combined to Total revenue in a parent model
- Generally, a minimum number of data points are expected for paid media spend; if not present, the model flags this out as a channel for experimentation and subsequent calibration

Meta Open Source Robyn

Specifications for providing advertising and media data to your company:

Being open-source, it is the end user's responsibility to collect, clean and QC the input data before modelling begins in Robyn. The general guideline for data collection to be used in Robyn is relatively standard and similar to other MMM solutions:

- ***Historical time period:*** The required historical data period will depend on how granular the data will be. If using weekly data, it is recommended to collect at least two years' worth of historical data. If using daily data, one year's worth of historical data is recommended – this is less than weekly data as there are more data points with daily data, however still aim for at least one year to at least capture any seasonal effects.

- ***Granularity:*** If there is an option to collect data with any extra granularity (e.g. total Meta activity vs. campaign-level Meta activity), it is recommended to collect the data with the most granularity as possible. This will give flexibility in modelling at more granular levels – for example, if a certain level of granularity is too granular and is not picked up in the model, the end user can group the input data and model without having to re-collect any data.

From a Meta data collection perspective, any brand can leverage the Meta MMM Data Feed for a high quality and granular Meta data to be used in any MMM, including those run by 3rd party vendors. The MMM Data Feed can be accessed in two ways:

- MMM Breakdown on Insights AI: https://developers.facebook.com/docs/marketing-api/insights/marketing-mix-modeling/;

- MMM report in a brand's Ads Reporting: https://www.facebook.com/business/help/1386210265640297

Key media metric/s used to run the model:

The general advice for the key media metrics to be collected and used in Robyn models is to start with metrics that reflect how many "eyeballs" have seen or have been exposed to the media e.g. impressions. Where possible, this should be the main metric used as a direct input into the model.

Spends should also be collected to calculate a Return On Ad Spend. Impressions are generally always preferred over spends as a model input, as spends are influenced by costs and aren't the most accurate reflection of media exposure. However in situations where it is not possible to collect impressions, spends can be used as proxy model inputs.

If available, other quality measures such as viewability and attention can also be collected to contextualise and supplement model results.

Other data (non-media data) used in models:

Robyn provides a flexible approach to MMM, allowing users to build custom models tailored to their specific business needs. Brands can experiment with using many different KPIs as the dependent variable in Robyn, depending on their product and category. We have seen a wide variety of use cases across the industry, such as:

- Revenue and sales for more traditional businesses;
- New customer acquisitions and purchases for digital-first D2C (direct to consumer) businesses;
- App installs or paying users for online gaming brands.

When using Robyn, it is strongly recommended to collect and include non-media data for any variables that could have an impact on sales. The types of activities and desired input data can include:

- ***Other marketing activities*** (e.g. promotions, discounts): This can be represented in a dataset by having % discount by day/week. If this level of information is not available, then dummy variables can be used i.e. a value of 1 for the days/weeks where there was a discount, a 0 if not;
- ***Seasonality:*** With the purpose of reducing human bias in the modelling process, Robyn can provide trend, season, holiday & weekday data by using Prophet, a popular time-series forecast package by Meta Open Source. Prophet will calculate these trends from the dependent variable data, where no additional data is required to be collected.
- ***Macroeconomic factors*** (e.g. economic growth, unemployment): This data can be collected online from credible sources such as the ABS;
- ***Other external factors*** (e.g. competitor activity) : If the data is available, competitor activity can be a useful dataset to include.

Being open-source, any brand can experiment with running Robyn and hence there are no technical restrictions on minimum revenue, marketing spend, etc. That said, the general guideline is to have at least one year's worth of historical data to give the sufficient data points for Robyn to work with and be active in at least >2 channels for the model to be worthwhile running.

Mutinex

Specifications for providing advertising and media data to your company:

Media and advertising data are provisioned via DataOS, Mutinex's proprietary secure platform which is part of the GrowthOS platform. DataOS supports automated integrations with major digital platforms (e.g. Meta, Google Ads, Apple Search Ads), as well as secure connections to cloud data warehouses such as BigQuery and Snowflake for broader marketing data inputs.

For traditional media or bespoke activities, customers may upload CSV files—such as Spectra or SMD extracts—directly into the platform or connect them via data warehouse.

DataOS includes AI-powered labelling tools that standardise naming conventions and ensure consistency across historical datasets.

We require media data with at least weekly granularity, covering a minimum of two years. This enables robust modelling of trends, seasonality, and long-term effects. Media channels which are unable to provide weekly level data are subject to transformations to accurately represent marketing exposure.

There is no specific minimum marketing spend, but we recommend GrowthOS for customers with annual budgets of ~$3M and above.

Key media metric/s used to run the model:

Our core modelling metric is media spend, as it provides a consistent, comparable input across all channels. By standardising media inputs to financial investment, we allow advertisers to forecast future ROI and optimise media mix without requiring granular assumptions around impressions or platform-specific engagement metrics.

We do not use Impressions or Reach metrics due to the inconsistency across channels and platforms unless it is paired with spend data. We do use some performance data (e.g clicks) within certain points of the funnel.

Buying objective is a key field we use and care about when modelling media.

Other data (non-media data) used in models:

Sales/Revenue Data Requirements

- Minimum of two years of weekly historical data
- Quantity-based sales metrics are essential
- Where applicable, customer lifetime value (CLV) or similar metrics may be incorporated
- Product/brand portfolio must be clearly identifiable through relevant fields to enable our platform to represent your organisation and media influence accurately.

Non-Media Inputs

- Pricing (including discounts and promotional mechanics) is a critical input. Competitor pricing is recommended where available.
- Other relevant variables include Owned Media, Earned Media, Trade Marketing, Events, and Co-op activity.
- For Brand Equity measurement, we require at least two years of monthly prompted and unprompted awareness and consideration metrics.

External Data

Mutinex integrates external datasets such as economic indicators and competitive activity, enabling richer modelling of external influences. Customers are able to supply their own tracked datasets, while Mutinex also has a library of verified third-party datasets.

Prophet

Specifications for providing advertising and media data to your company:

For optimal results, Prophet requires detailed, granular media data, adhering to these specifications:

- ***Timeframe and Granularity:*** Daily-level data spanning at least two years to capture detailed seasonality and trends.
- ***Required Metrics:*** Media spend, impressions, clicks, conversions, reach (where available), frequency, and viewability metrics.
- ***Segmentation:*** Data segmented by channel (e.g., social, search, programmatic), platform (e.g., Google, Meta), device (e.g., mobile, desktop), creative variations, targeting parameters (demographics, geographic locations), ad placements, and frequency caps.
- ***Data Delivery Formats:*** Direct API integration (over 590 APIs) with major platforms, secure file transfers (CSV, XLSX, JSON), and cloud-based solutions (AWS S3, Google Cloud Storage) with structured schemas clearly labelled (campaign name, spend, impressions, device, geography, date).
- ***Data Transformation:*** With Prophet users can upload multiple CSVs and then merge and transform that data using an AI-hybrid approach - allowing the flexibility for manual/human transformation and/or AI to do it for the user.

Key media metric/s used to run the model:

The key media metrics Prophet utilises include:

- ***Media Spend:*** Primary foundational input for models.
- ***Additional Media Measures:*** Impressions and clicks, following closely to standardised IAB impression counting guidelines.
- ***Quality Measures:*** Metrics such as viewability rates, ad attention scores to accurately evaluate advertising effectiveness.
- ***Reach and Frequency:*** Data capturing both the extent of audience coverage and exposure frequency to further refine attribution and optimisation insights.

Other data (non-media data) used in models:

Prophet requires extensive sales/revenue and other marketing data:

- ***Sales and Revenue Data:*** Detailed at daily or weekly intervals, covering at least two years, at granular levels (product, store, region). Data to include net sales, units sold, gross revenue, margins, and cost of goods sold (COGS).
- ***Additional Marketing Data:*** Information on trade promotions, price adjustments, CRM activities, and distribution measures.
- ***External Factors:*** Economic indicators (inflation rates, unemployment figures), competitor activities (pricing strategies, promotional efforts), weather patterns, and seasonal fluctuations, typically sourced from authoritative government and commercial databases.
- ***Emissions and Sustainability Data:*** Prophet has the capability to integrate emissions data, providing insights to help clients identify and optimise their marketing mix to reduce their overall carbon footprint.
- ***Client Participation Qualifications:*** Prophet recommends client participation with a minimum annual revenue of AUD 10 million, consistent marketing expenditure across multiple channels, and a minimum of two years' historical campaign data for robust model accuracy.

Recast

Specifications for providing advertising and media data to your company:
Recast can ingest a variety of data sources, including sales, media spend, pricing, customer and other marketing data. Daily sales and spend data by media channels are the primary inputs to drive the model. Most other data types live as flexible, contextual variables.

Recast is channel agnostic and uses customer first party spend and conversion data from customer data warehouses. Recast generally recommends starting with 27 months of historical data. Recast can in some circumstances use less data and still be successfully deployed.

Recast is designed to connect directly to your marketing data warehouse so that it is working off of the same source-of-truth as your other reporting. The granularity is flexible with most brands modelling at the channel and tactic level.

Key media metric/s used to run the model:
The primary inputs to Recast are daily sales and spend data by each media channel (both online and offline). The platform can also ingest impression data or other types of data depending on the channel and the data available.

In cases where impressions are the best measure of a marketing channel, Recast will recommend using impressions as inputs for that channel, however in many cases impressions are not the best measure of a marketing channel, in which case Recast recommends using a different input.

Recast can also incorporate any number of data types – including brand sentiment, price changes, economic data, etc. – as contextual variables.

Other data (non-media data) used in models:

Recast ingests daily sales and spend data for each media channel in a company's mix–including both online and offline channels.

Recast can also incorporate any number of data types–including brand sentiment, price changes, economic data, etc–as contextual variables. Where possible, these data are uploaded with daily or weekly granularity and ingested into Recast alongside media spend and KPI data (revenue, acquisitions, etc.).

Seasonality is handled naturally by Recast's time series model without any specific inputs. Longer term factors such as economic factors are often incorporated as contextual variables in Recast models, while short-term events–such as promotional events or website outages–are modeled as "Spikes".

Recast can technically incorporate emissions data as a dependent variable and optimize for improved emissions via its Optimizer tool.

Overall, the model is extremely flexible and can work with many different types of businesses, objectives, and data.

chapter 4

market mix modelling vendor landscape

metrics, output and insights

Your MMM project needs to start with the overall business strategy and long-term goals and a clear vision for the role that marketing plays in driving business growth and how that should be measured.
Begin with business questions and then choose the best approach to answer them. MMM may not be able to answer all your questions. Marketers are learning how to integrate multiple measurement tools as there is no silver bullet, no one technology, methodology or metric that will alone provide the full picture of marketing effectiveness and ROI. Successful, sustainable measurement requires a measurement framework that aggregates multiple techniques and data sources and synthesises into an overall view of performance.

Even with MMM, complementary techniques such as experimentation (brand lift and geo-lift studies) and attribution will likely still be needed for tactical insights on individual campaign effectiveness. Most MMM vendors have also indicated the capability to *integrate the insights from other measurement methods to calibrate the MMM* and help validate and fine-tune the model's accuracy and effectiveness.

Different media campaigns drive different outcomes. While some campaigns drive brand perceptions, others generate leads or drive sales online or offline. In MMM, sales revenue is the primary dependent variable that the model aims to predict and explain. The participating vendors have outlined the range of sales related metrics and KPIs supported by their models. *Today, it is not uncommon to see MMM built around several KPIs via a model design known as nested models.* Models can provide a full-funnel view (not just impact on sales) by modelling for a range of other KPIs such as brand and brand equity related metrics.

Successful MMM is forward-looking, enabling companies to anticipate how to make better future investments that produce measurable business growth. It is common across the participating vendors to provide tools for scenario planning, optimisations and simulations of future outcomes. You will need to consider the level of consultation support your company requires from a vendor to translate model findings into executable actions and socialising recommendations within your company. Participating vendors demonstrate the spectrum of support from full consultation through to the end user being fully responsible for analysing model results and turning them into business actions.

Vendors have highlighted that *successful MMM implementation requires securing stakeholder buy-in from the start* (including marketing, analysts, finance, media agencies). Infrastructure, resources, capability building, cultural change, dedicated champions and education teams on how to interpret and act on MMM outputs is essential for realising ROI.

"Ultimately, MMM works best as a collaborative discipline. Advertisers who are transparent with their reporting outcomes and actively engage with publishers, platforms, and partners create a shared view of what's driving success. This openness enables ongoing refinement of models, as well as more productive conversations around optimizing investments and creative strategies."

- Dave Goodfellow, Head of Measurement Solutions, APAC at Pinterest

Participating vendors have outlined the process undertaken with clients to turn modelled data into insights and business actions, how the model integrate with other marketing measurement tools, along with any independent audits or accreditation received, and demonstration of data through case studies, charts, reports.

metrics to quantify the impact of advertising and marketing

Analytic Edge

Incremental sales contribution of all marketing activities (often expressed as a percentage of total sales).

Annual "due-to" waterfalls identifying all marketing and non-marketing drivers that have driven y-o-y changes in sales.

ROI of all marketing tactics including all components of ROI – notably CPM and effectiveness.

Sales response curves for all marketing tactics.
A simulator delivers fast optimisations of marketing spends.

Analytic Partners

The metrics are dependent on customer and industry rather than being locked to one set but include the incremental volume of all marketing and non-marketing factors in the business. This can be expressed as unit sales, revenue, margin, traffic, churn, lifetime value, customer acquisition, and brand impact. These are covered at the response per impression/GRP etc, with a cost and ROI expressed alongside.

A larger portion of engagements include multiple performance indicators to facilitate more comprehensive planning and sustainable growth strategies. Access to GPSE and the various client tools are standard for Scenario Planning and accessing response curves for all media.

Annalect

Key KPIs include incremental revenue, media ROI (return on investment), cost per incremental impression, and marginal returns by channel.

We decompose performance into base and incremental contributions to isolate the uplift generated by media and other marketing levers.

For more advanced use cases, we provide channel-level response curves and diminishing returns analysis to guide spend allocation. Long-term brand effects or customer acquisition metrics can also be modelled with appropriate data inputs.

Circana

High priority KPIs are:

Effectiveness: an equivalent metric ignoring difference in cost for comparing individual executions within a tactic.
Efficiency: allows for comparison of all tactics regardless of unit of measure.
Sufficiency: defines the minimum threshold level to expect advertisement effectiveness where GRPs translated into sales revenue.
ROI/ROAS: a universal measure of payback comparable across tactics accounting for the finances of an advertiser's business.

Any level of the conversion funnel can be evaluated.

Gain Theory

Sales-Related Metrics: Incremental Sales, Profit Return on Investment (ROI), Revenue Return Investment (ROAS), Customer Lifetime Value (CLTV), Market Share, Price elasticities.

Media Metrics: Effective frequency, recency of ad exposures
Brand-Related Metrics: Brand Awareness, Consideration, Preference etc, percentage lift of marketing (by channel, campaign, etc.) per $X invested.

Engagement Metrics: Website Traffic, Search Volume, Number of web searches driven by channel, campaign, creative, tactic, etc, App Engagement.

Meridian

ROI measures the efficiency of spend by comparing incremental outcome (KPI or revenue) to the cost of paid media.

Marginal ROI (mROI) estimates the return from an additional unit of expenditure, identifying potential saturation.

Effectiveness quantifies the outcome per ad unit.

Contribution attributes the percentage of impact to each marketing activity.

Response Curves visualize outcome changes with varying impressions, reach, or frequency.

For channels with reach and frequency data, Optimal Frequency estimates the ideal frequency for maximum ROI.

Meridian also provides Budget Optimization to perform What-if Scenario Estimation

metrics to quantify the impact of advertising and marketing

Kantar

KPIs/outcome variables modelled are related to specific business needs and objectives and can include; sales (units, volume, $s), subscriptions, visitations, retention / churn, quotes, transactions, member acquisition, brand health and footfall.

Key model outputs typically include incremental media-driven impacts; media-driven ROI; incremental impacts from non-marketing factors and the ability to deliver optimised media budget allocations.

Lifesight

The primary KPI is incremental ROAS or incremental CPA, along with marginal ROAS or marginal CPA per channel / tactic and a quantification of brand baseline (the conversions not explained by paid marketing).

We also quantify the halo effect and interaction effect (synergy and cannibalisation) in our models.

Meta Open Source - Robyn

The standard outputs from Robyn include Response decomposition and Share of Spend vs. Share of Effect.

Models can be built using different KPIs such as sales/revenue for traditional businesses, new custom acquisitions for D2C businesses and app installs for online gaming brands.

Mutinex

Mutinex key performance indicators:

- Media-attributed revenue and ROI
- Media-driven outcomes and outcomes driven by other external factors (sales volume, acquisitions, leads etc)
- Marginal ROAS by media channel
- Ad stock peak and decay duration per channel
- Brand Equity contribution in monetary terms
- Diminishing point of returns by channel and minimum/maximum spend

Prophet

Prophet's suite of KPIs and metrics includes:

- Return on Investment (ROI): Financial returns per marketing dollar.
- Incremental Sales/Revenue: Sales uplift directly attributable to marketing activities.
- Media Contribution: Channel-specific and campaign-specific contribution to overall results.
- Cost per Incremental Outcome (CPI, CPIS): Efficiency benchmarking for incremental conversions or leads.
- Optimised Budget Allocation: Recommended budget distributions to maximise desired outcomes.
- Marginal Return Curves: Analysis of diminishing returns for informed budget allocations.
- Channel Synergies: Interaction effects between channels informing integrated marketing strategies.
- Brand Impact Metrics: Upper and mid-funnel measures linked to long-term sales.
- Customer Acquisition Cost (CAC) and Lifetime
- Value (LTV): Evaluation of marketing effectiveness in customer acquisition and long-term customer profitability.

Recast

Recast tracks key marketing KPIs, including

- ROAS
- CPA
- marginal ROI
- marginal CPA

at aggregate, "channel" and "subchannel" levels.

Recast models can be built based on revenue or acquisition data (ex. new customers, leads, app downloads, etc.).

Analytic Edge

Metrics to quantify the impact of advertising and marketing

Standard outputs of our MMM model will include:

- Identification of the incremental sales contribution of marketing and all marketing activities (often expressed as a percentage of total sales). This includes all paid, owned & earned marketing tactics.
- Annual "due-to" waterfalls identifying all marketing & non-marketing drivers that have driven y-o-y changes in sales.
- ROI of all marketing tactics including all components of ROI – notably cpm and effectiveness
- Sales response curves for all marketing tactics
- A Simulator is built for all MMMs that delivers fast optimisations (in seconds) of marketing spends.

Process undertaken with clients to turn modelled data into insights and business actions:

Once the model is finalised, i.e., the client signs off on the contributions, ROI, magnitude of the drivers of growth or decline in the KPI across reference periods, we use the model to inform budget allocation decisions. An in-built budget optimiser module is shared with the client that they can use to run multiple what-if scenarios by setting different business constraints at the total budget level as well as at multiple levels of the media classification hierarchy, i.e., digital vs traditional, social vs search vs OLV, Google vs Meta vs TV vs OOH, Facebook Conversion vs Instagram Awareness. This way the client teams can run aggressive vs conservative scenarios to find the least risky approach to meeting incrementality targets.

There is also a comprehensive Planning module that allows you to create granular forecasts by providing forecast assumptions for media and non-media tactics by week. This includes testing multiple media plans with varying flighting plans, different price and promo calendars, macroeconomic and competitor projections (optimistic, pessimistic, BAU scenarios). Once the plans are locked in, we can load the latest data to monitor the accuracy of the forecasts. A detailed Gap Analysis module allows you to assess the reasons for any deviations between the actual performance vs the planned forecast. This further informs and guides any deficit mitigation strategies creating a powerful always-on feedback loop.

Model integration with other marketing measurement tools:

Our modeling platform allows you to use insights obtained from other measurement methods such as incrementality testing (test and learn experiments, geo-lift studies, A/B tests, attribution analyses, etc.) to calibrate the MMM model. This is done using the "Priors" feature during model setup where you can provide a narrow range for the expected contribution from a specific media tactic. The model fit statistics will reveal if the "priors" applied are appropriate. We recommend using MMMs as a strategic planning tool that provides directional guidance regarding decisions such as optimal budget allocation. It does not delve into measuring individual campaign effectiveness/efficiency. It should be used in conjunction with more tactical granular tools/methods like attribution.

A selection of resources from Analytic Edge:

- How Melia Hotels used MMM automation to optimize digital advertising ROI
- How to get the MMM Journey Right: A Playbook for DR Heavy Advertisers
- Unleashing the Power of Digital Upper Funnel Campaigns
- Next Wave Measurement: Market Mix Modelling in the Age of Retail Media

Analytic Partners

Metrics to quantify the impact of advertising and marketing

The metrics are dependent on customer and industry rather than being locked to one set but include the incremental volume of all marketing and no-marketing factors in the business. This can be expressed as unit sales, revenue, margin, traffic, churn, lifetime value, customer acquisition, and brand impact. These are covered at the response per impression/GRP etc, with a cost and ROI expressed alongside. A larger portion of engagements include multiple performance indicators to facilitate more comprehensive planning and sustainable growth strategies.

Access to GPSE and the various client tools are standard for Scenario Planning and accessing response curves for all media.

Process undertaken with clients to turn modelled data into insights and business actions:

Our GPS-Enterprise platform includes robust scenario planning and optimisation capabilities. Users are provided with the ability to simulate future outcomes in real-time as well as provide optimisations and budget recommendations, across multiple KPIs, dimensions and long-term and short-term goals.

The ROI Genome is a key strength for providing value add intelligence to drive business action. With 25 years of collected wisdom from measuring and optimising 100s of billions of marketing spend across hundreds of categories and countries. This means it can broaden the aperture of where to experiment and value growth outside of the range of activities clients may have yet executed, and this is bought into the analysis.

To promote insights a dedicated account manager and a senior executive relationship sponsor to ensure that the partnership objectives, best deployment, and capability adoption practices are leveraged.

The granularity of analysis is only limited by data- typically for example TV would be split by creative, duration, network, day of week, time of day, location, weights, flighting strategy etc and this granularity is replicated across all channels to ensure that we have as much ability to find value maximising opportunities.

Model integration with other marketing measurement tools:

We have proprietary methods to combine with attribution models, and ways that learnings from experiments (especially where contamination has been taken into account like in Agile Learning) can help inform MMM and integrate our incrementality with ROAS tools.

Accreditations, standards, external audits or validations:

Analytic Partners continuously receives industry recognition from organisations such as Gartner, Forrester Research, ANA, the Advertising Research Foundation. We have been the highest ranked leader in all versions of the Forrester Wave over the last decade, including the only AsiaPac version of the report which highlighted Analytic Partners as the only leader in the region based upon our commitment to and success in the market. We were also the highest ranked leader in the 2024 inaugural Gartner Magic Quadrant in Marketing Mix Modelling Solutions. We are consistently the highest ranked both for our current offering as well as our vision.

From a security perspective our application (GPS-E) is deployed at high-grade state-of-the-art facilities and meets multiple certifications regarding their operational controls, including but not limited to SOC (Type I, II, II), PCI-DSS, ISO (20000-1:2011, 22301, 27001, 27017, 27018, 27701, 9001), PCI DSS, CIS Benchmark, CSA-STAR (attestation, certification, self-assessment), WCAG, CDSA.

Resources from Analytic Partners:

As a leading provider we believe we have a responsibility to shape and educate the industry. We do through customer stories, licensing content from credible sources, original thought leadership, proprietary benchmarks and partnering with industry organisations.

All these sources can be found at: https://analyticpartners.com/roi-genome/ and https://analyticpartners.com/resources/

Case studies from Analytic Partners:

Relieving data pain and accelerating speed to insights
Reframing Marketing from a cost to a profit centre
60% of Growth Comes From Beyond Marketing
Why Omnichannel Still Matters for Marketing Execution and Measurement
Brand Marketing Outperforms Performance Marketing 80% of the Time

Annalect

Metrics to quantify the impact of advertising and marketing:

Our models are designed to quantify the revenue impact of marketing activity. Key KPIs include incremental revenue, media ROI (return on investment), cost per incremental impression, and marginal returns by channel. We decompose performance into base and incremental contributions to isolate the uplift generated by media and other marketing levers.

For more advanced use cases, we provide channel-level response curves and diminishing returns analysis to guide spend allocation. Long-term brand effects or customer acquisition metrics can also be modelled with appropriate data inputs.

Process undertaken with clients to turn modelled data into insights and business actions:

Once modelling is complete, we work closely with stakeholders to interpret the results and translate them into actionable insights. The output includes granular breakdowns at channel, region, and time levels — enabling tactical decisions such as optimizing weekly media flighting or reallocating spend between digital sub-channels.

We provide scenario planning tools based on media response curves, allowing teams to test different budget allocation strategies and forecast revenue impact. Optimization simulations help identify the best-performing media mix within a defined budget, supporting strategic investment decisions. These insights are shared via clear visualizations and dashboards that are accessible to both technical and non-technical stakeholders.

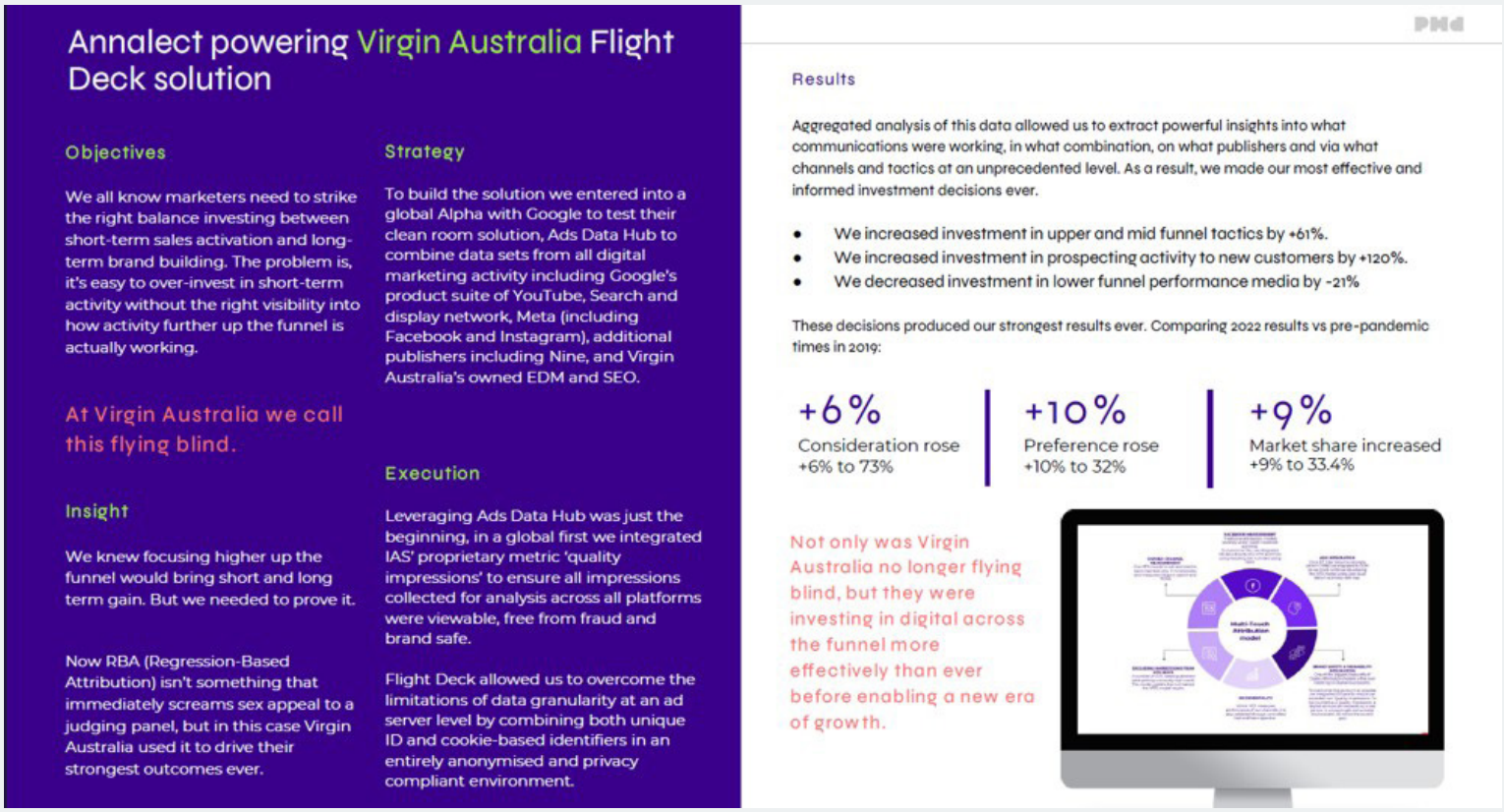
Model integration with other marketing measurement tools:

Our MMM is designed to complement attribution, brand tracking, and incrementality studies. We often triangulate MMM results with digital attribution and platform data to contextualize short-term and long-term performance. This integrated approach helps clients balance top-down modeling with bottom-up activation insights and make holistic measurement decisions.

Accreditations, standards, external audits or validations:

Annalect adheres to global data governance and modelling standards in line with Omnicom Group policies. Our measurement team are Google's meridian and Meta Marketing Data Analyst certified. These credentials reflect our commitment to platform-aligned best practices.

Our methodology is reviewed regularly and has been applied across multiple industries and markets.



Source; Annalect

Circana (formerly Nielsen MMM)

Metrics to quantify the impact of advertising and marketing

Circana's MMM (formerly Nielsen MMM) models conversion metrics such as Sales, Store Visitation, New Customers, Customer Churn, Volume, Leads, etc, depending on the industry and KPI outcome for the advertiser. Circana models multiple outcome KPIs as separate models though the media setup within each of those distinct models would likely be the same.

High priority KPIs of advertising impact are effectiveness, efficiency, sufficiency, and ROI/ROAS against a given conversion KPI. Any level of the conversion funnel can be evaluated. Effectiveness is an equivalent metric ignoring difference in cost for comparing individual executions within a tactic. Efficiency is a metric which allows for comparison of all tactics regardless of unit of measure. Sufficiency defines the minimum threshold level to expect advertisement effectiveness where GRPs translated into sales revenue. ROI/ROAS is a universal measure of payback comparable across tactics accounting for the finances of an advertiser's business.

Circana is on the forefront of assessing long-term media impacts having developed a revolutionary process working with Dr. Carl Mela. Not only does this process assess the direct (short and long-term) impacts of media on a conversion KPI, but it also simultaneously assesses the impact that media is having in on brand attitudes (and the impact those attitudes have on outcomes).

Process undertaken with clients to turn modelled data into insights and business actions:

Decisions made leveraging Marketing Mix insights are typically strategic in nature. As part of an annual, or perhaps more frequent, planning cycle Marketing Mix first and foremost helps advertisers make strategic allocation decisions across their media portfolio. Facilitated by response curves generated as part of the analysis our advertiser partners are able to understand the marginal benefit of choosing to invest more or less heavily in each tactic. These decisions can be balanced against the business priorities at that time, balancing between possible extremes such as maximizing ROI, maximizing profit or driving maximum possible sales while ensuring ROI neutrality. As part of this decision process the insights generated also allow our advertiser partners to make decisions about weekly executional weight, delivering timing and flighting patterns. Collectively the decisions made using Marketing Mix insights allows for the creation of a complete strategic media plan. Decisions are supported by both presentation materials as well as, significantly, our Marketing Planner Optimizer platform.

This platform allows users to run unlimited what-if scenarios as well as optimizations generated while accounting for business constraints. Based on our impact benchmarks we typically see insights generated as part of the Marketing Mix engagement result in ROI/efficiency improvements of 20%-50% vs. historical execution.

Clients receive a high-level summary deck with final base and incremental sales decompositions, financial return metrics with business interpretations and actionable recommendations designed for senior leaders.

Model integration with other marketing measurement tools:

Circana (formerly Nielsen MMM) recommends an integrated approach to marketing measurement, combining Market Mix Modeling with other tools like attribution and incrementality testing. By integrating MMM with other measurement tools and following these recommendations, clients can develop a more comprehensive, accurate, and actionable understanding of their marketing performance across channels and over time.

Here's how Circana's MMM integrates with other measurement tools and how clients are advised to use them together:

Integration with Attribution Models:

- ***Data sharing:*** MMM can use aggregated results from attribution models as inputs, while attribution models can use MMM insights to refine their algorithms.
- ***Channel-level insights:*** Attribution provides granular, user-level data for digital channels, which can complement the broader, long-term view of MMM.
- ***Cross-validation:*** Results from both methods can be compared to identify consistencies and discrepancies, leading to more robust insights

Complementing Incrementality Testing:

- ***Test design:*** MMM insights can inform the design of incrementality tests by identifying high-impact channels or tactics.
- ***Result interpretation:*** Incrementality test results can be used to validate or refine MMM coefficients.
- ***Holistic view:*** While incrementality tests provide causal evidence for specific campaigns or channels, MMM offers a comprehensive view of all marketing activities.

Model integration with other marketing measurement tools:

Circana (formerly Nielsen MMM) recommends an integrated approach to marketing measurement, combining Market Mix Modeling with other tools like attribution and incrementality testing. By integrating MMM with other measurement tools and following these recommendations, clients can develop a more comprehensive, accurate, and actionable understanding of their marketing performance across channels and over time.

Here's how Circana's MMM integrates with other measurement tools and how clients are advised to use them together:

Integration with Customer Data Platforms (CDPs):

- ***Enhanced data inputs:*** CDPs can provide rich, first-party data to improve the accuracy of MMM.
- ***Audience segmentation:*** MMM results can be applied to customer segments identified in the CDP for more targeted marketing strategies.

Combining with Brand Health Tracking:

- ***Long-term effects:*** Brand health metrics can be incorporated into MMM to better understand and quantify long-term marketing effects.
- ***Brand-sales relationship:*** MMM can help quantify how brand health metrics translate to sales performance.

Accreditations, standards, external audits or validations:

Circana's Marketing Mix Modeling (formerly Nielsen MMM) has undergone various forms of external validation and adheres to industry standards. Here's a brief outline of the independent audits, accreditations, academic reviews, and global standards applied to Circana (formerly Nielsen MMM):

- ***Media Rating Council (MRC) Accreditation:*** MRC accreditation for various measurement services, including aspects of its marketing effectiveness solutions.
- ***Academic Review:*** collaboration with academic institutions and researchers to validate their methodologies.
- ***Industry Standards:*** adherence to guidelines set by industry bodies such as the Advertising Research Foundation (ARF) and the Interactive Advertising Bureau (IAB).
- ***Third-Party Audits:*** regularly undergoes third-party audits of its methodologies and processes.
- ***Global Standards:*** global presence means frequent alignment with international standards for data quality and analytics, such as ISO certifications for data security and quality management.
- ***Peer Review:*** participation in industry forums and conferences where their methodologies, including MMM, are subject to peer review and discussion.
- ***Client Validation:*** MMM methodologies are often validated through rigorous testing and comparison with client-held data and other measurement approaches.

A selection of resources from Circana (formerly Nielsen MMM):

- Circana (formerly Nielsen MMM) Case Studies
- The ROI of AI - Nielsen + Google: Quantifying the Power of AI in Advertising
- CPG Marketing Mix Modeling meta analysis - Nielsen and TikTok: MMM accurately measures the impact of TikTok advertising
- Unleashing the Power of Creator Content - Nielsen and Whalar: Predictive ROI accurately estimates what creators bring to the Mix
- Leveraging the Power of LinkedIn to Build Your B2C Financial Services Brand
- Outcomes, not output: Measuring impact across the full marketing funnel
- The Long and Short of It: Mark Ritson on how YouTube works for Mondelez and Uber - Nielsen MMM + Mondelez MMM + Google
- A Case for Analyzing AR Investments Within Marketing Mix Models - Nielsen + Snap
- How well does Meta drive incremental sales for Restaurant advertisers? - Nielsen + Meta
- Reddit helps consumers discover and Food & Bev brands grow - Nielsen + Reddit

Gain Theory

Metrics to quantify the impact of advertising and marketing:

Gain Theory's MMM models can track a wide range of KPIs and metrics to quantify and analyse the impact of advertising and marketing. Including:

Sales-Related Metrics:

- Incremental Sales: sales generated by marketing activities, by channel, campaign, creative, tactic, etc.
- Profit Return on Investment (ROI): The ratio of incremental profit to marketing investment, by channel, campaign, creative, tactic, etc.
- Revenue Return Investment (ROAS): The ratio of incremental revenue to advertising spend, by channel, campaign, creative, tactic, etc.
- Customer Lifetime Value (CLTV): The predicted revenue a customer will generate throughout their relationship with the brand.
- Market Share: The brand's percentage of total sales in a given market.
  Price elasticities, particularly where these change over time due to client activity (eg brand marketing)

Media Metrics:

- Effective frequency, and recency of ad exposures for media campaigns required to meet objectives, as measured by Gain Theory's AdModel™.

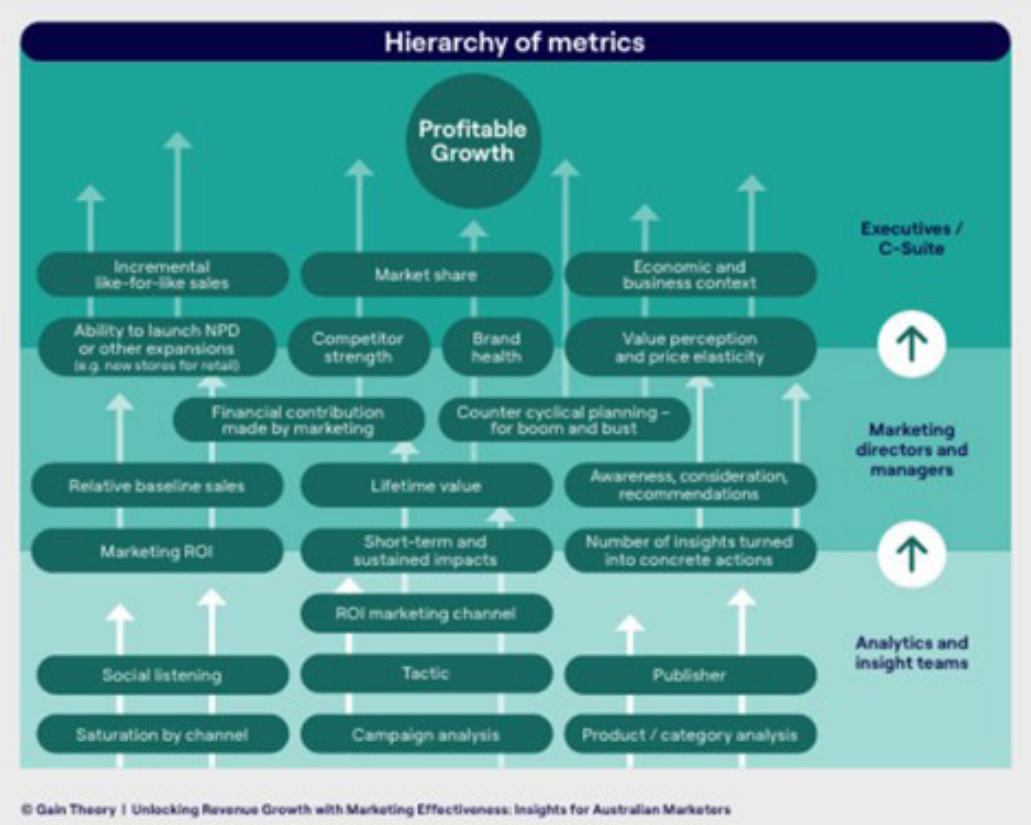
Brand-Related Metrics:

- Brand Awareness / Consideration / Preference / etc. The percentage lift of marketing (by channel, campaign, etc.) per $X invested.

Engagement Metrics:

- Website Traffic: Number of visitors driven to the brand's website by channel, campaign, creative, tactic, etc.
- Search Volume: Number of web searches driven by channel, campaign, creative, tactic, etc.
- App Engagement: Metrics such as downloads and sessions driven by channel, campaign, creative, tactic, etc.

Changes in both Brand Metrics and Engagement metrics can also be linked through to sales KPIs, with KPIs and metrics based customized to the client's specific business objectives.



Source; Gain Theory

Process undertaken with clients to turn modelled data into insights and business actions:
Gain Theory follows a structured process to transform modelled data into actionable insights and drive business results for our clients:

1. ***Insights Generation:*** Our team of experienced consultants analyses the model outputs to identify key drivers of performance and uncover actionable insights. We go beyond the "what" to understand the "why" and "what to do next."
   - Granularity: Our models deliver granular outputs—channel, partner, tactic, campaign, and creative level—tailored to data availability and business needs.

2. ***Collaboration and Validation:*** We work closely with our clients to validate the insights and ensure they align with their business knowledge and objectives. This collaborative approach helps to build trust and ensure that the insights are relevant and actionable.

3. ***Scenario Planning:*** We use Gain Theory Interactive (GTI), our client-facing business intelligence platform, to create scenarios and forecast business outcomes for different budget levels and allocations, including:
    - Optimizing a fixed budget
    - Forecasting the impact of an existing plan
    - Adding or cutting marketing budgets
    - Determining the budget required to achieve a specific business goal

4. ***Optimization and Action Planning:*** Based on the scenario planning results, we develop a set of actionable recommendations for optimizing marketing investments. We work with our clients to prioritize recommendations and develop a detailed action plan for implementation.

5. ***Tracking and Validation:*** We track the performance of the implemented recommendations and validate the model's accuracy and the value driven back to the client. This helps us to continuously improve our models and provide our clients with the most effective strategies.

Model integration with other marketing measurement tools:

Gain Theory advocates a "Unified Measurement" approach, combining MMM with other methods for a holistic view of marketing performance:

- ***Unified Framework***: Integrates MMM and MTA-type approaches into a single framework for consistent insights across channels and activities. This ensures alignment between measurement methods and supports data-driven decision-making based on a comprehensive understanding of the marketing landscape.
- ***Bayesian Methods:*** Incorporates results from other approaches as priors in the modelling process, reflecting confidence levels to enhance accuracy and reliability.
- ***Integration with Testing***: Combines MMM with incrementality testing to validate model results and uncover optimization opportunities. Testing outcomes are incorporated into MMM as priors, further improving precision.

By integrating MMM with complementary methods, Gain Theory delivers actionable insights that enable clients to make informed decisions and achieve measurable improvements in marketing performance.

Accreditations, standards, external audits or :

Gain Theory is committed to providing our clients with robust and reliable measurement solutions. We have received several external validations of our approach, including:

- ***Forrester Leader:*** Gain Theory was recognized as a Leader in The Forrester Wave™: Marketing Measurement and Optimization, 2023. Gain Theory received the highest scores possible in 17 criteria across three assessment categories: Current Offering, Strategy, and Market Presence.
- ***SOC-2 Accreditation:*** Gain Theory maintains SOC-2 Type 2 certification, demonstrating our commitment to data security and privacy.
- ***Industry bodies:*** Gain Theory works with and provides technical +guidance to industry bodies such as the IPA, Warc, Effies, The ANA, DataIQ.
- ***Partnership with PyMC Labs:*** We partner with PyMC Labs, a leading Bayesian statistical computing firm, to ensure that our models are based on the latest and most advanced techniques.
- ***Gain Theory has Partner or Preferred Vendor status*** with companies such as Amazon, Google, iSpot.tv, Meta, Circana (formerly Nielsen MMM) , Circana (formerly Nielsen MMM) IQ, The Trade Desk, TikTok.

A selection of resources from Gain Theory

Reports & Research

- Unlock growth in 2025 with our trusted marketing effectiveness framework
- Unlocking revenue growth with marketing effectiveness: Insights for Australian marketers

Case Studies

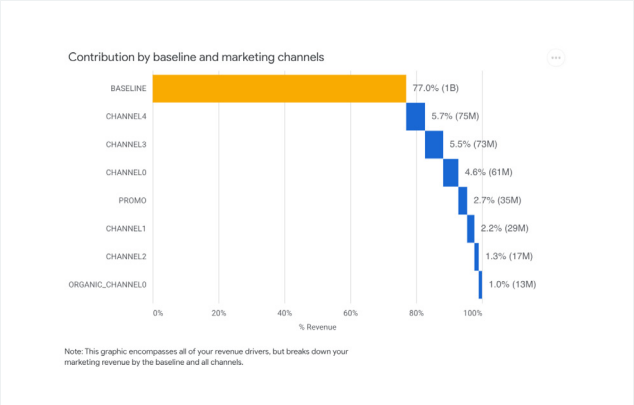
- Guiding marketing investment to support growth by balancing brand vs. activation activity
- Identifying insights to optimize business driver investments
- Optimizing marketing investments in uncertain times
- Transforming measurement frameworks to enable in-flight optimization
- Understanding the impact of rising inflation, interest rates, and energy costs
- Optimizing the media mix to drive growth
- Proving effectiveness to defend media budgets
- Using unified measurement to achieve incremental revenues

Google Meridian

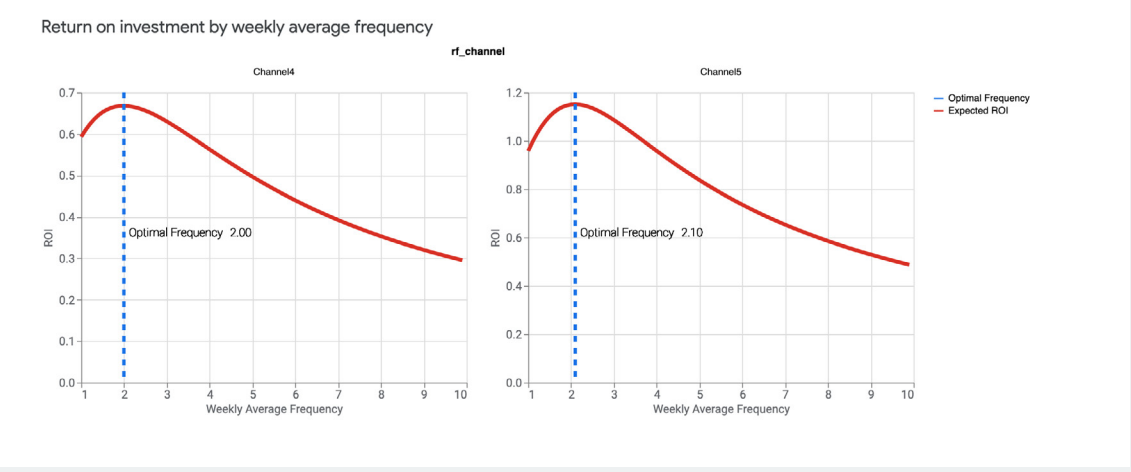
Metrics to quantify the impact of advertising and marketing:

Meridian offers a suite of metrics and tools to analyse the impact of paid media, organic media, and non-media treatments, such as price or promotion, on the model's outcome.

- ROI measures the efficiency of spend by comparing incremental outcome (KPI or revenue) to the cost of paid media.
- Marginal ROI (mROI) estimates the return from an additional unit of expenditure, identifying potential saturation.
- Effectiveness quantifies the outcome per ad unit.
- Contribution attributes the percentage of impact to each marketing activity.
- Response Curves visualize outcome changes with varying impressions, reach, or frequency.
- For channels with reach and frequency data, Optimal Frequency estimates the ideal frequency for maximum ROI.
- Meridian also provides Budget Optimization, allowing users to determine optimal spend allocation across channels for fixed or flexible budgets based on ROI or mROI targets, and to perform What-if Scenario
- Estimation to predict outcomes of hypothetical budget changes.



Images courtesy of Google



Process undertaken with clients to turn modelled data into insights and business actions:
Meridian offers modelers the flexibility to produce results at the level of granularity that 1) matters for their business and 2) can be supported by their input data. For example, geo-level modelling enables the generation of insights at both local and regional scales, facilitating localized marketing strategies. Meridian reports and key metrics such as ROI, mROI, and incremental impact can be produced with this crucial geo-level granularity, providing a comprehensive understanding of performance.

Meridian scenario planning further enhances this process by allowing for the estimation of "what-if" scenarios, enabling businesses to estimate ROI under various spend allocations. Response curves aid in estimating performance across different spend levels, while budget optimization provides the flexibility to determine the most effective allocation under both fixed and flexible budget scenarios. Optimization scenarios include maximizing ROI for a fixed budget, maximizing spend while maintaining a target ROI, and maximizing spend until a target marginal ROI is achieved. Soon, Scenario Planner will be accessible through Looker Studio making sharing results with non-technical teams easier via a live dashboard without needing to interact with code.

When a channel is modeled using reach and frequency data, the optimal weekly frequency can be identified to maximize ROI. Channel-level spend constraints can be applied during this optimization process, providing greater control.

Model integration with other marketing measurement tools:
Meridian's Bayesian framework facilitates seamless integration with other marketing measurement tools, enabling the use of their data as informative priors. Specifically, incrementality experiments (e.g., A/B tests and conversion lift studies), are vital for informing ROI priors and calibrating Meridian. Such priors can regularize inference towards experiment-based, causal estimates. Additionally, attribution models offer context for channel effectiveness, guiding variable selection and revealing areas for deeper MMM analysis.

Ultimately, combining insights from incrementality, attribution, and MMM -- the "Modern Measurement" approach -- provides a holistic view of marketing effectiveness, bridging short-term granularities with long-term strategic insights.

A selection of resources from Google:

- Meridian Website
- Meridian GitHub page
- Meridian blog post
- Geo-level Bayesian Hierarchical Media Mix Modeling
- Media Mix Model Calibration With Bayesian Priors
- Bayesian Hierarchical Media Mix Model Incorporating Reach and Frequency Data
- Bayesian Methods for Media Mix Modeling with Carryover and Shape Effects

Kantar

Metrics to quantify the impact of advertising and marketing:
These would be related to specific business needs and objectives and can range from:

- Sales (units, volume, $s)
- subscriptions
- visitations
- Retention / churn
- Quotes
- Transactions
- Member acquisition
- Brand Health
- Footfall
- Can also use indexed numbers if an advertiser is hesitant about sharing their other data

We will use the initial scoping / kick-off sessions with customers to determine the most suitable metric for their business. It will always be specific to them and their internal reporting needs. We will also provide advice on the metrics that we see the best results from, dependent on their industry.

Process undertaken with clients to turn modelled data into insights and business actions:
Our solution follows a structured process to allow clients to get the most out of their models, all delivered via a user-friendly interactive platform.

All insights are available at both granular tactical and higher strategic levels.

Granularity of Output for Tactical Decisions: Our solution provides highly granular insights by modelling at various levels, including product, segment, media publisher, media format and campaign type. This granularity allows clients to make precise tactical decisions based on detailed data.

Scenario Planning: We also enable scenario planning empowering clients to simulate the impact of different marketing strategies and non-marketing factors. This helps in understanding the influence of various factors on sales and brand equity, enabling informed decisions to be made

Optimisation and Process for Determining Best Allocation of Marketing Budgets: Our modelling and optimisation methodologies means that different budget levels will produce a different optimal mix, with the interactions between all factors accounted for. This enables clients to determine the best allocation of their marketing budgets by analysing the effectiveness of different channels and strategies.

Understanding and socialising insights: With on the ground seasoned MMM experts, we support our clients in understanding the insights and making recommendations for future plans. We are then on hand to help to socialise this through the business – from detailed planning workshops to board-ready reports.

Model integration with other marketing measurement tools:
Bayesian modelling methodologies utilise priors in the modelling process. Where a client has done other measurement tests, such as attribution or incrementality, we can use these results as our priors. This doesn't mean that the results will necessarily match, but we are open to using prior testing to calibrate and potentially improve our models.

Additionally, we work closely with media agencies and can supply response curves for them to integrate into their other planning tools.

MMMs are one way to allocate spends, but not the only way and so we highly recommend using in conjunction with other solutions, including measurement methods such as Cross Media, Attribution, A/B and Incrementality tests

Accreditations, standards, external audits or validations:
AURAs Innovation of the Year Award 2023 LIFT ROI shortlisted
IPA Effectiveness Award 2022 Silver for submission 'Making Purpose Taste Good' with client Waitrose and Partners

Consultancy Australia – top award winner

- Kantar Australia is a Diamond winner in the ConsultancyAU Top Consultancy Firms 2024 rankings for the Marketing Consultancy and Services category.
- We're proud to be one of just four winners in the top echelon of firms in this category, which ranks leading consultancies across 40+ sectors and 40+ areas of expertise.

According to The Forrester Wave™: Marketing Measurement and Optimisation (Q3 2023)

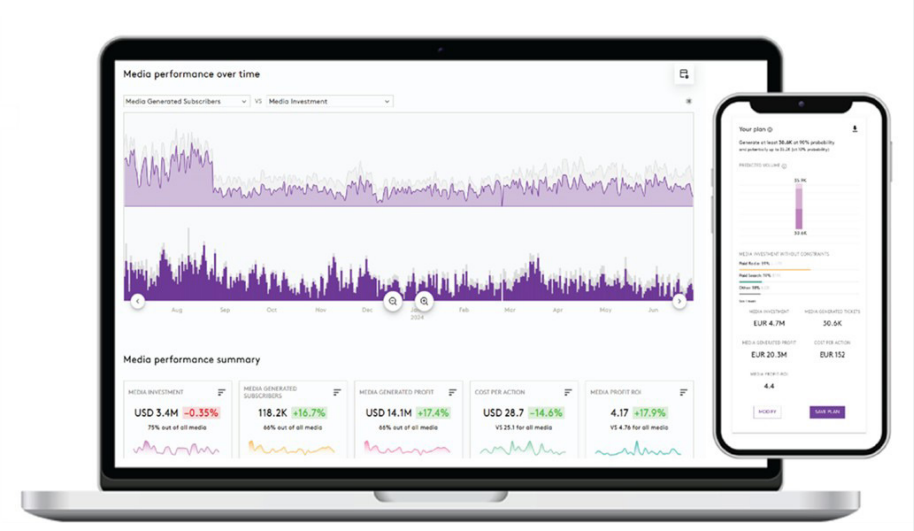
Its vision combines brand and performance insights to marketing value through data and technology.
The company's impressive client roster and global presence allow it to support large enterprise clients in various locations without the need for extensive third-party partnerships.

Kantar's core strengths lie in its onboarding, client management, and deep brand and performance insights.
The company's strategic marketing analysis capabilities are very strong because it provides a spectrum of complex brand, performance, and customer insights and analysis, like impact of marketing on brand equity and short-term sales.

Enterprises that have complex marketing- and brand-related questions should consider Kantar.

A selection of resources from Kantar:

- Leveraging LIFT ROI for Telcos: Balancing the Short and Long-Term Advertising
- Kantar unifies AI product suite with AI Lab launch
- A new era of storytelling: Inspiration for today's brands



Lifesight

Metrics to quantify the impact of advertising and marketing

The primary KPI is incremental ROAS or incremental CPA, along with marginal ROAS or marginal CPA per channel / tactic and a quantification of brand baseline (the conversions not explained by paid marketing).

These metrics inform users of 2 things - current incremental performance of each channel / tactic toward conversions and the optimal allocation between these channels for future time periods (between 1 month and 1 year into the future), taking into account planned control variables (pricing changes, product launches, promotions, etc.)

Typical process undertaken with clients to turn modelled data into insights and business actions:

- Collect data required to run a marketing mix model (through native integrations, flat files)
- Run a model at the desired channel / tactic
- Insights:
  - Descriptive - understand incrementality at tactic level across the historical date range
  - Prescriptive - understand marginal metrics for paid marketing allowing for scenario planning
  - Advanced Analytics - compute interaction effects (synergy and cannibalization) to give qualitative insights about scale up / scale down decisions across all the factors
- Calibration (optional):
  - If required, specific channels may be flagged for experimentation (e.g. not enough observations, not enough variation, multi-collinearity etc.)
  - The results from these experiments are used to calibrate the model
- Scenario planning:
  - Run scenarios and plans for a period of 1 month - 12 months into the future - these scenarios are run to optimize for a given budget or a desired conversion target / ROAS / CPA
  - Include advanced pacing configurations at channel / tactic, if required
  - Include planned control variables, like planned promotions, product launches etc., as applicable

    >Lifesight provides an ideal allocation across this future date range, including pacing details

    > Forecast vs Actual progress is tracked in the Goals dashboard

- Causal Attribution:
  - Incremental insights are used to calibrate ad-platform-reported numbers or GA4-reported attribution numbers through multipliers
  - Recommendations provided at the channel / tactic level are broken down into Campaigns and Ad sets in the Causal Attribution module
- Optimizer:
  - Can make automated or semi-automated budget changes in the ad platforms directly from Lifesight's optimizer interface

Model integration with other marketing measurement tools:

MMM is used to complement the following solutions:

Experiments (Incrementality Testing): The model is used to form hypotheses that can be tested using Geo experiments (provided on the Lifesight platform). After Lift is measured, this incremental ROAS / CPA is used to calibrate the MMM. This is a continuous process of testing and calibration

Causal Attribution: Incremental insights from the MMM are used to calibrate ad-platform-reported numbers or GA4-reported attribution numbers through multipliers. Additionally, spend recommendations from scenarios created on the Lifesight platform are broken down to the level of Campaigns / Ad sets in the Causal Attribution module

A selection of resources from Lifesight:

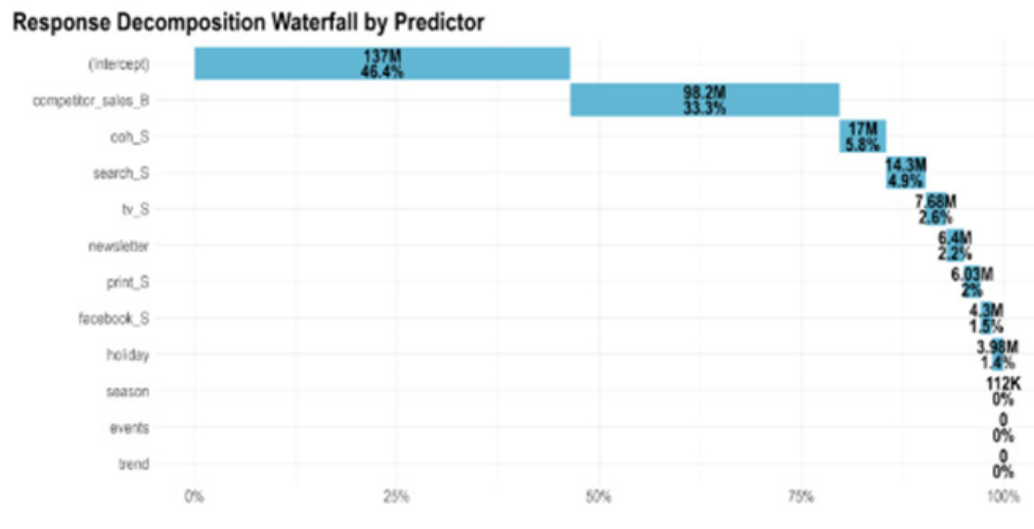
- Methodology Document
- Case Studies
- Product Updates
- Interactive Product Demo

Meta Open Source Robyn

Metrics to quantify the impact of advertising and marketing:

When it comes to model outputs, the standard outputs from Robyn include:

Response decomposition - This chart depicts the absolute and percentage contribution of all of the independent variables to the dependent variable. The percentages sum up to 100% and can be interpreted as "X% of the revenue can be explained by variable A". This is useful to understand which variables are the biggest drivers of the overall KPI:



Share of Spend vs. Share of Effect - This chart shows the comparison between the total effect share (or % contribution to sales) and total spend share for all paid media variables within the entire modeling window (side note: the bar charts are a visual representation of the Business Error or DECOMP.RSSD mentioned in section C!) The Return on Ad Spend (ROAS) of each media variable are also included in the chart, with ROAS being defined as total revenue driven by the channel divided by the amount spent:

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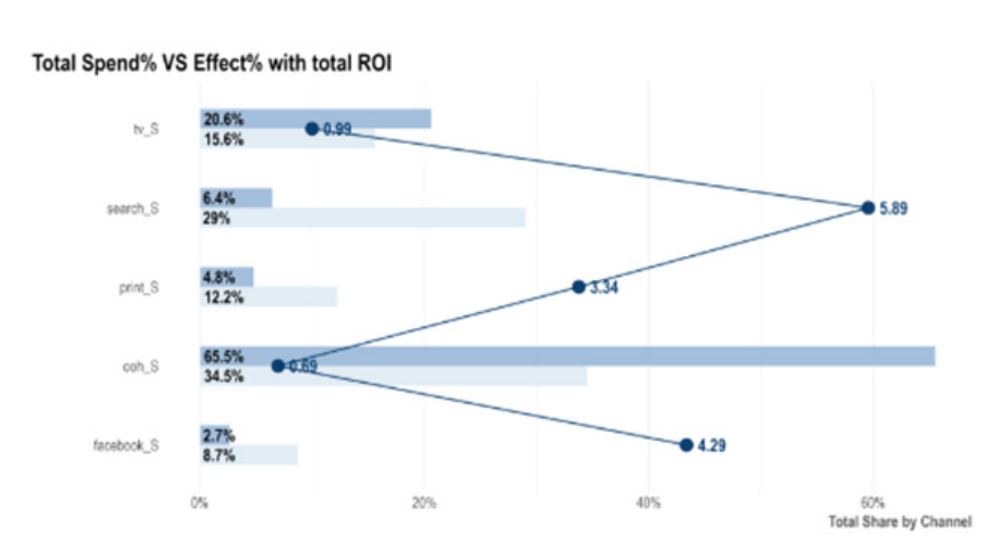

This chart is useful to contextualise the response decomposition output, as something may have a significant contribution but it may also account for a significant part of overall spend. ROAS is a relatively standard but useful MMM metric to understand a media channel's efficiency, where moving spend from lower ROAS to higher ROAS is a potential decision.

Robyn is flexible and models can be built using different KPIs such as sales/revenue for traditional businesses, new custom acquisitions for D2C businesses and app installs for online gaming brands. So depending on whatever metric was used as the dependent variable, the above outputs will be relevant to that (e.g. in the above output, 1.5% of total app installs were driven by Facebook/Meta).

Process undertaken with clients to turn modelled data into insights and business actions:
Being open-source, the end user is responsible for analysing the model results from Robyn and turning it into insights and business actions. Consequently, it is recommended for Robyn users to have historical MMM experience to extract its full value and maximise business impact.

One of Robyn's key features is Budget Allocator, which takes the model results and allows end users to scenario plan and simulate the impact of different marketing budgets. Budget Allocator also comes with two different scenarios:

- ***Maximum response:*** Given a total budget and media-level constraints, the allocator calculates the optimum cross-media budget split by maximising the response. For example: "What's the optimum media split if I have budget X?"
- ***Target efficiency (ROAS or CPA):*** Given a target ROAS or CPA and media-level constraints, the allocator calculates the optimum cross-media budget split and the total budget by maximising the response. For example: "What's the optimum media split and how much budget do I need if I want to hit ROAS X?"

Model integration with other marketing measurement tools:

At Meta, we believe there is no silver bullet to measurement and that brands should adopt a Measurement 360 approach by incorporating multiple measurement sources. Brands can acknowledge and use each measurement sources' unique strengths to make better decisions to improve their marketing effectiveness:

- Use MMM for more strategic budget allocation decisions, as it can holistically measure multiple media channels;
- Use attribution for more tactical day-to-day channel optimisations, as it can provide granular channel insights with speed;
- Use incrementality experiments to validate or test any decisions made from MMM or attribution insights, as it is the gold standard for measuring causality.

Accreditations, standards, external audits or validations:

Robyn has been reviewed in an academic paper by Julian Runge called "Packaging Up Media Mix Modelling: An Introduction to Robyn's Open-Source Approach1".

1Runge, J., Skokan, I., Zhou, G., & Pauwels, K. (2024). 'Packaging Up Media Mix Modeling: An Introduction to Robyn's Open-Source Approach'. arXiv. arXiv:2403.14674

A selection of resources from Meta:

- How BARK Optimized Budget Allocation With Marketing Mix Modeling | Meta for Business
- How Olive Young empowers partner brands with budget optimization using open source MMM from Meta
- How Robyn from Meta Open Source enabled Echo Marketing to efficiently optimize its ad spend
- How open-source marketing mix modeling enabled YOTTA to quickly optimize the brand media mix
- How Glint and Realtime Agency drove marketing efficiency by using Robyn:
- How Parmalat improved its understanding of performance with MMM powered by Robyn
- How the Travel industry can harness Robyn (Deloitte Whitepaper)

Mutinex

Metrics to quantify the impact of advertising and marketing:

- Media-attributed revenue and ROI
- Media-driven outcomes and outcomes driven by other external factors (sales volume, acquisitions, leads etc)
- Marginal ROAS by media channel
- Ad stock peak and decay duration per channel
- Brand Equity contribution in monetary terms
- Diminishing point of returns by channel and minimum/maximum spend

Process undertaken with clients to turn modelled data into insights and business actions:

Mutinex's platform, GrowthOS, translates complex model outputs into intuitive, actionable insights for marketers, finance teams, and executive stakeholders. Through a dynamic dashboard and our AI assistant, MAITE, users can query results in natural language and receive data-backed answers instantly.

Each client is supported by a dedicated Marketing Science Partner, who ensures insights are understood and embedded in regular decision-making to drive continuous performance improvement.

GrowthOS supports a range of planning and optimisation activities:

1. ***Channel ROI and Segmentation***
   Assess ROI by channel, brand, region or funnel stage to identify over- or under-performing investments.
2. ***Performance Optimisation***
   Review investment curves, campaign and creative effectiveness, publisher and format-level results, and ad stock dynamics to guide tactical refinement.
3. ***Budget Planning and Forecasting***
   Run forward-looking scenarios with budget constraints to simulate outcomes at brand or portfolio level.
4. ***Planning and Optimisation***
   Generate optimised media plans that maximise ROI and support integrated planning across teams with various factors considered and included.

By combining robust modelling with an intuitive platform and expert guidance, Mutinex empowers marketers to move from insight to action—building long-term value through data-driven planning.

Model integration with other marketing measurement tools:

The Mutinex Marketing Science team has a wealth of experience in supporting advertisers embed ROI insights from GrowthOS within their other media measurement solutions.

This includes support on deploying Test & Learn agendas that consider the strengths and limitations of various measurement practices in order to prove or explore opportunities.

Our interface can integrate data, PDFs and more from a range of other tools.

Accreditations, standards, external audits or validations:

Mutinex undertakes regular model validation directly with customers (as described above). We have also been vocal in our support for higher standards of transparency and standardised validation in the industry.
Many of our customers have noted that this level of transparency has helped to drive confidence and credibility for marketing within their business.

Asahi Group Head of Consumer Experience, Megan Coutts-Quinn says "We've seen that Mutinex GrowthOS is empowering for businesses, it builds belief - you can see the impact of your actions."
We provision all governance and testing code to our customers directly - meaning they can review the code should they wish to do so.

A selection of resources from Mutinex:

- Mutinex publishes the Marketing ROI Index Report biannually, most recent Mutinex Marketing ROI Index Report
- A full list of our customer case studies is available on our website
- Lion Strikes a balance between in house and agency
- Dominos Australia eye a bigger slice
- How Optus supercharged its marketing with MAITE
- The strategic marketing transformation at Michael Hill

Prophet

Metrics to quantify the impact of advertising and marketing:

- Incremental Sales/Revenue: Sales uplift directly attributable to marketing activities.
- Media Contribution: Channel-specific and campaign-specific contribution to overall results.
- Cost per Incremental Outcome (CPI, CPIS): Efficiency benchmarking for incremental conversions or leads.
- Optimised Budget Allocation: Recommended budget distributions to maximise desired outcomes.
- Marginal Return Curves: Analysis of diminishing returns for informed budget allocations.
- Channel Synergies: Interaction effects between channels informing integrated marketing strategies.
- Brand Impact Metrics: Upper and mid-funnel measures linked to long-term sales.
- Customer Acquisition Cost (CAC) and Lifetime Value (LTV): Evaluation of marketing effectiveness in customer acquisition and long-term customer profitability.

Process undertaken with clients to turn modelled data into insights and business actions:

At Prophet, our Marketing Science team works closely with clients to turn model outputs into actionable insights that drive real business impact.

We follow a structured four-step process to ensure insights are not only statistically valid but also commercially meaningful:

1. Deep-Dive Analysis - We begin by unpacking the model's outputs — examining cross-channel and individual channel effectiveness, diminishing returns and ad-stock decay rates. This diagnostic phase highlights the true performance drivers across the marketing mix.

2. Holistic, Cross-Channel Review - We evaluate performance across paid, owned, and earned media holistically, capturing indirect effects and broader business dynamics. This prevents channel-level optimisation from undermining total business outcomes.

3. Experimental Design Alignment - Working with the channel owners and wider Marketing and Agency team, we align on appropriate experiments that may provide either improved performance or uncover underlying performance of an existing or new channel. These experiments are then either run through our platform or on a publisher's platform.

4. Scenario Planning and Media Plan Optimisation - Finally, we use our Predictive Intelligence feature to simulate alternative media investment strategies — incorporating budget constraints and business priorities. This enables us to generate media plans that maximise return, balance short- and long-term objectives, and guide planning across internal teams and media agencies.

Model integration with other marketing measurement tools:

Prophet complements other measurement tools, such as multi-touch attribution (MTA) and incrementality testing. Integration via API allows seamless data exchange, using MMM for strategic oversight and MTA and incrementality testing for tactical fine-tuning.

Prophet works directly with CDP platforms, enabling measurement down to cohort level, not just marketing/media/channel level.

Accreditations, standards, external audits or validations:

Prophet holds ISO 27001 certification and aligns with IAB Tech Lab and MRC standards. Core statistical methodologies employed are academically validated. Clients may engage third-party audits to verify model integrity and compliance. .

Recast

Metrics to quantify the impact of advertising and marketing:

Recast tracks key marketing KPIs, including ROAS, CPA, marginal ROI and marginal CPA at aggregate, "channel" and "subchannel" levels.

Recast models can be built based on revenue or acquisition data (ex. new customers, leads, app downloads, etc.). Because of its hierarchical structure, Recast can also model and optimize across various segments (e.g., different geographies, product lines, new vs. returning customers, etc.).

Process undertaken with clients to turn modelled data into insights and business actions:

After Recast's rigorous model building process is complete, clients meet with their dedicated Recast team to start building action-based Incrementality Systems of planning, experimentation, validation, and optimization of marketing performance. These systems turn modelled data into business actions, and ultimately, improved marketing performance over time.

- Planning: Clients use Recast's scenario-planning tools–including Plans, the Forecaster, and the Optimizer–to create initial budget plans that are rooted in the platform's measurements of incrementality across channels.
- Experimentation: Clients use Recast to build experimentation roadmaps, focusing on channels with high uncertainty in their measurement and channels with divergent performance across attribution methods.
- Validation: Experiments run in Recast GeoLift and budget changes are used to validate the model's output and provide signal that will calibrate future model runs.
- Optimization: With more calibrated tooling, clients use Recast's suite of marketing insights dashboards–showing incremental ROI or CPA at the aggregate, channel, and tactic levels–to optimize marketing budgets and inform new plans for upcoming periods.

The Incrementality System process is then repeated, yielding improved marketing performance over time.

Model integration with other marketing measurement tools:

Recast integrates with other measurement tools by providing a holistic, top-down view of marketing effectiveness, complementing attribution and incrementality testing. Recast's suite of forecasting and optimization tools also allows users to engage in Incrementality Systems of planning, experimentation, validation, and optimization that ultimately yield improved marketing performance.

- MMM as the Strategic Layer: Recast measures total marketing impact, including long-term effects and offline channels, which attribution models miss.
- Holistic Measurement Across Channels: Attribution models track user-level interactions but often over-credit digital channels. Recast corrects for this by measuring true incrementality across marketing channels.
- Incrementality Testing for Validation: Lift tests can be used to validate previous estimates and calibrate the model for improved accuracy.
- Unified Platform: Recast's suite of planning, optimization, forecasting, experimentation, and goal-tracking tools can be used for dynamic media mix optimization, building experimentation roadmaps, and more.

A selection of resources from Recast:]

- Recast Public, Technical Model Documentation
- Recast Platform Overview
- Recast Case Studies

chapter 5
industry perspectives

A range of industry leaders from agencies and media owners have provided their perspectives on MMM.

a) Market Mix Modelling in Practice, a Strategic Lens for Advertisers

Andy Macdonald, National Head of Digital at Carat
James Morgan, Head of Data & Analytics at dentsu Media ANZ

Market Mix Modelling (MMM) has re-emerged as a critical tool in the advertiser measurement stack, and we have seen a shift across our client base. Its ability to quantify the contribution of media and non-media drivers to business outcomes, particularly in a signal-constrained environment, makes it a valuable asset for strategic planning and media optimisation. However, its effectiveness depends not just on technical sophistication, but on how well it is embedded within a broader measurement framework that reflects the realities of modern marketing.

From an advertiser's perspective, *MMM must be evaluated not only on its statistical rigour but on its ability to answer meaningful business questions.* The best MMM implementations we've seen are those that start with a clear business problem. Not "what's my ROI?" but "How can I manage creative proposition for the best ROI", "What are the drivers of ecommerce growth, and how can I balance with brick and mortar", or "how do I balance price promotions with brand investment?" These are the kinds of questions that unlock real value, and they require a model that's tailored, not templated.

It's important to understand that MMM is not a silver bullet but instead belongs to a broader measurement framework covering MMM, incrementality testing, and real time metrics. Each method has its strengths; MMM provides a macro-level view of media effectiveness across channels and time; real time platform metrics offer tactical insights for in-platform optimisation; and incrementality testing validates causal relationships through controlled experiments. Used together, these tools provide a much more complete picture of marketing performance.

We also recognise that MMM is not a one-size-fits-all solution. *The choice of methodology is complex, but important.* At our agency, we approach MMM as part of a holistic and agnostic analytics offering that includes open source and vendor solutions depending on the client's required outcomes, and budget. For some clients, particularly those new to MMM, open-source models give the ability to quickly create a model as a proof-of-concept. This gives them directional insights, allows them to get a feel for what they want MMM to answer for them, and importantly whether they even have the data to answer key questions. In other instances, vendor-led solutions provide the scale and support needed to operationalise insights across teams.

As alluded to above, we find that *data readiness remains a key barrier to adoption.* Granular, clean, and timely data is essential, but so is organisational alignment. Successful MMM implementations can require collaboration across marketing, finance, analytics, and IT. Assigning internal champions and investing in education around model interpretation are critical steps toward driving adoption and impact.

MMM should not be treated solely as a retrospective reporting and insights tool. *Real value is generated by balancing strategic insight with future forecasting.* Scenario planning and budget optimisation are critical for marketers and advertisers to simulate outcomes under different investment strategies and align media planning with business objectives.

Our agency's approach is grounded in ensuring that MMM is directed towards answering actual business problems and decision making for our clients. This helps with ensuring that socialised recommendations are relevant to the overall uptake of the findings. Realising that MMM is one of multiple layers to measurement, we also ensure that it is surrounded by the appropriate testing roadmap to validate key hypotheses and budgeting decisions that come out of MMM.

In summary, MMM is a powerful tool and one we are committed to as an agency. It can help mitigate ongoing challenges in signal loss, privacy legislation and evolving consumer behaviours.
MMM's resurgence is a good thing. But if we want it to stick, we need to move beyond the hype. Advertisers don't just need more models. They need more clarity, more context, and more confidence in the decisions they make.

b) The Case for Objectivity: Why MMM Belongs in the Boardroom

Liam Loan-Lack, Chief Customer Officer at Keystart

In my view, a core advantage of MMM is its ability to add objectivity to marketing measurement. Traditional "softer" metrics like brand health, while important, often lack the rigor and credibility needed for boardroom discussions. MMM, by contrast, *quantifies the incremental impact of each marketing activity on sales and ROI, moving the conversation from efficiency metrics like cost-per-acquisition to effectiveness and incremental growth*. Importantly, it enables the missing conversation at the decision-making table: 'have we reached a point of diminishing return on our current marketing channels/strategy?' This objectivity elevates marketing's role in strategic decision-making and ensures that investment decisions are grounded in evidence rather than intuition. This can be an exposing time for Marketers and business leaders alike as many "sacred cows" could be revealed as untrue or less effective than previously thought.

Crucially, given MMM isolates the true drivers of the chosen business KPIs, *MMM ensures that marketing is not held solely accountable for outcomes influenced by forces beyond its control.* I found this clarity essential during annual budgeting cycles, as it doesn't just acknowledge market factors, it quantifies the impact which I have found leads to fairer whole of business OPEX allocation. Oftentimes, without an MMM, Marketers are on the hook for the whole increase in Revenue YoY, without any acknowledgment that typically Marketing is only responsible on a causative basis for about 30-40% of business KPIs (significant variance by vertical exists).

My experience also indicates that, *despite the sometimes painful experience of organising the data for ingestion into the initial model creation; this exercise is highly helpful* in:

1. "forcing" collaboration cross-functionally on what independent variables actually matter in affecting the modelling (dependent) KPI,
2. accelerating a conversation about democratising business, customer and market data internally, beyond the usual silos which form in an enterprise and
3. pinning down the single most valuable contribution that marketing makes (I.e. business KPIs of - volume of new customers, gross Revenue, eCommerce v Retail Sales etc.). Whilst this is reductive, I think it so key to gaining C-Suite buy-in and to focus marketing efforts. This helps avoid the temptation of tactics on tactics, which don't meaningfully drive the single business KPI the business cares about.

c) The Role of Marketing Mix Modelling in the Measurement Framework

Lillian Zrim, Head of Research at PHD

In today's competitive marketing landscape, the ability to make data-driven decisions is not just beneficial; it's essential for success. Marketing Mix Modeling (MMM) stands out as a cornerstone of this approach, linking media spend directly to tangible business outcomes. By providing a holistic view of marketing performance through the demonstrable effectiveness of channels and tactics, MMM informs budget allocation and predicts the outcomes of future marketing activity.

As data abundance increases, marketers face heightened pressure to demonstrate the effectiveness and ROI of their marketing spend. However, effective decision-making requires a well-considered measurement framework that gives data true purpose and meaning. Here, MMM emerges as a critical tool, integrating key data sources amid the chaos and serving a clear role in the overall measurement framework.

Key Components of a Comprehensive Measurement Framework

An effective measurement framework encompasses multiple pillars, including:

- Media Performance: Assessing the effectiveness of different channels.
- Brand Equity: Understanding brand health and the funnel
- Business Outcomes: Linking marketing activities to tangible business results.

This framework should enable marketers to grasp both macro and micro-level impacts, ensuring a comprehensive understanding of marketing performance for effective optimisation. There is no one tool to rule them all; different KPIs across these pillars require varied tools for effective measurement. MMM connects media spend to business results, particularly at the bottom funnel, making it a favorite among marketers.

While MMM is a critical tool, it should be used alongside other metrics and tools for a truly holistic measurement approach. A well-rounded framework includes metrics measured at the macro-market level using longitudinal data sets, alongside specific campaign or micro insights either in-platform or cross-platform for more tactical optimisations.

The Complementary Role of MMM in Marketing

It is essential to recognise that relying solely on MMM for performance insights may overlook critical drivers of channel success. Instead of viewing MMM as a standalone tool, marketers should consider it part of a broader toolkit that includes various measurement methods tailored to specific purposes and KPIs.

MMM provides valuable insights into media investments and business results, but other tools in the measurement framework cover important channel and audience insights. A bias towards ROI has made MMM a key tool; however, it does not encompass the complete measurement framework. Understanding the "why" and "how," the consumer journey, and building brand equity all matter, as does optimising along the path to business outcomes.

Complementary metrics and tools include:

- Media performance and conversion metrics
- Brand health data
- Attribution studies
- Incrementality studies

These metrics and tools provide a fuller picture of the drivers of performance and success.

Challenges and Considerations in Utilising MMM

Traditional challenges with MMM include the frequency and timeliness of insights generated. As decision-making timeframes shorten, the need for MMM models to deliver timely outputs becomes increasingly important. However, marketers must remain mindful of data input availability and volatility with shorter timeframes; quick reporting timelines may not always provide the full picture and there is a need for robust data governance. Continuous feeding of high-quality data into MMM models is essential, as measurement is never a "set and forget" process.

Ultimately, MMM is vital within a comprehensive measurement framework, enabling marketers to navigate data-driven decision-making effectively. Its ability to link media investments to business outcomes is greatly enhanced when combined with other tools that provide deeper consumer insights and improve channel effectiveness. By adopting an integrated approach, marketers can align strategies with evolving business goals, ensuring every dollar spent drives sustainable growth.

d) A Journey to Smarter, More Data Driven Marketing Strategy

Ashley Spinks, Head of Research and Effectiveness at Seven Network

Seven plays a dual role in Market Mix Modelling (MMM), as both a client leveraging MMM through our internal marketing team, and as a publisher, supporting our clients on their own MMM journey.

Seven as an MMM Client:

We recently partnered with Prophet (a MMM provider profiled in this report), to build a custom solution to determine the optimal media mix for Seven's paid, earned and owned marketing. The engagement was driven by a need for more strategic media planning, more precise allocation of resources and spend, and a deeper understanding of media effectiveness. We're using the insights from this model to inform our FY26 planning, helping us prioritise the most effective combinations of media channels and investments to drive efficient, high-value audience (HVA) viewership uplift.

The customised MMM approach enables us to tackle several longstanding business challenges:

- ***The value of owned media:*** As a broadcaster with substantial owned media inventory, we face the challenge of balancing the use of cost-effective internal channels with the imperative to reach new or lapsed audiences externally. While owned media is efficient, it may limit growth if we're only reaching to existing viewers. We've developed methods to assign appropriate value to these placements, allowing us to evaluate whether we're relying too heavily on internal channels at the expense of broader audience growth.
- ***Modelling for Viewership:*** For most businesses, MMM is used to optimise for sales or conversions which are tied to goods and services, however, free-to-air TV operates on a different premise - it's free to the consumer. As a result, our business objective is modelled not on transactions but on viewership, requiring a nuanced approach to modelling.
- ***Quantifying the impact of organic social:*** Seven operates several large, highly engaged social channels, however, assigning a dollar value to the influence this content has on our audience has been a challenge. Through this modelling, we will better understand how our social content and channels contribute to awareness, engagement, and ultimately audience conversion to our screens.

Data inputs:

A critical component of our MMM is the selection and integration of high-quality data inputs. The model is only as good as the data you put in. For Seven, the inputs include Seven's owned media inventory, paid media such as radio, OOOH, Digital etc., historical brand tracking data and lastly and most importantly, daily VOZ data to determine the impact of our marketing on our audience volume with greater precision. MMM is helping us produce insights that compare the value and effectiveness of owned media and organic social against paid media outcomes, providing more effective, data-driven marketing strategies.

Seven's role in supporting clients with MMM:

Our investment in MMM not only enhances our planning capabilities but also strengthens our ability to support clients in unlocking greater value from their Total TV investment.
At our 2024 Upfronts, we announced an exciting opportunity for our clients to access a comprehensive and independent MMM study. As part of the opportunity, Seven will contribute $2 million in advertising inventory value across our full media ecosystem, including Channel 7, 7plus, 7NEWS.com.au, The Nightly and more.

This collaboration offers clients a data driven understanding of what is truly driving performance relative to their entire media mix, not just TV, while also giving our business access to Total TV learnings and case studies so we can better understand the role Total TV plays in overall campaign effectiveness. All data is analysed independently of Seven, ensuring complete objectivity and transparency. We are currently in the early stages of onboarding clients and excited to unveil results later in the year.

We recognise that MMM has a pivotal role to play in guiding media investment decisions, however, it is just one part of a broader measurement framework. We are mindful to not treat MMM as a single source of truth – a trap that brands can so easily fall into. Marketing effectiveness is influenced by a range of factors beyond the model itself, including media quality, creative excellence, audience engagement, channel context and more. A holistic view to measurement is essential. That said, we still value the insights MMM provides; for Seven, it is more than an internal planning tool; it's about building a deeper, more objective understanding of how our channels contribute to campaign success and supporting our clients and the wider industry to do the same.

At Seven, we're committed to leading the way towards a more data-driven, transparent and effective future for media planning and buying –both for yourselves and the wider industry.

e) How to unlock the maximum ROI from Media Mix Modelling

Dave Goodfellow, Head of Measurement Solutions, APAC at Pinterest

Advertisers have adopted Media Mix Modelling (MMM) solutions in droves over recent years in response to reduced deterministic attribution data, siloeing of reporting across media channels, and an increased business need for deepening the understanding of ROI across the media mix. For many marketers, the view of marketing outcomes offered by MMM brings measurement breadth and flexibility. And for many others, it can provide a stark contrast to previously held views of ROI.

Creating a view of marketing outcomes that encompasses a diverse and expanding set of platforms, their nuances and the roles they play at each stage of the marketing funnel, requires both a rigorous scientific method and artful experimentation to find the best fit for each business. And while MMM can do an excellent job of analysing cross-channel media ROI, effectiveness, and the factors that influence them, there are a handful of factors that are incredibly important to get right to ensure that your MMM model — whether run in-house or via a third party — is finely tuned to represent the reality of your business.

1. Use High Quality Data Inputs

MMM outcomes are only as good as the inputs that power the models. Too often, we see brands relying on manual data exports, templated input specifications that ignore platform nuances, or sporadic, incomplete data drops that create risks of error and lag. In a best-practice approach, MMM vendors should ingest data directly from automated, API-based reporting solutions, and collaborate with media owners to determine how best to ingest and model the data taking into account the unique mechanics of each media channel (e.g. different ad formats, user behaviours, high or low viewability etc).

As a media owner, Pinterest invests in building and maintaining API connections to support clean, timely, and granular data feeds into advanced measurement systems. Advertisers should pressure test their partners: Are they leveraging API solutions, or are they dependent on manual, error-prone data pulls? Automated data integration ensures the consistency of the inputs delivered and enables models to capture the full fidelity of campaign performance. Clean, high quality data isn't just a technical detail—it's the foundation of credible, actionable MMM results.

2. Getting Granularity Right

A fundamental strength of MMM is its ability to disentangle the impact of diverse marketing channels on marketing outcomes. However, modeling often lumps together disparate platforms into broad categories, such as grouping Pinterest, Meta, TikTok and others under the singular umbrella of "social media." This masks the unique ROI and role that each channel plays in the consumer journey, based on the differing shares of investment and impact that each channel provides. Each platform offers different audience segments, creative formats, and engagement patterns — lumping them together can lead to significant misattribution and underinvestment in platforms delivering incremental ROI.

We strongly encourage advertisers to ensure their MMM solutions provide granular, channel-level insights — for all media types, not just 'Social media'. Expect your models and reports to explicitly identify platform-specific ROI, and don't hesitate to push for analysis that separates out investments by media owner in both Traditional and Digital media channels.

Channel level reporting is an absolute minimum, but within each channel there are also a number of factors that can further enhance the actionability of your MMM findings to maximise ROI. Three primary ones to consider are:

1. Different buying objectives (e.g. Awareness, Consideration and Conversion)
2. Individual campaigns
3. Ad Formats.

Each of the underlying aspects of a channel's performance mentioned above can vary significantly in reach, cost, engagement and effectiveness. This highlights how understanding MMM ROI and effectiveness only at the channel level can still dilute understanding of ROI significantly. Those and other individual factors within an individual media channel often play a significant role upstream ROI result, making it valuable to also request reporting granularity deeper than channel level to best test, analyze and optimize the greatest drivers of ROI. Only from this vantage point can marketers confidently rebalance budgets towards the platforms and strategies that are truly driving business results.

3. Calibrate with Incrementality Studies

MMM is a powerful tool, but like all models, it is fundamentally a representation of reality, not reality itself. One of the most effective ways to maximize confidence in MMM outcomes is to calibrate models with incrementality studies, such as sales lift, conversion lift, brand lift, geo experiments or other randomized control trials. These studies directly measure the causal impact of media by comparing exposed and control groups in the real world. Advertisers that calibrate MMM findings with results from incrementality tests can identify and adjust model assumptions to create a view of ROI that is as aligned as possible to their tangible marketing outcomes by channel. This iterative calibration sharpens the reliability of most MMM models as a strategic decision tool—especially in fast-evolving, data-rich environments like digital media.

4. Interrogate model's fit for your business

MMM is not a 'one-size fits all' methodology. The specific methods used, underlying assumptions, and the volume or types of data used can vary significantly from business to business and vendor to vendor. Some opt for traditional linear or multivariate regression models and the make-up of each can vary significantly from one to the next—some opting for Bayesian or Frequentist frameworks, and many offer ensemble approaches that combine multiple modelling strategies. The key inputs, data weighting, and even optimization objectives can vary just as much.

As an advertiser, you should probe vendors and partners deeply—ask how the models are constructed, which variables consume the greatest weight, what time lags are considered, how external factors are controlled, and what validation exercises have been performed. The best MMM application is one that closely aligns with your business context and reflects the actual consumer behaviors you want to measure.

5. Transparency and Partnership

Ultimately, MMM works best as a collaborative discipline. Advertisers who are transparent with their reporting outcomes and actively engage with publishers, platforms, and partners create a shared view of what's driving success. This openness enables ongoing refinement of models, as well as more productive conversations around optimizing investments and creative strategies.

Platforms like Pinterest support these collaborative efforts by providing transparent data, technical resources, and best-practice consultation to brands and their MMM partners. Our mutual goal is to ensure that marketing investments are measured accurately, and that brands realize the full, enduring value of every media dollar.

Conclusion

MMM offers the potential to transform marketing measurement, but realizing this promise requires vigilance on several fronts—granular measurement across the media mix, high quality data flows, rigorous calibration, methodological scrutiny, and transparent partnership. By embracing these principles, advertisers can cut through complexity and chart a path to smarter, more effective cross channel media investment.

chapter 6

appendix - market mix modelling glossary

Compiled by IAB Australia to support greater understanding and clarity

Adstock

A mathematical function used in MMM to model the delayed and diminishing effect of advertising over time. It reflects how past advertising continues to influence consumer behaviour even after the campaign has ended.

Attribution

A technique used to assign credit for conversions or outcomes to specific marketing touchpoints. MMM differs from attribution by focusing on aggregate rather than user-level data and is better suited for privacy-conscious environments.

Bayesian Modelling

A statistical approach that combines prior knowledge (e.g., benchmarks or lift studies) with observed data to produce probability-based outcomes. Widely used in modern MMM for its flexibility, ability to probabilistically regularize, and its probabilistic interpretation of uncertainty.

Calibration

The process of adjusting a model's outputs using real-world benchmarks or controlled experiments (e.g., lift tests). Calibration improves accuracy and helps ensure that modelled outputs reflect causal impact.

Causal Inference

A method used to determine whether a specific action (like ad spend) actually caused an outcome (like increased sales), rather than just being correlated with it.

Control Variables

Variables included in a model to account for external influences (e.g., economic conditions, weather, public holidays). These help isolate the true impact of marketing by reducing bias in the case of confounding variables and reducing variance in the case of predictor variables.

Cross-Validation

AA statistical technique used to test how well a model performs on unseen data. Common in MMM to avoid overfitting and validate model stability.

Elasticity

A measure of how responsive an outcome (e.g., sales) is to a change in a variable (e.g., ad spend). High elasticity means small changes in input drive large changes in outcome.

Econometrics

A field of economics that uses statistical models to test hypotheses and forecast outcomes. MMM is a form of econometrics applied to marketing investment.

GeoLift (Geographic Lift Test)

An experiment that tests advertising effectiveness by comparing similar regions—with and without exposure to a campaign—over time. Often used to calibrate MMM models.

Holdout Testing

A method of validating a model by withholding a portion of the data during training and then testing the model's predictions on that unseen "holdout" data.

Hierarchical Models

Statistical models that analyse data across multiple levels (e.g., region, campaign, time period). Useful in MMM for sharing statistical strength across groups, ultimately increasing statistical power and leading to better estimates.

Incrementality

The additional value generated by a marketing activity that wouldn't have happened otherwise. A core concept in MMM used to distinguish between correlation and causation.

Lag Variables

Variables that capture the effect of a marketing action after a delay (e.g., brand campaigns taking weeks to influence purchase behaviour). Essential in modelling real-world media effects.

MAPE (Mean Absolute Percentage Error)

A statistical measure of prediction accuracy. Lower MAPE values indicate better model performance. Commonly used in MMM validation.

Multicollinearity

When two or more independent variables in a model are highly correlated, making it difficult to separate their individual effects. Addressed through regularisation techniques such as Ridge regression or Bayesian priors.

Nested Modelling

A modelling approach that breaks the analysis into multiple layers (e.g., brand awareness •consideration •purchase).

OLS (Ordinary Least Squares)

A traditional regression method used in early forms of MMM. Estimates relationships between variables by minimising the squared differences between observed and predicted values.

Open-Source Model

Software or tools (like Robyn or Meridian) freely available for anyone to use or modify. Open-source MMM allows for transparency and customisation, but often requires technical expertise

Posterior Distribution

In Bayesian modelling, this is the updated probability distribution for a variable after taking both prior beliefs and new data into account.

Regression Analysis

A statistical technique that estimates the relationships between a dependent variable (e.g., sales) and independent variables (e.g., media spend, pricing). Core to most MMM approaches.

Regularisation

A method used in modelling (e.g., Ridge regression and Bayesian priors) to prevent overfitting by penalising overly complex models. Helps improve stability and generalisation.

ROI (Return on Investment)

The amount of business value (e.g., revenue or profit) generated for each dollar spent. MMM often estimates channel-level or media-type ROI.

Scenario Planning / Simulation

A feature in many MMM platforms that allows marketers to test "what if" scenarios—e.g., what would happen if TV spend were shifted to digital.

Seasonality

Recurring patterns in data that happen at the same time every year (e.g., December retail uplift). Models adjust for seasonality so marketing impact isn't overstated.

Statistical Significance

A measure of how likely it is that an observed effect is real rather than random. In MMM, used to determine the reliability of a positive effect.

Saturation Curve / Diminishing Returns

Refers to the point at which increasing media spend results in smaller incremental gains. MMM models account for this using non-linear functions.

Time-Series Analysis

A statistical method focused on analysing data points collected or recorded at specific time intervals (e.g., weekly sales). Key in modelling trends, seasonality, and lag effects.


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