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Coalition for Innovative Media Measurement

ARF

Models as Masters?

Marketing Mix Modeling and AI-Driven Media Decision Making

July 2026

Forward

Marketing Mix Modeling (MMM) is evolving from a specialist analytical technique into a form of market infrastructure. It increasingly determines how marketing value is defined, how performance is compared, and how capital is allocated across the media ecosystem.

This transition fundamentally changes the role of MMM. It is no longer confined to interpreting past performance. Its outputs are increasingly embedded within planning systems, financial decision-making processes, and programmatic and AI-driven optimization workflows — directly shaping future market outcomes.

As MMM becomes operationalized in this way, its influence extends beyond analysis into execution. Models do not simply inform decisions; they increasingly structure how decisions are made, scaled, and automated across the market. When embedded in shared tools, planning systems and AI-enabled workflows, MMM's influence increasingly shifts upstream from model outputs to model inputs. Data availability, priors, taxonomies and calibration evidence shape how media value is represented before any model result is produced.

The central question is whether MMM can function as a trusted, transparent and decision-ready system at market scale — and whether the inputs that shape it are complete, consistent and well documented enough to support fair and effective market outcomes.

About CIMM

The Coalition for Innovative Media Measurement (CIMM) is a nonpartisan, pan-industry coalition of companies focused on cultivating and supporting improvements, best practices, and innovations in measurement and currency; data collaboration and enablement; and the use of new metrics and approaches to understanding the value of media. CIMM embraces the entire media and advertising ecosystem and prioritizes effective collaboration to deliver meaningful change.

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Acknowledgements

We would like to extend our gratitude to the following industry leaders for their input to this study:

Arthur Anglade, Principal Measurement Strategist, Haus.

Claire Browne, Head of Research, Adelaide Metrics.

David Fogarty, Executive Vice President, Data Excellence & Privacy, Association of National Advertisers.

Ed Smallwood, Senior Director, Spectrum Reach.

Greg Iocco, VP Audience Research, Warner Bros Discovery.

Gufeng Zhou, Marketing Scientist, Meta.

Henry Innis, Co-Founder, Mutinex.

Hitesh Wadhwani, Group Product Manager, Google.

Jim Gianoglio, Founder, Cauzle Analytics.

Judy Davey, VP Media Policy, Association of Canadian Advertisers.

Nick Pugh, Chief Marketing Effectiveness Officer, Ebiquity.

Peter Daboll, Head of North America, Daivid.

Rick Bruner, CEO, Central Control.

Sable Mi, Industry Chair, CIMM Identity and Data Collaboration Working Group.

Winston Li, Founder, Arima Data.

Research Objectives and Approach

This paper examines the changing role of Marketing Mix Modeling, with particular attention to the TV and video marketplace. It explains why MMM is becoming more influential in media evaluation and planning, identifies structural challenges in how media value is represented, and asks what practical steps could improve the shared inputs, evidence assets and documentation practices on which private MMM systems depend.

The argument develops in four stages.

- First, it explains the changing role of MMM in media evaluation, planning and execution.
- Second, it examines why MMM, in its current form, cannot reliably perform this role due to structural weaknesses in data, modeling, and ecosystem incentives.
- Third, it analyzes how the integration of MMM into AI-driven systems amplifies these weaknesses into systemic risks.
- Finally, the paper asks what practical steps could improve the shared evidence assets that private MMM systems use to interpret media value. The focus is on shared inputs and evidence, not on standardizing advertiser-specific models.

This paper represents an analytical consolidation and original synthesis of third-party research and discussions with senior executives across the marketplace. While it draws on insights shared by participants, the interpretations, conclusions and recommendations are those of the authors and CIMM.

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Executive Summary

Marketing Mix Modeling is moving from a specialist analytical technique into a foundational component of modern marketing decision infrastructure. It now shapes how advertisers allocate investment, evaluate performance and optimize outcomes across media channels. This reflects a broader shift toward cross-media, outcome-based measurement in a marketplace where no single currency, platform dataset or attribution system can provide a complete view of performance.

This shift changes the role of MMM. Historically, MMM was used to interpret past performance and inform human judgment. Today, it also produces forward-looking decision outputs: forecasts, budget allocations, response curves, scenario plans and optimization recommendations. As these outputs are embedded in planning systems, financial decision-making processes and AI-enabled workflows, MMM becomes part of the mechanism through which market decisions are made and executed.

MMM does not, however, produce objective facts. It produces model-based estimates shaped by data quality, model design, priors, transformations and assumptions. Different data inputs and modeling choices can produce materially different views of channel contribution, return on ad spend and optimal allocation. These differences are manageable when MMM is used as one analytical input among many. They become more consequential when MMM outputs are operationalized inside planning platforms, automated optimization systems and future agentic buying workflows.

The central risk is that weaknesses in MMM are no longer confined to analysis. Incomplete data, inconsistent taxonomies, opaque priors, weak validation evidence and asymmetries in data access can be translated directly into allocation decisions. Channels that are easier to measure, faster to report or more fully represented in default data pipelines may be more consistently valued, while channels with slower, more fragmented or less standardized inputs may be under-represented.

As open-source MMM frameworks and AI-enabled modeling workflows become more widely adopted, the structure of available data, default assumptions, priors and built-in data integrations becomes more consequential. These tools can improve accessibility and consistency, but they also give channels with more complete, timely or consistently structured inputs a modeling advantage.

For media owners, particularly in television and premium video, this creates a practical representation risk. Where media inputs, priors, validation evidence or data transformations do not adequately account for the characteristics of premium video — including long-term effects, cross-channel interactions, co-viewing, brand effects, delayed response and offline outcomes — its contribution may be harder for MMM systems and automated decision workflows to detect, validate and act upon. Addressing this challenge does not require competing models. It requires better, more consistent and better documented inputs into the private MMM systems that advertisers already use.

The appropriate response is not to standardize private MMM models or require advertisers to disclose proprietary business outcomes. MMM will remain advertiser-specific, model-dependent and commercially sensitive. The more realistic opportunity is to improve the shared foundations on which private MMM systems depend.

The paper identifies six practical areas for improvement:

1. Develop an MMM-ready media data specification for TV, CTV, streaming, digital video and related media inputs.
2. Create a standard MMM model factsheet documenting data sources, transformations, priors, validation methods, uncertainty ranges, refresh cadence and limitations.
3. Establish an experimentation and validation playbook for geo tests, lift tests, calibration studies, sensitivity analysis and out-of-sample validation.
4. Build an independently overseen premium video evidence library that provides evidence ranges, confidence levels and applicability notes rather than fixed priors.
5. Translate these materials into RFP language, contractual clauses, audit rights, data-sharing requirements, change-control expectations and AI safeguards.
6. Engage with agentic advertising protocol developers so MMM-informed evidence can be represented in machine-readable form without being treated as deterministic truth.

These actions will not eliminate uncertainty, make all MMM outputs comparable or determine how any advertiser should allocate budget. Their purpose is narrower and more practical: to reduce avoidable distortion in media inputs, improve transparency around assumptions, strengthen validation evidence and ensure that MMM can function as a more credible, auditable and accountable component of an increasingly automated media marketplace.

Definitions: A Short Note on Terminology

The following definitions are used throughout this report to ensure clarity and consistency in how key terms are applied.

Buy-side: Refers to the advertiser and its agents (typically media and creative agencies) responsible for planning, buying, and evaluating media investment.

Sell-side: Refers to media owners and distributors (e.g., broadcasters, publishers, platforms), as well as their authorized sales representatives, responsible for selling advertising inventory.

Closed-loop attribution: A measurement approach that links ad exposure to a specific outcome (e.g., purchase, site visit, or conversion) using identifiers to establish a direct relationship between media exposure and user behavior. Typically operates within a single platform or dataset and may not account for broader cross-media effects.

Cross-media vs. cross-platform

- **Cross-media** refers to the full set of media channels available to advertisers (e.g., television, digital, audio, out-of-home), considered collectively.
- **Cross-platform** refers to activity within a single media owner or ecosystem, or within a defined media category (e.g., all video within one platform).
  MMM operates across **cross-media** inputs.

Impressions: A unit of advertising delivery representing the opportunity for an advertisement to be viewed. Definitions vary depending on the measurement point (e.g., server-side delivery, client-side rendering, viewability standards), as defined by industry bodies such as the Media Rating Council (MRC).

Media currency: The unit of measure used to transact advertising inventory between buyers and sellers. Examples include impressions, clicks, and gross rating points (GRPs). Media currencies define the terms of trade but do not, in themselves, measure business outcomes.

Outcomes: The business results that marketing activity seeks to influence, such as sales, revenue, profit, customer acquisition, or brand metrics. In MMM, outcomes typically serve as the dependent variable against which marketing inputs are evaluated.

Independent and dependent variables (MMM context)

MMM estimates the relationship between two sets of variables:

1. **Independent variables** represent inputs into the model, including media spend, pricing, promotions, and other external factors.
2. **Dependent variables** represent the outcomes being explained or predicted (e.g., sales or conversions).

Joint Industry Committee (JIC): An independent, typically not-for-profit organization that develops, governs, and oversees audience and media measurement standards for a specific market or medium. JICs are generally designed to provide transparency, comparability, and industry-wide trust in measurement outputs.

Model validation: The process of assessing how well a model's outputs correspond to observed data and whether the model provides reliable and stable estimates. Common approaches include out-of-sample testing, back-testing, and sensitivity analysis.

1. MMM as Emerging Decision Infrastructure

Marketing Mix Modeling (MMM) has re-emerged as a central framework for evaluating marketing effectiveness. Its role is no longer confined to retrospective analysis: MMM outputs now inform planning, budgeting and optimization systems that shape how marketing investment is allocated across the media ecosystem.

The Shift to Outcome-Based, Cross-Media Integration

The growing role of MMM reflects a broader transition in measurement. As media consumption fragments and platform-based measurement systems proliferate, no single source provides a complete view of performance. Advertisers are turning to MMM to integrate multiple signals — across media, markets, and time horizons — into a unified, outcome-based framework for decision-making.

> ***As an advertiser-focused association, we advise members on best media measurement practice. Media is often the largest line item in the budget and, with the right measurement framework, becomes a powerful tool for sustainable brand growth. MMM provides a holistic view across all channels, enabling advertisers to define their own marketing science approach that balances short-term performance with long-term brand building.***
>
> *— Judy Davey, VP of Media Policy, Association of Canadian Advertisers*

As MMM becomes more central to decision-making, it is also reshaping relationships across the ecosystem. Historically, MMM has been developed and controlled by advertisers and their partners, contributing to asymmetries in data access and interpretation between buyers and sellers.

The sell-side must recognize that the buy-side typically operates with a more complete view of the factors influencing business outcomes. Despite this, media owners, particularly in television and video, are increasingly questioning whether their contribution to downstream outcomes — such as sales — is fully or fairly represented in model outputs. These concerns are amplified as MMM tools and frameworks, including open-source solutions, become more directly integrated into buy-side planning and buying systems.

These concerns are not limited to individual model outputs. They reflect a deeper shift in where influence over measurement resides. As MMM becomes embedded within standardized tools and AI-driven workflows, control over model inputs — particularly priors, data representations, and calibration frameworks — becomes increasingly consequential.

Open-source MMM does not eliminate asymmetry. It can reconfigure it. Default priors, embedded assumptions, and integrated data sources shape how models interpret the world, particularly where underlying data is incomplete or inconsistent. Channels that are more fully represented in these inputs may be more consistently valued, regardless of their true incremental contribution.

Blurring Boundaries in Advanced TV and Video Advertising

The expansion of advanced TV and video advertising has increased complexity in how media is defined, measured, and valued. The sell-side now offers a mix of traditional inventory and data-driven addressable advertising. These developments blur historical distinctions between media types. Additionally, the sell-side offers proprietary attribution tools, and outcome-based measurement systems which raise questions about the value of the sell-side's efforts when the buy-side's MMM has a more complete data scope.

1. MMM as Emerging Decision Infrastructure

Reconciling Conflicting Measurement Paradigms

These tensions reflect deeper structural differences between measurement approaches. Platform-based systems often operate with granular, real-time, and proprietary data, while traditional industry frameworks — such as Joint Industry Committees (JICs) — prioritize transparency, standardization, and independent governance. MMM sits across these systems, attempting to reconcile heterogeneous inputs into a single analytical framework. In doing so, it inherits many of the inconsistencies and limitations of the underlying data landscape.

MMM also operates alongside, but distinct from, media currency. While currency defines the terms on which media is bought and sold, MMM evaluates the contribution of those investments to business outcomes. This distinction is increasingly important in a cross-media environment where currencies differ in definition, methodology, and scope. Differences between impressions, GRPs, and other measures of exposure complicate the integration of media data within MMM and contribute to ongoing challenges in comparability.

Efforts to address these differences are emerging, including the development of attention-based and media-quality metrics intended to provide more consistent measures of exposure and impact. However, these approaches are themselves evolving, with varying methodologies and limited standardization. As a result, they introduce additional complexity into MMM rather than fully resolving underlying comparability challenges.

Cross-media measurement fragmentation remains a defining feature of the current landscape, increasing reliance on model-based inference such as MMM. Even as efforts continue to improve measurement consistency, outcome-based evaluation remains essential to how advertisers assess performance and allocate investment.

Advances in artificial intelligence and machine learning are also accelerating the integration of MMM into planning and optimization systems. Section 4 examines how this changes the risk profile of MMM when model outputs are used to guide automated decisions.

This operational role changes how MMM should be evaluated. A model used by analysts can be challenged, interpreted and triangulated. A model embedded in decision systems can influence allocation repeatedly and at scale. The relevant test is therefore broader than statistical soundness: whether the data, assumptions and decision processes around the model are sufficiently transparent, validated and accountable for the decisions they inform.

From Analytical Tool to Market Infrastructure

The operational consequences are practical rather than abstract. MMM-derived budget allocations can inform bidding strategies. Channel valuations can influence pricing and supply-demand dynamics. Forecasts can shape both planning decisions and optimization logic.

This has three practical effects:

- Budget allocations derived from MMM are translated directly into bidding strategies.
- Channel valuations inform pricing and supply-demand dynamics.
- Forecasts influence not only planning, but real-time optimization decisions.

MMM outputs increasingly shape:

- How inventory is valued.
- How budgets flow across channels.
- How performance is interpreted and reinforced.

MMM becomes part of the market infrastructure through which economic decisions are shaped. This shifts the practical focus from model development alone to the conditions under which model outputs are interpreted, validated and translated into allocation decisions.

1. MMM as Emerging Decision Infrastructure

A Transitional Moment: Automation Ahead of Governance

This question is not theoretical. AI is already being used across the media campaign lifecycle to support audience segmentation, media mix planning, forecasting, real-time optimization, attribution, and performance analysis, including applications that touch MMM directly. Full-scale adoption remains incomplete: a large majority of organizations have not yet fully integrated AI across planning, activation, and analysis, even though many expect to do so in the near term. This matters because the industry is entering a transitional phase in which MMM-informed decision systems are becoming operational before shared governance norms are fully established. In other words, automation is advancing faster than institutional control.

From Analytical Tool to Operational System

Because MMM incorporates both media and non-media inputs, it informs decisions beyond media budget allocation. MMM includes all types of media plus data on pricing promotions, in addition to competitive activity, all of which enable the marketer to act and react using a wide scope of tools the marketer has on hand.

While MMM is often described as a retrospective analytical tool, this understates its primary function in practice. The decomposition of past performance is an intermediate step. The central purpose of MMM is to generate forward-looking forecasts and recommended actions that shape future sales and profit outcomes.

As such, MMM should be understood not simply as an explanatory model, but as a predictive decision system whose value is realized through execution. MMM generates estimated Return on Ad Spend (ROAS) metrics for each marketing channel, which should be interpreted as model-derived indicators rather than precise measures of causal impact.

In practice, MMM supports decisions across three core areas:

1. Budget setting and forecasting.
2. Cross-channel allocation.
3. Scenario planning and optimization.

MMM primarily informs strategic and mid-term planning. Its role in real-time campaign execution is usually indirect, mediated through planning systems, heuristics and experimentation. This distinction is important: MMM can guide execution, but it does not operate in the same way as real-time attribution or platform optimization systems.

MMM is now widely adopted among large advertisers, particularly those operating in complex, multi-channel environments. However, adoption remains uneven, and relatively few organizations have fully integrated MMM with experimentation and other measurement approaches.

Estimates across multiple studies converge around similar adoption levels, confirming that MMM is now a mainstream component of marketing measurement among larger organizations (Supermetrics, 2025). When used correctly, it allows for more disciplined budget allocation, particularly in complex, multi-channel environments where direct attribution is limited or unreliable.

Some broadcasters and media organizations are also applying MMM-derived evidence within their own marketing and sales strategies. These efforts often emphasize the relationship between long-term brand building, short-term activation and balanced media investment. Where the evidence is robust, it can help advertisers evaluate the contribution of premium video and television within broader outcome-based planning.

In response, some sell-side organizations have developed tools and guidance frameworks based on aggregated MMM findings. These are designed to help advertisers who currently do not have an MMM, explore budget allocation scenarios and better understand the potential relationship between media investment and business outcomes. While these tools can provide useful directional guidance, they are typically based on generalized models and should be interpreted accordingly.

1. MMM as Emerging Decision Infrastructure

Beyond high-level budget allocation, MMM informs more granular decisions across campaigns and channels. While individual teams may optimize for specific metrics — such as reach, traffic, or conversions — MMM provides a unifying decision framework across teams, linking each team's tactical objectives to overall business outcomes. In addition to channels, input data can be organized by specific media vendors and media products. This helps ensure that short-term performance metrics are interpreted within a broader context of diminishing returns, cross-channel interaction, and long-term value creation.

Section 2 examines the weaknesses in data, modelling and ecosystem incentives that become more consequential when MMM outputs are used in this operational way.

2. Fragile Foundations: Data, Models, and Assumptions

MMM's effectiveness as decision infrastructure depends on the quality of the data, assumptions and incentives that sit beneath it. Weaknesses in any of these areas affect how value is measured and how model outputs are acted upon.

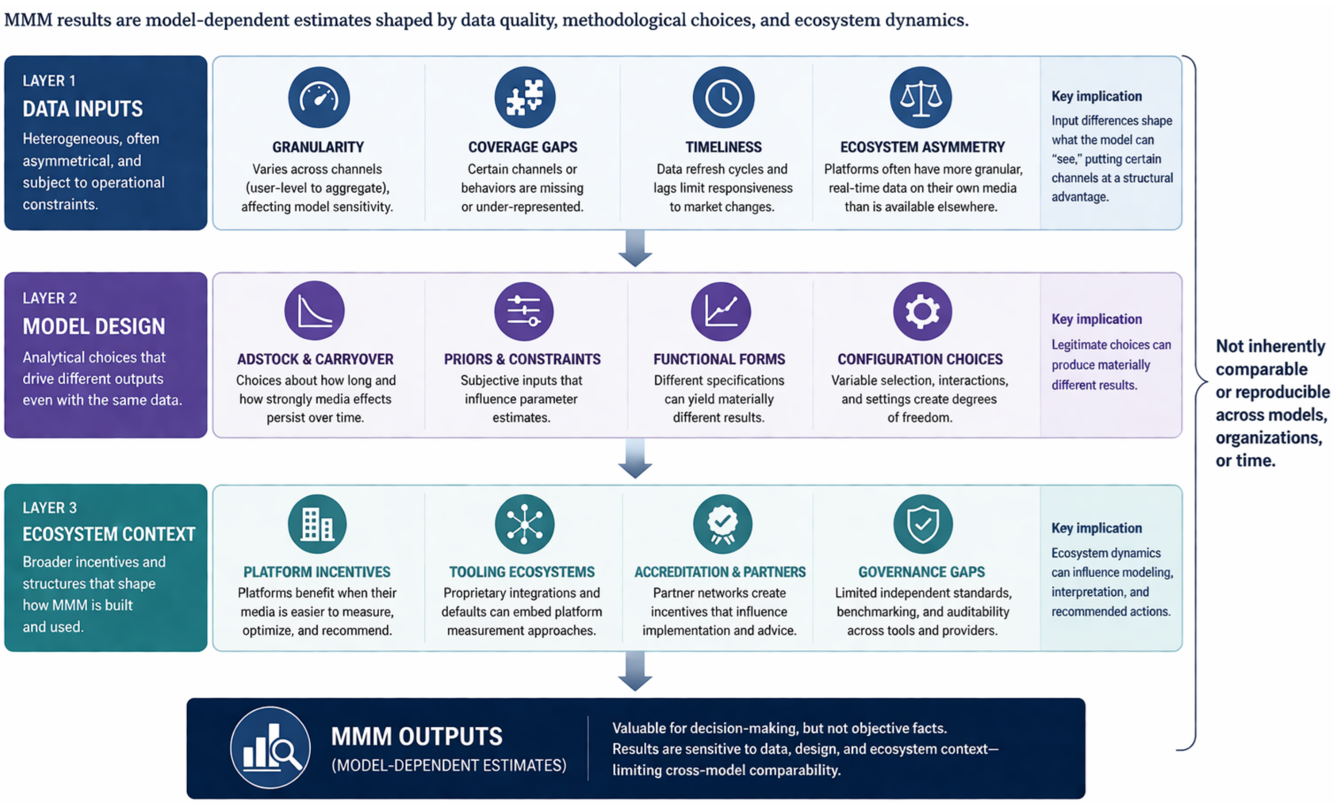
As MMM outputs move into planning systems and AI-driven optimization workflows, these weaknesses have operational consequences. They influence how capital is allocated across channels, platforms and partners.

The sources of fragility in MMM can be understood across three interdependent dimensions:

1. Data comparability.
2. Model stability and interpretation.
3. Structural asymmetry within the ecosystem.

Together, these factors define the conditions under which MMM outputs should be interpreted, validated and used in decision-making.

Figure 1: Sources of Variability in MMM Outputs



Source: Analysys Mason, drawing on ISBA/PwC (2020); ANA (2023-2025); CIMM (2025); Meta Robyn and Google Meridian documentation.

2. Fragile Foundations: Data, Models, and Assumptions

2.1 Data: The Problem of Comparability

MMM depends on the integration of data from multiple sources, including media delivery, pricing, promotions, and external factors such as seasonality and economic conditions. In practice, these inputs are not standardized, and often differ materially in definition, granularity, and availability.

At the core of this issue is a failure of comparability. Media inputs are constructed using fundamentally different measurement systems. Impressions, clicks, and gross rating points (GRPs) are not equivalent representations of exposure. They reflect different measurement points, methodologies, and assumptions about what constitutes an “opportunity to see.”

Additional inconsistencies arise from:

- Divergent audience definitions across channels.
- Variations in reporting cadence and latency.
- Differences in aggregation and smoothing practices.
- Inconsistent taxonomies across platforms and vendors.

These differences mean that MMM does not operate on a uniform dataset. Instead, it reconciles heterogeneous inputs into a single analytical framework.

One practical implication is that MMM fragility often begins before modeling decisions are made. If media inputs are inconsistently named, classified, aggregated or timed, the model must reconcile differences that originate in the data supply chain rather than in real differences in media performance. This is particularly important for video, where linear TV, CTV, streaming, online video, social video, addressable TV and premium video may be defined and reported differently across agencies, publishers, platforms, DSPs, ad servers and measurement providers.

Apparent differences in performance across channels may reflect differences in measurement rather than true differences in effectiveness. MMM outputs can embed distortions that are not easily observable or correctable within the model itself.

Data availability further compounds this issue. Some platforms operate with highly granular, real-time datasets, while other media channels rely on aggregated or delayed reporting. These asymmetries influence how channels are represented within MMM, often favoring those with richer and more timely data.

Latency is particularly important for television and premium video. Where final delivery data requires reconciliation between what was bought, what ran, what was measured and what was cleared through agency or measurement workflows, TV data can arrive materially later than digital platform data. In a slower, periodic MMM environment, this may be manageable. In a more frequent, API-driven or agentic environment, delayed or provisional TV inputs may reduce the visibility and responsiveness of TV within model refreshes. This creates a practical disadvantage: channels with faster and more structured data may appear more actionable, even where slower channels are delivering substantial incremental value.

Incorporating reach into MMM highlights these challenges more explicitly. Reach is typically expressed as a percentage of a defined audience, but those audience definitions vary significantly across media. A campaign reaching 80% of a broad demographic segment is not directly comparable to one reaching 80% of a highly specific behavioral audience.

Without consistent audience definitions, reach becomes an unstable input. This instability affects not only model outputs, but also optimization decisions, particularly where diminishing returns and saturation effects are central to allocation logic.

In aggregate, these issues mean that MMM operates on data that is structurally inconsistent. This limits the reliability of outputs and introduces uncertainty into any decisions derived from them.

2. Fragile Foundations: Data, Models, and Assumptions

These challenges are compounded by the increasing standardization of MMM workflows through shared tools and platforms. Where data gaps exist, models rely more heavily on priors and assumptions to stabilize outputs. In practice, this creates a secondary layer of dependency: not only on the data itself, but on how missing or incomplete data is inferred.

If these priors are derived from limited datasets, platform-specific evidence, or generalized assumptions, they may not fully capture the characteristics of media channels that are less directly observable within those systems.

2.2 Models: The Problem of Interpretive Instability

MMM outputs are estimated, not observed. They depend on assumptions about how marketing inputs influence business outcomes and are sensitive to model design choices.

Key modeling decisions include:

- Adstock and carryover assumptions.
- Functional forms (e.g. linear vs non-linear relationships).
- Variable selection and feature engineering.
- Use of priors and external constraints.
- Data transformations and aggregation levels.

Each of these choices can materially influence model outputs. Different specifications applied to similar datasets can produce divergent estimates of channel contribution, return on ad spend (ROAS), and optimal allocation.

This creates interpretive instability: different model specifications can produce different estimates from similar underlying data.

The increasing use of experimentation and empirically derived priors represents an important step toward improving causal inference and stabilizing estimates. However, the adoption of these practices remains uneven, and their implementation varies in rigor and consistency.

MMM’s value lies in integrating multiple signals into a coherent system-level view of performance. Differences between MMM, experimentation and attribution should therefore be interpreted as differences in evidentiary perspective, not simply as disagreement between methods.

The role of MMM is best understood alongside other measurement approaches. MMM provides system-level inference, integrating multiple inputs to estimate how marketing activity relates to overall business outcomes.

Experimentation provides causal validation, isolating the incremental impact of specific interventions under controlled conditions. Attribution provides directional diagnostics, offering granular but inherently partial views of user-level behavior within defined environments.

Each approach serves a different role. High-confidence decisions emerge not from reliance on any single method, but from convergence across these complementary perspectives.

As MMM outputs are increasingly used to inform or automate decision-making, this interpretive instability becomes more consequential. Decisions based on model outputs are only as robust as the assumptions embedded within the model itself.

2.3 Ecosystem: The Problem of Structural Asymmetry

MMM operates within a broader ecosystem characterized by uneven access to data, differing commercial incentives, and varying levels of transparency across stakeholders.

These conditions introduce a third source of fragility: incentive distortion. Platforms often have access to more granular, real-time data for their own media, while other channels are represented through less detailed or less frequent inputs. This asymmetry can influence how channels are modeled and valued, particularly where data richness affects model sensitivity and responsiveness.

MMM tools and frameworks are increasingly developed within platform ecosystems or by stakeholders with commercial interests in specific media channels.

This does not require intentional bias to create unequal outcomes. Data access advantages can become modeling advantages. Default configurations may reflect ecosystem-specific assumptions, and channels with more complete, timely or consistently structured data may be modelled with greater confidence, responsiveness or stability than channels with delayed, incomplete or less standardized inputs.

The growing adoption of open-source MMM frameworks reinforces these dynamics. While such tools increase transparency and accessibility, they also introduce standardized configurations, default priors, and integrated data pathways that reflect the perspective of their developers.

Influence over measurement outcomes is no longer exercised solely through proprietary models, but through the design of widely adopted modeling frameworks and their underlying assumptions.

In this environment, the absence of shared evidence standards, transparent priors and validation benchmarks increases the risk that channels represented by more complete or more standardized data are modeled with greater confidence than channels whose effects are less directly observable, less consistently documented or less well supported by calibration evidence.

For media sellers, these dynamics introduce a layer of opacity. Sellers are often required to respond to MMM outputs without access to the underlying data, transformations, or assumptions that produced them. This limits their ability to diagnose performance, challenge results, or improve representation within models.

More broadly, the absence of standardized benchmarking or independent validation frameworks makes it difficult to distinguish whether differences in MMM outputs are driven by data quality, modeling choices, or structural bias.

These factors do not invalidate MMM, but they show that MMM is not a neutral system operating in isolation. It is embedded within a commercial and institutional context that shapes how it is constructed, interpreted, and applied.

As MMM becomes more central to decision-making, these asymmetries can affect how confidently different channels are assessed, how easily their effects are validated, and how readily their value is translated into budget-allocation decisions.

In combination, these factors create a representation risk. Where certain channels are less completely captured in underlying data, priors or validation evidence, their contribution may be estimated with lower confidence or may be more sensitive to modeling assumptions. As MMM outputs become more directly connected to planning and optimization systems, this can increase the risk that channels with incomplete, delayed or poorly documented inputs are less effectively represented in budget-allocation decisions, even where they deliver meaningful incremental value.

2. Fragile Foundations: Data, Models, and Assumptions

From Analytical Limitations to Systemic Risk

The limitations of MMM are not independent. Data inconsistency, model sensitivity, and structural asymmetry interact to create compounding sources of uncertainty.

When MMM is used as a retrospective analytical tool, these limitations can be managed through expert interpretation and triangulation with other methods. However, as MMM becomes embedded within planning systems and AI-driven optimization workflows, these same limitations take on a different character. They are no longer contained within analysis — they are operationalized.

Weaknesses in data, modeling, or ecosystem design do not simply affect interpretation. They directly influence decisions, shaping how capital is allocated and how performance is evaluated across the market.

These limitations do not invalidate MMM. They define the conditions under which MMMs should be interpreted, documented, validated and used in decision-making. Data inconsistency, model sensitivity and ecosystem asymmetry are manageable when MMM is used as one analytical input among several, interpreted by expert practitioners and triangulated with experiments, attribution, business judgment and market knowledge. They become materially more significant when MMM outputs are embedded into planning systems, optimization workflows or automated budget-allocation processes.

The causal chain is straightforward. MMM relies on structured inputs. Where inputs are inconsistent, delayed or incomplete, models depend more heavily on assumptions, priors and transformations. Where those assumptions are opaque or derived from partial evidence, model outputs may become less stable or less representative. Where those outputs are embedded into planning, optimization or automated buying systems, analytical uncertainty can translate into allocation consequences. This is why the quality, documentation and validation of MMM inputs are no longer narrow technical concerns.

MMM risk should not be treated as a narrow methodological issue. If MMM is becoming more influential in how marketing capital is allocated, then the quality, provenance, comparability and validation of its inputs become matters of shared market importance.

3. From Models to Systems: Validation, Execution, and Control

As MMM becomes embedded within decision systems, the focus shifts from model accuracy to system performance. The critical question is no longer whether a model fits historical data, but whether it produces reliable outcomes when used to guide real-world decisions.

A model can fit historical data well and still fail as a decision system. What matters is not explanatory power, but predictive reliability under real-world conditions. This shifts the focus of MMM from model construction to system design, including how models interact with experimentation, execution systems, and feedback loops.

From Model Validation to System Performance

Operationalizing MMM requires more than faster dashboards. It requires clear separation between data refresh, model rescore, and full retraining, each governed by different thresholds and controls. In practice, this means refreshing inputs frequently enough to keep guidance current, while retraining models only when new data, changed assumptions, or validated experimental evidence justify structural adjustment. It also means designing MMM as a modular system in which seasonality, media response, and promotional effects can be updated without destabilizing the entire framework. Without that discipline, faster cycles can amplify noise rather than improve decision quality. The core issue is not speed alone, but controlled speed: the ability to update guidance at the pace of the market while preserving stability, interpretability, and accountability.

This is well supported by recent industry guidance emphasizing weekly input refreshes, monthly or quarterly retraining, modular model design, and the use of experiments as calibration anchors rather than treating every fluctuation as a reason to reset the model.

Geo-hierarchical modeling plays a critical role in this validation process. By enabling structured test-and-control experiments across matched markets, it allows organizations to directly compare predicted outcomes with observed results. These frameworks provide one of the few practical mechanisms for testing the predictive validity of MMM in live market conditions, rather than relying solely on historical fit or simulated scenarios.

> ***To close today's measurement gaps, marketers need to evolve their MMM capabilities – from static to dynamic modeling; from linear to nonlinear and causal approaches; from channel-level views to customer-level understanding; from siloed metrics to fully integrated systems; from internal-only focus to ecosystem-wide awareness; from black-box outputs to transparent, actionable insights; and from manual processes to automated, scalable solutions.***
>
> *— David Fogarty, ANA*

MMM must be understood as part of an integrated system comprising:

- Data inputs (cross-media exposure + outcomes).
- Modelling frameworks.
- Experimental validation.
- Execution systems (planning, bidding, optimization).
- Feedback loops (learning and recalibration).

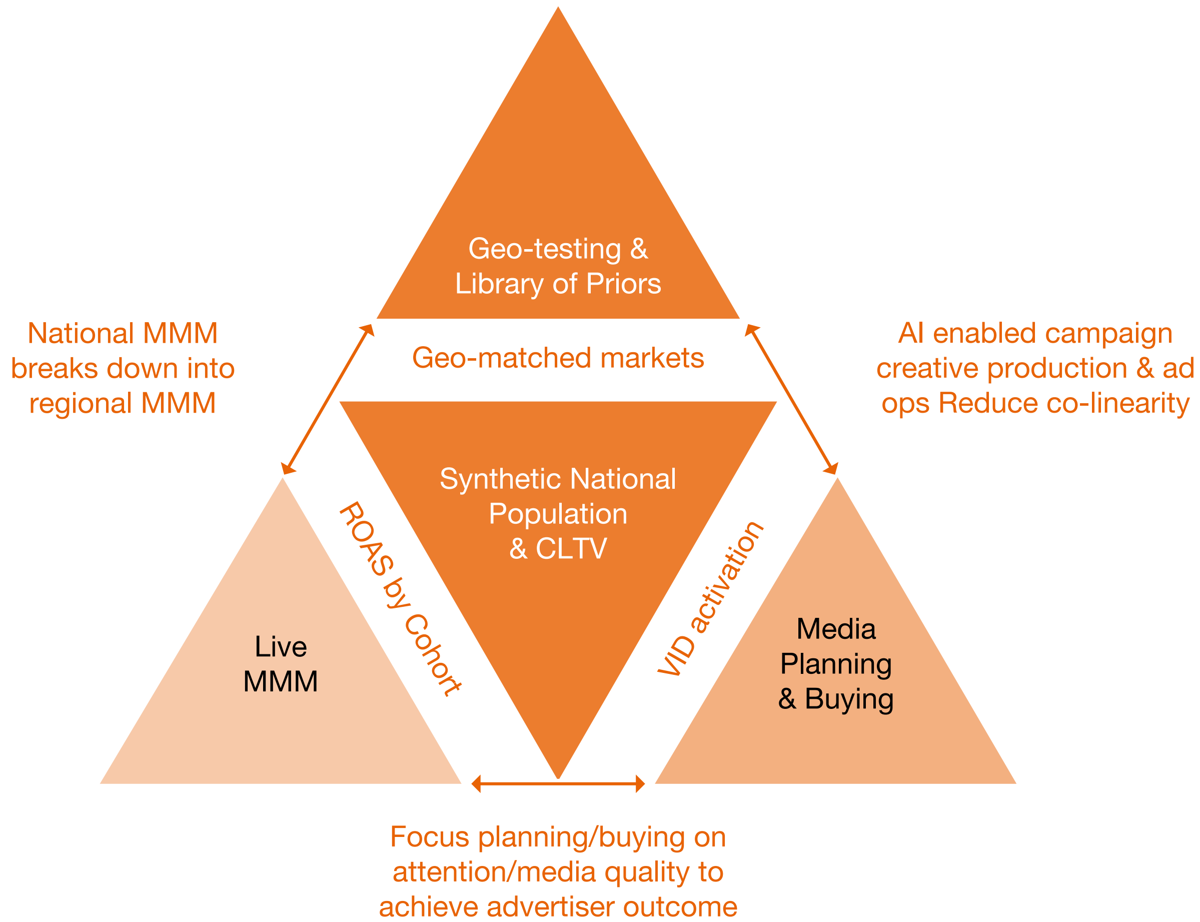
3. From Models to Systems: Validation, Execution, and Control

The performance of MMM depends on the integrity of this entire system — not the model in isolation. Within this system:

- The sales-response curve becomes a central planning input.
- Cross-media effects are explicitly modelled.
- Testing frameworks continuously refine model assumptions.
- Data flows bi-directionally between measurement and execution.

Over time, these testing frameworks also generate structured bodies of evidence that can be used as priors within MMM systems. As such, experimentation does not only validate models — it shapes the assumptions that guide future model behavior.

Figure 2: Ideal implementation of MMM



Source: the authors

MMM is not simply changing how marketing effectiveness is measured. It is reshaping how economic value is determined across the media marketplace.

Historically, MMM required significant investment in time, expertise, and data, limiting its use to large advertisers. Advances in cloud computing and data infrastructure have since reduced cost and increased speed, expanding access and enabling more frequent model updates.

3. From Models to Systems: Validation, Execution, and Control

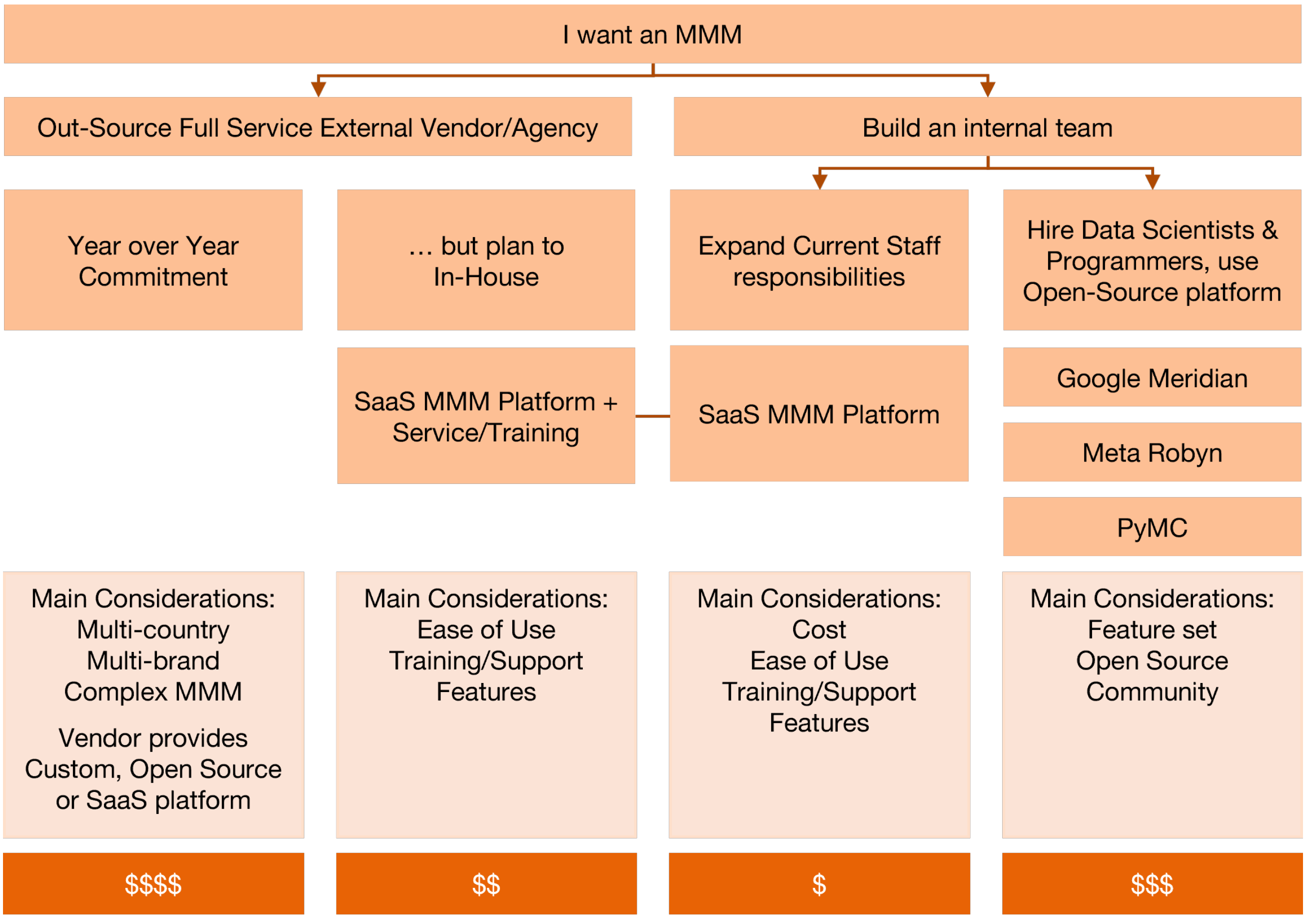
> ***The release of Robyn and Meridian acted as a massive, free marketing campaign for the concept of MMM, dramatically increasing awareness across the industry. But as companies eagerly downloaded the code and tried to implement it, they ran headfirst into the immense practical difficulties: the nightmare of data collection and cleaning, the ambiguity of model validation, and the challenge of turning dense statistical outputs into actionable business strategy. The commoditization of the core MMM algorithm, spurred by open-source, was a necessary and welcome step. But the real, sustainable value for enterprises lies in the commoditization of the entire workflow. The company that wins won't be the one with the cleverest algorithm in a GitHub repo. It will be the one that makes it easiest for a marketing team to go from messy, disparate data to a confident, optimized budget decision with the least amount of friction.***
>
> *— Henry Innes, Founder, Mutinex.*[1]

The operational economics of MMM have changed substantially. Cloud infrastructure, API-based data flows, SaaS platforms and open-source frameworks have reduced the cost and complexity of model deployment. This has expanded access beyond the largest advertisers and enabled more frequent refresh cycles. Lower barriers to model execution do not remove the hardest implementation challenges. Data collection, cleaning, reconciliation, validation and interpretation remain the principal constraints. In practice, the commoditization of algorithms increases the importance of the surrounding workflow: how data is prepared, how assumptions are documented, how experiments are incorporated, how uncertainty is communicated and how recommendations are translated into decisions.

[1] Marketing economics, *The Great Ticking Economic Time Bomb of Open Source MMM (or why closed source will win)* (2025).

3. From Models to Systems: Validation, Execution, and Control

Figure 3: Navigating options for MMM provision



Source: the authors

Models are increasingly incorporating broader datasets, including geographic hierarchies, experimentation frameworks, identity systems, and synthetic population models. Search data is being integrated both as a marketing channel and as an indicator of underlying demand. Attention and media-quality metrics are being introduced to better account for differences in exposure and engagement across media types.

These developments improve the potential explanatory power of MMM and enable more sophisticated analysis of marketing effectiveness. A growing culture of testing, supported by structured experimentation and the development of priors, is strengthening the empirical foundations of models and improving their ability to capture causal relationships.

> ***Experiments are the gold standard, but of course they have weaknesses. Many advertisers don't even have signals because they have offline outcomes, retailers, CPGs, telecoms, and others. We asked, how can we solve the challenge for them when conversion lift isn't possible? Can we improve causal inference of a model even when experiments aren't available?***
>
> *— Gufeng Zhou, Marketing Science, Meta*

3. From Models to Systems: Validation, Execution, and Control

Leading organizations are also exploring new classes of AI-enabled modeling architectures that move beyond traditional aggregate time-series approaches. Sequential and transformer-based models, originally developed for applications such as language modeling, offer the potential to represent marketing as a dynamic sequence of consumer exposures, responses, and decisions over time. Rather than estimating static relationships between weekly spend and outcomes, these approaches can model the ordering, spacing, interaction, and persistence of marketing touchpoints across channels and customer journeys.

While still emerging, such techniques may help address several longstanding MMM challenges, including complex cross-channel interactions, long-term carryover effects, and highly granular behavioral dynamics. However, they do not eliminate the need for experimentation, causal validation, or governance. As with traditional MMM, the quality of outputs remains dependent on the quality of data, assumptions, and validation frameworks used to constrain and interpret model behavior.

All of these advances introduce additional complexity. Each new data source or modeling technique brings its own assumptions, dependencies, and potential sources of inconsistency. In many cases, they do not resolve underlying comparability challenges but instead add new layers to an already complex system.

For example, attention metrics aim to improve comparability across media by capturing qualitative differences in exposure and engagement. However, methodologies for measuring attention vary across providers, and there is limited standardization. Similarly, the integration of identity data and synthetic populations expands modeling capabilities, but introduces additional questions around data quality, linkage accuracy, and governance.

Figure 4: Impact of Attention Metrics in MMM

Using AU In MMM: Impression Weights

Traditional MMM

Week	Display Imp	Social Imp	OLV Imp	TV GRP	Sales
1	62.06M	16.33M	19.21M	1150	**20,704**
2	73.75M	13.50M	24.10M	1060	**44,665**
3	115.28M	4.19M	27.94M	940	**59,025**
4	78.39M	5.77M	18.85M	160	**24,146**
5	78.04M	8.84M	22.72M	510	**50,125**

Correlation to Outcomes: 0.45

vs.

Attention-Weighted MMM

Week	Display Imp	Attn. Rating	Social Imp	Attn. Rating	OLV Imp	Attn. Rating	TV GRP	Attn. Rating	Sales
1	62.06M	**15.1**	16.33M	**21.2**	19.2M	**30.2**	1150	**40.1**	**20,704**
2	73.75M	**18.9**	13.50M	**22.0**	24.1M	**25.7**	1060	**45.7**	**44,665**
3	115.28M	**28.8**	4.19M	**24.7**	27.9M	**39.0**	940	**50.9**	**59,025**
4	78.39M	**27.4**	5.77M	**25.1**	18.8M	**36.1**	160	**48.3**	**24,146**
5	78.04M	**29.8**	8.84M	**22.6**	22.7M	**40.8**	510	**51.7**	**50,125**

Correlation to Outcomes: 0.72

Source: Adelaide Metrics, *MMM Implementation Guide* (Oct 2025).

3. From Models to Systems: Validation, Execution, and Control

Geography, Experimentation and Priors

Geographic modeling provides one of the most practical routes for strengthening MMM validation. By enabling matched-market and test-and-control designs, geographic frameworks allow modelled predictions to be compared with observed outcomes under real market conditions. These tests can then generate empirical evidence that informs future priors, response curves and calibration benchmarks.

This creates a reinforcing cycle. Geographic variation supports experimentation; experimentation improves causal confidence; validated results strengthen priors; and stronger priors improve the stability and interpretability of future MMM outputs. The value of geographic modeling therefore lies not only in identifying regional differences, but in creating a practical framework for continuous validation.

Identity frameworks and synthetic population models are increasingly used to integrate data and support advanced modeling approaches. Individual-level data creates the basis for agent-based modeling for predictive analytics derived from MMM analysis.

> ***The development of a national synthetic population allows experiments to be built into media plans that not only uncover campaign insights based on MMM ROAS but also continue to enrich the model. Connecting MMM to a synthetic national population enables agent-based modeling to predict advertiser outcomes, such as changing consumer opinion, sales or customer acquisition.***
>
> *— Winston Li, Founder of Arima Data.*

A Culture of Testing: Building Priors

A culture of testing creates a library of priors whose empirical insights operate as known reference points to inform and guide MMM. These historical patterns can then help shape MMM estimates for future media channel performance. Experiments conducted across different times, regions, audiences, or variables can all serve as priors within the MMM framework.

This approach grounds MMM in observed evidence rather than relying solely on post-hoc interpretation. It does not eliminate uncertainty, but it improves the evidentiary basis for model assumptions and helps practitioners distinguish between stable patterns, directional indications and areas requiring further testing.

Probabilistic Decision Frameworks

A related development is the growing use of probabilistic decision frameworks within MMM systems. Historically, MMM outputs have often been communicated as single-point estimates such as ROAS or channel contribution. However, leading practitioners increasingly emphasize confidence ranges, uncertainty intervals, and risk-adjusted recommendations alongside traditional metrics. This reflects an important shift in how MMM outputs are interpreted: not as deterministic answers, but as estimates with varying levels of confidence.

As MMM becomes more deeply embedded within planning and optimization systems, the explicit representation of uncertainty may become increasingly important. Decision-makers, whether they be human or agentic buyers, may need to evaluate not only expected returns, but also the confidence associated with those estimates, particularly when making large budget reallocations or responding to rapidly changing market conditions.

3. From Models to Systems: Validation, Execution, and Control

Search as Both Channel and Demand Signal

Search plays a dual role within MMM. It is both a marketing channel and a signal of underlying demand. This dual role requires careful treatment because increased search activity may reflect the effect of other media rather than the independent causal impact of search itself.

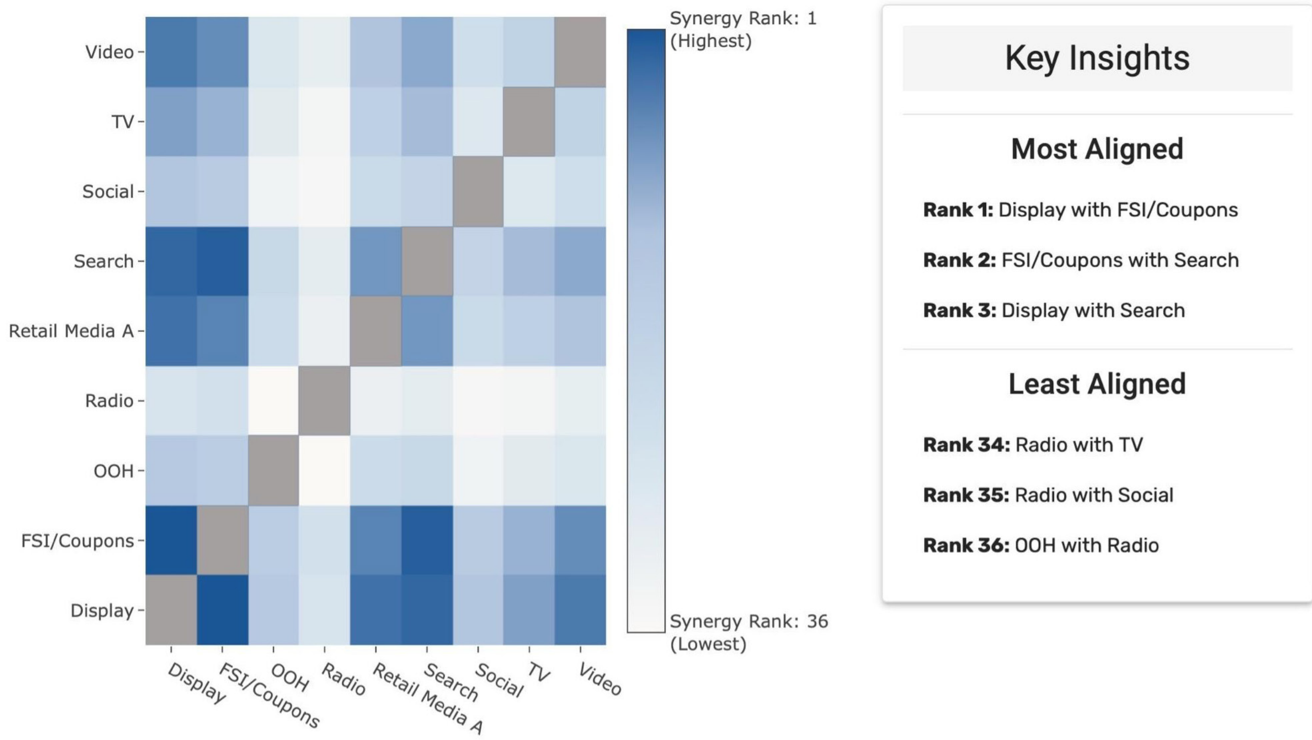
When awareness media increases consumer interest, advertisers may need corresponding investment in paid search and search engine optimization to capture that demand. MMM should therefore distinguish between search as a driver of outcomes and search as a response to demand generated elsewhere.

Media Channel Synergies

MMM recognizes that no media channel operates in a vacuum and that some media channel combinations work together better than others. Using next dollar spent analysis, MMM providers are able to report which combinations of media hold the best optimization options.

MMM's effectiveness as a decision framework depends not only on methodological sophistication, but on the strength, consistency, and governance of the foundations on which it is built.

Figure 5: Media Synergy Combinations



Source: Arima (2025)

In Summary

The evolution of MMM is not simply a story of faster models or more sophisticated techniques. It is a shift from model construction to system performance. The most effective MMM implementations combine structured data, transparent assumptions, experimental calibration, disciplined refresh and retrain rules, uncertainty reporting and clear decision accountability.

The value of MMM is realized only when its recommendations improve real-world decisions. A model that fits historical data but produces unstable, poorly documented or weakly validated recommendations is not decision-ready. As MMM becomes more operational, the industry must focus less on whether models can be built and more on whether they can be interpreted, validated and used responsibly when they inform capital allocation.

4. Automation, AI and the Amplification of Model Risk

The integration of MMM into AI-driven execution systems changes the risk profile of marketing measurement. MMM has traditionally informed human judgment, supporting strategic planning, budget allocation and retrospective evaluation. As its outputs are connected to automated systems — including budget allocation, bid optimization and campaign adjustment — model assumptions can be translated directly into operational decisions.

This includes:

- Programmatic bidding strategies informed by MMM-derived value signals.
- Automated budget allocation across channels and platforms.
- AI agents optimizing toward outcome-based objectives derived from model outputs.

When MMM operates as an input to automation, its assumptions, biases and limitations are no longer moderated in the same way by human judgment. They can be applied continuously, at scale and with limited intervention.

From Decision Support to Decision Automation

In a human-mediated environment, the limitations of MMM — imperfect data, model specification constraints, and uncertainty in estimates — are typically moderated by expert interpretation. Analysts contextualize outputs, challenge assumptions, and incorporate external knowledge before decisions are made.

In AI-driven systems, this layer of interpretation is reduced or removed. Model outputs are operationalized directly via APIs into execution systems. Any underlying weaknesses in the model are no longer contained — they are systematically propagated through automated decision-making processes.

The central issue is amplification. Weak data, opaque assumptions and uncertain estimates can move from analysis into operational rules, influencing allocation decisions at greater speed and scale. This dynamic is particularly relevant where MMM frameworks incorporate standardized priors or default assumptions. In AI-driven systems, those priors become operational parameters. They influence not only model interpretation, but also the allocation rules and optimization signals that act on model outputs.

The origin, evidentiary basis and documentation of these priors become critical. Where they are derived from limited datasets or controlled by a subset of market participants, they may embed a partial view of the market into automated decision systems.

Where priors are derived from incomplete or asymmetric data, automated allocation patterns may reinforce those asymmetries over time. Systems may become more responsive to channels with faster, richer or more structured feedback signals, while channels whose effects are longer-term, less directly observable or less consistently documented may be harder to represent in optimization logic. The result is not necessarily intentional bias, but a greater risk that automated systems privilege what is easier to observe over what is incrementally valuable.

The principal barriers to AI adoption in media decision systems are not primarily fears of labor substitution, but weaknesses in data readiness, transparency, governance, and system integration. Survey evidence from agencies, brands, and publishers shows widespread concern about setup complexity, data security, AI accuracy and transparency, legal and compliance obligations, fragmented technology stacks, weak data quality or accessibility, and the absence of clear standards. This is significant for MMM. It suggests that the core risk in AI-enabled optimization is not simply that machines will make decisions faster, but that they may operationalize inconsistent data, opaque assumptions, and poorly documented or weakly controlled workflows at greater scale and with less friction than before.

This does not mean that AI-driven MMM should be resisted. Properly governed, AI can improve the MMM workflow by accelerating data integration, identifying anomalies, supporting scenario generation, improving documentation, enabling more frequent monitoring and helping decision-makers interpret uncertainty. The risk is not automation itself. The risk is automation without sufficient controls over data quality, model assumptions, validation evidence, feedback loops and human accountability.

4. Automation, AI and the Amplification of Model Risk

Agentic Planning and Buying

A further standards and interpretation issue is emerging as the advertising industry begins to develop protocols for agentic planning and buying. Initiatives such as AAMP and AdCP are early-stage but strategically important because they seek to define how AI agents may discover inventory, interpret campaign requirements, exchange data, execute buying instructions and evaluate performance across advertising systems.

These initiatives remain in development, and their eventual market impact is uncertain. Their significance for MMM lies less in their current adoption than in the direction of travel they signal. Advertising workflows are moving toward more structured, machine-readable and automated forms of planning, buying and optimization. If these systems scale, they will require feedback signals that agents can ingest and act upon.

The unresolved measurement question is what evidence buying agents should use when evaluating media value. If agentic systems rely primarily on deterministic conversion feeds, closed-loop attribution or platform-specific APIs, they may reproduce many of the limitations that MMM is designed to address: short attribution windows, weak treatment of offline outcomes, under-representation of long purchase cycles, limited recognition of brand effects and insufficient visibility into cross-channel interaction.

MMM can help address this gap because it can incorporate cross-media exposure, non-media drivers, long-term effects and broader business outcomes. However, MMM-derived signals are probabilistic, model-dependent and often slower-moving than platform conversion signals. They therefore need to be translated carefully into machine-readable forms that preserve context, uncertainty and limitations.

The standards question is not whether agentic systems should use “an MMM signal.” It is how future protocols should distinguish between different classes of evidence: deterministic conversions, experimental results, MMM-derived response curves, confidence ranges, priors, validation evidence, data provenance and known limitations. Without this distinction, there is a risk that probabilistic estimates will be treated as deterministic instructions, or that richer evidence about long-term and cross-media effects will be excluded because it is harder to operationalize.

Industry work on MMM-ready inputs and evidence should be designed not only for human analysts, but also for future machine-readable workflows. Media data, validation evidence, priors and documentation should be structured in ways that automated systems can ingest without stripping away the context required for responsible interpretation.

The Mechanisms of Risk Amplification

AI-driven optimization systems, including agentic ad planning and buying, amplify model risk through three primary mechanisms:

→ **Scale and Speed of Execution:** Automated systems act continuously and at scale. Small biases or errors in model outputs can lead to large cumulative effects when applied across millions of impressions, bids, or budget decisions.

→ **Feedback Loops and Recursive Bias:** Many AI systems operate in closed-loop environments, in which past decisions influence future training data. If a model over-allocates budget to a particular channel due to biased or incomplete inputs, subsequent performance data will reflect that allocation, reinforcing the original bias. Over time, this can entrench structurally distorted allocation patterns.

→ **Objective Function Misalignment:** AI systems optimize against defined objectives, often derived from available data. Where data is incomplete — such as in single-platform or walled garden environments — optimization may prioritize locally observable outcomes rather than true cross-media effectiveness. This raises a critical question: whose objectives are these systems optimizing for, and within what data constraints?

4. Automation, AI and the Amplification of Model Risk

Data Fragmentation and Platform Bias

The risks associated with AI-driven optimization are compounded by fragmentation in measurement and data access. Single-platform measurement systems, while increasingly sophisticated, provide inherently partial views of performance. When AI systems are trained or optimized against constrained datasets, they may allocate more confidently toward channels and outcomes that are most visible within those environments, while under-representing effects that occur outside the platform, over longer time horizons or through indirect cross-media pathways.

MMM remains one of the few methodologies capable of integrating cross-media exposures and non-media drivers into a unified analytical framework. However, when MMM outputs are themselves used as inputs into automated systems, their limitations — particularly around data quality, identity resolution, and model specification — become more consequential.

The Shift to Continuous, API-Driven Systems

The growing adoption of API-based architectures further accelerates these dynamics. By connecting MMM inputs and outputs directly to planning and execution systems, advertisers can update models more frequently and act on insights in near real time. While this increases operational efficiency, it also introduces new challenges:

- **Model instability and drift** as inputs are updated continuously.
- **Reduced transparency** in how decisions are derived and executed.
- **Diminished opportunity for human oversight and intervention**.

As MMM becomes embedded within continuous decision systems, it transitions from a periodic analytical tool to a persistent component of the execution layer.

MMM in Programmatic and Real-Time Markets

The integration of MMM into programmatic infrastructure is a particularly significant development. Traditionally, programmatic systems optimize toward proxy metrics such as clicks, conversions, or platform-defined outcomes. MMM introduces the possibility of optimizing toward **modeled business outcomes**, such as incremental sales or profit.

This creates a powerful but complex dynamic:

- Bidding decisions may be informed by modeled, probabilistic estimates with the aim of achieving forecasted sales and profit.
- Different actors may operate on different models, assumptions, and data inputs.
- Optimization signals may be filtered by MMM to remove those which were not generated by media.

Programmatic markets may become **model-mediated markets**, where:

- Prices reflect modeled value rather than proxy metrics.
- Allocation decisions are driven by competing model outputs.
- Feedback loops combine model-driven interpretations of effectiveness and actual sales/profit.

Without shared standards or governance, this can lead to fragmentation, opacity, and divergence in how value is defined across the ecosystem.

4. Automation, AI and the Amplification of Model Risk

Implications for the Market

The convergence of MMM and AI-driven automation has significant implications for the structure and governance of the advertising ecosystem:

- **Increased asymmetry of information**, particularly where platforms control both data and optimization systems.
- **Greater risk of systemic bias**, embedded within automated allocation decisions.
- **Erosion of comparability**, as different actors optimize against different data sets and objectives.
- **Shift in accountability**, as decision-making becomes distributed across models, data, and algorithms.

The Need for Transparency, Control and Accountability

AI-driven measurement and optimization systems therefore require stronger transparency, control and accountability. At a minimum, advertisers and the industry more broadly should consider the following principles:

- **Transparency:** Clear understanding of data inputs, model assumptions, and optimization logic.
- **Auditability:** Ability to validate and interrogate model outputs and automated decisions.
- **Data completeness:** Incorporation of cross-media data to avoid platform-constrained optimization.
- **Separation of roles:** Distinction between measurement, optimization, and media selling functions.
- **Human oversight:** Retention of expert review, particularly for strategic decisions and model validation.

The effectiveness of AI-driven MMM systems is not determined solely by modeling techniques or computational power, but by the controls, documentation and accountability mechanisms that shape how those systems operate. Weak controls risk embedding bias, opacity and misaligned incentives into automated decision-making. Strong controls — grounded in transparency, data completeness and accountability — enable AI to enhance, rather than distort, cross-media optimization.

4. Automation, AI and the Amplification of Model Risk

Figure 6: Control Models for AI-Driven MMM — From Opaque Automation to Accountable Systems

How transparency, control and accountability determine whether AI-driven MMM improves or distorts market outcomes

Dimension	Weak / High-Risk Model (Opaque Automation)	Robust / Low-Risk Model (Accountable System)
System Objective	• Optimization defined by **available platform data.** • Opaque or implicit objectives. • Bias toward **short-term, observable outcomes.**	• Optimization defined by **advertiser business outcomes** (e.g. incremental sales, profit). • Explicit, documented objectives. • Balances **short- and long-term effects**.
Data Inputs	• Reliance on **single-platform / walled garden data**. • Limited cross-media visibility. • No validation of data quality or provenance.	• **Cross-media, multi-source datasets**. • Independent validation of inputs. • Transparent data lineage and refresh cadence.
Measurement & Modelling	• MMM treated as a **black box**. • No audit of assumptions or specification. • Outputs treated as deterministic "truth".	• MMM treated as an **estimative framework**. • Clear documentation of assumptions and limitations. • Regular validation, stress-testing, benchmarking.
Decisioning & Execution	• Fully automated execution with **minimal oversight**. • Optimization coupled to **media sellers' systems.** • No interrogation or override capability.	• **Human-in-the-loop oversight** for critical decisions. • Separation between **measurement, optimization, and selling**. • Clear escalation and override mechanisms.
Feedback Loops	• Closed-loop systems reinforce **existing biases.** • No monitoring of model drift or instability. • Performance data reused uncritically.	• Active monitoring of **feedback effects and drift.** • Controlled training data inputs. • Periodic recalibration using independent benchmarks.
Transparency & Accountability	• Limited visibility into inputs, models, and decisions. • Accountability diffused across systems and vendors.	• End-to-end transparency across inputs, models, and outputs. • Clear ownership and accountability for decisions and outcomes.

4. Automation, AI and the Amplification of Model Risk

System-Level Outcomes

Weak Control Model (Risks)	Strong Control Model (Benefits)
Structural bias in media allocation	More accurate cross-media optimization
Platform-favoring optimization dynamics	Alignment with true business outcomes
Reduced comparability across channels	Greater transparency and comparability
Erosion of advertiser trust and control	Increased trust, accountability, and control

Source: the authors

The effectiveness of AI-driven MMM systems depends not only on modeling techniques or computational power, but on the controls, documentation and accountability mechanisms that govern how those systems operate. Weak controls risk embedding bias, opacity and misaligned incentives into automated decision-making. Strong controls — grounded in transparency, data completeness and accountability — allow AI to improve cross-media optimization without distorting the evidence base on which decisions depend.

In Summary

AI does not automatically resolve the limitations of MMM. In poorly governed systems, it may amplify them. However, AI also creates opportunities to improve measurement through richer data integration, more frequent model refreshes, enhanced experimentation, better representation of uncertainty, and more sophisticated modeling architectures. The challenge is not whether AI should be applied to MMM, but how. The benefits of AI-driven MMM will ultimately depend on the quality of data, the rigor of validation practices, the transparency of assumptions, and the governance frameworks within which these systems operate.

5. Stakeholder Implications

The effects of MMM's operational role are distributed unevenly across the media ecosystem. Advertisers benefit most directly from better outcome-based decision-making, but they also carry responsibility for supplier requirements, interpretation of uncertainty and controls over how model outputs are used. Media sellers have a strong incentive to improve the quality and usability of their data, but limited visibility into advertiser-specific model outputs. Platforms may benefit from granular data advantages while facing greater scrutiny where they provide media, data, tools and optimization systems within the same ecosystem. Agencies and MMM providers face a shift from model execution toward interpretation, validation, workflow integration and accountability.

These differences in incentives explain why collective action is difficult and why any practical response must be carefully bounded.

5.1 From Analytical Tool to Decision Infrastructure

MMM changes stakeholder incentives because control over data, methodology, interpretation and execution becomes economically consequential. These forms of control influence not only measurement outcomes, but competitive advantage.

MMM introduces four interrelated dimensions of control: data, methodology, interpretation and execution. Data determines what the model can observe. Methodology determines how those observations are transformed into estimates. Interpretation determines how outputs are translated into recommendations. Execution systems determine how those recommendations are operationalized in planning, buying and optimization workflows.

As MMM becomes embedded in AI-driven platforms, the locus of influence shifts from analysis alone to system design: who supplies the data, who defines the assumptions, who interprets the outputs and who controls the execution logic.

To meet the expectations of senior leadership, MMM must evolve across five interdependent capabilities:

1. **Causal robustness**: Integrating experimental design and testing frameworks to distinguish correlation from causation.
2. **Representation of long-term effects**: Capturing the sustained impact of brand investment alongside short-term performance.
3. **Operational relevance**: Delivering more timely, granular outputs to support in-flight decision-making.
4. **Integration with AI and advanced analytics**: Enabling scenario planning, forecasting, and automated optimization.
5. **Transparency and accountability**: Ensuring models are interpretable, auditable and trusted.

These capabilities signal a fundamental shift: MMM is no longer an isolated analytical exercise, but a **core component of enterprise decision infrastructure**.

As one industry leader observed, the goal is to move from "interesting analysis" to a disciplined system capable of informing board-level decision-making and financial planning. Achieving this requires not only technical improvement, but a step-change in documentation, validation and operational discipline.

5.2 Data Quality, Integrity, and the Limits of Scale

The expansion of MMM places increasing demands on data. However, more data does not automatically lead to better models.

The principle of "garbage in, garbage out" remains highly relevant. Campaign data is often inconsistent, incomplete, or contaminated by invalid activity. Variability in measurement methodologies across media suppliers introduces additional noise. In some cases, incorporating additional data can degrade model performance rather than improve it.

MMM therefore requires greater data integration but is simultaneously exposed to greater data risk.

The challenge is not simply data availability, but **data integrity**. This includes:

- Verification of media delivery and spend.
- Consistency of measurement definitions across channels.
- Stability of data over time.
- Protection against invalid or manipulated signals.

As data flows between buyers, sellers, and intermediaries increase, new vulnerabilities emerge. For example, actors may attempt to manipulate delivery patterns to artificially strengthen correlations between media exposure and outcomes. In increasingly automated environments, distinguishing between legitimate optimization and strategic gaming becomes more difficult.

These risks elevate data governance from a technical concern to a strategic priority. Rigorous auditing, validation, and reconciliation processes are essential to ensure that MMM outputs are grounded in verified inputs.

5.3 Organizational Readiness

As MMM capabilities become more sophisticated, organizational readiness is increasingly emerging as a critical determinant of success. Across many organizations, the primary constraint is no longer access to data or analytical capability, but the ability to integrate measurement outputs into planning, budgeting, and decision-making processes.

Effective use of MMM often requires coordination across marketing, finance, analytics, media, and executive leadership teams. Different stakeholders may operate with different objectives, metrics, and time horizons, creating challenges in interpretation and adoption. As MMM becomes more central to capital allocation decisions, questions of governance, accountability, transparency, and organizational trust become increasingly important.

In practice, the organizations deriving the greatest value from MMM are often not those with the most sophisticated models, but those that have successfully embedded measurement into broader planning and decision-making workflows.

Organizational capacity will become even more important as agentic planning, buying and selling systems develop. These systems will require structured, machine-readable inputs and feedback signals that can be interpreted by automated agents operating within advertiser, agency, platform or publisher workflows.

Both the buy side and the sell side face a readiness challenge. Advertisers will need clear internal controls determining which signals agents are allowed to use, how uncertainty is represented and when human oversight is required. Media owners will need to ensure that campaign data, evidence, documentation and validation materials are available in formats that can be ingested by automated systems without stripping away important context.

The risk is that agentic systems default to the easiest available signals: short-term, platform-specific or deterministic conversion measures. The opportunity is to ensure that MMM-informed evidence — including response curves, confidence ranges, validation evidence and known limitations — can also be represented in machine-readable form.

5. Stakeholder Implications

5.4 Stakeholder Implications

Advertisers

Advertisers are the primary beneficiaries of MMM's evolution, gaining more comprehensive, outcome-based views of performance. However, this increased capability comes with greater responsibility.

As MMM becomes embedded in financial planning, it intersects directly with capital allocation decisions typically governed by finance functions. This raises important questions around auditability, consistency with financial reporting, and the treatment of uncertainty.

Advertisers will need to review supplier contracts for data rights, documentation obligations, automated decision parameters, auditability, portability and compliance with agreed controls. As MMM becomes more connected to planning and execution systems, contractual terms will need to specify not only what data is supplied, but how it may be used, refreshed, validated and transferred if the advertiser changes suppliers.

As with financial forecasting, MMM forecasts are probabilistic and model-dependent. Bridging this gap between future sales and current marketing budgets will be critical to adoption at the CFO and board level.

Media Sellers (Broadcasters and Publishers)

For media sellers, MMM represents both opportunity and constraint.

On one hand, outcome-based evaluation can better capture the long-term contribution of premium media environments. On the other, MMM introduces a layer of abstraction that reduces transparency into how inventory is assessed.

This creates a structural asymmetry: sellers are expected to respond to model outputs without visibility into the underlying data, assumptions, or calibration. As MMM becomes more influential in budget allocation, this asymmetry may shape competitive dynamics — particularly where certain media types are more fully represented in model inputs.

As MMM becomes more influential, media sellers have a practical interest in improving the inputs that shape how their inventory is represented. The most credible route is not to build competing MMM systems or promote seller-controlled priors, but to contribute to independently governed evidence resources, better data structures and transparent documentation practices. In a model-driven market, influence is exercised not only through inventory and pricing, but through participation in the evidentiary foundations that determine how value is assessed.

Platforms

Platforms occupy a structurally complex position, operating simultaneously as media suppliers, data providers, and — in some cases — measurement providers.

Their access to granular, real-time data creates clear advantages in model inputs. Their role in developing MMM tools and frameworks introduces potential influence over model configuration and interpretation.

This does not necessarily imply intentional bias, but it underscores the importance of independent validation and cross-platform comparability. Without these safeguards, differences in data access and system design may translate into structural competitive advantage.

5. Stakeholder Implications

Agencies

As MMM becomes more accessible through SaaS platforms, open-source tools and AI driven workflows, agencies face a shift in their role.

Executional advantage is increasingly commoditized. In its place, value shifts toward:

- Interpretation of model outputs.
- Governance and validation.
- Strategic advisory.

The central challenge for agencies is ensuring that decision-making remains grounded in expertise and judgment, rather than defaulting to automated outputs.

MMM Providers

MMM providers face intensifying competition as core modeling capabilities become commoditized.

Differentiation is shifting toward:

- Data integration and quality management.
- Workflow integration and usability.
- Interpretability and communication.
- Operational deployment within decision systems.

Success increasingly depends on delivering **end-to-end systems**, not just statistical models.

Joint Industry Committees (JICs)

MMM fundamentally changes the role of traditional measurement institutions.

Rather than serving solely as currencies, JIC outputs increasingly function as **inputs into modeling frameworks**. This raises a strategic question: do JICs evolve to support MMM through improved data provision and integration, provide their own MMM solutions governed by industry, or risk marginalization as modeling becomes the dominant mechanism of evaluation?

Their future relevance will depend on their ability to provide trusted, high-quality inputs into increasingly complex decision systems.

Media Auditors

Media auditors may become more important as MMM is connected to automated buying, API-based reporting and contractual data obligations. Their role is unlikely to be to audit proprietary model code or second-guess advertiser-specific allocation decisions. A more practical role is to verify whether agreed data, documentation, reporting, change-control and compliance requirements have been met.

This may include checking data provenance, reconciliation between planned and delivered media, adherence to reporting cadence, documentation of material changes, compliance with data-sharing provisions, and the availability of audit trails for automated decision systems. As media transactions become more machine-readable and model-informed, audit capability will need to evolve from retrospective cost and compliance review toward more continuous assurance of data integrity and contractual accountability.

5. Stakeholder Implications

Figure 7: Stakeholder Incentives and Feasibility Considerations

Stakeholder	Primary interest	Likely concern or resistance	Practical response
Advertisers	Better allocation, stronger outcome-based planning, improved financial confidence	Concern that industry initiatives could expose proprietary results or constrain modeling freedom	Keep the agenda focused on input quality, documentation and validation standards; do not require disclosure of advertiser outcomes, model code or budget strategy
Agencies	Stronger advisory role, better workflow integration, defensible planning recommendations	Concern about additional process burden or loss of proprietary differentiation	Position standards as baseline operating discipline, while preserving methodological and strategic differentiation
MMM providers	Better data inputs, clearer validation expectations, more scalable workflows	Concern that standardization could commoditize methods or impose rigid requirements	Focus on documentation, provenance and validation transparency rather than prescribed model design
Media owners	More accurate representation of media value, especially long-term and cross-channel effects	Limited access to advertiser-specific outputs; risk of appearing to lobby for favorable priors	Contribute independently governed evidence, better data structures and transparent documentation rather than seller-controlled models
Platforms	Ability to support automated planning and measurement at scale	Greater scrutiny of data access, conflicts of interest and platform-constrained optimization	Support interoperable data, transparent provenance and separation between measurement evidence and media-selling incentives
Auditors and assurance bodies	New role in data, documentation and contractual compliance	Need for new technical capabilities and clear remit	Focus audit activity on data lineage, documentation, change control, reporting obligations and AI safeguards
Industry bodies	Convening authority and standards development	Limited authority to compel adoption	Start with voluntary specifications, pilots, RFP language and contract templates that can become market practice over time

Source: the authors

5.5 Toward More Disciplined MMM Interpretation and Use

The stakeholder dynamics noted above are not abstract. They directly shape how MMM is implemented, interpreted and acted upon. As MMM becomes more influential in planning, budgeting and automated decision workflows, its effectiveness depends not only on technical capability, but on how roles, responsibilities, incentives and documentation practices are structured across the ecosystem.

The central challenge is not to govern MMM through a single institutional mechanism. It is to improve the conditions under which MMM outputs are interpreted, validated and used in decision-making. The next section asks what practical steps could help strengthen those conditions, while recognizing that no single institution currently governs the full MMM ecosystem.

6. From Diagnosis to Practical Improvement

The answer must be bounded. MMMs are proprietary, advertiser-specific and commercially sensitive, and their outputs may reflect confidential information about pricing, promotions, distribution, margins, customer behavior, sales performance and future budget strategy. Practical improvement should therefore focus on shared foundations — media input structure, taxonomy alignment, data provenance, assumption documentation, validation protocols, evidence-quality standards and commercial adoption tools — without requiring disclosure of proprietary models, advertiser-specific results or client business outcomes.

Four areas of practical improvement follow from this analysis:

→ **Data quality and provenance**: Inputs into MMM should be complete, consistent, timely, well documented and comparable across channels and platforms.

→ **Methodological transparency**: MMM outputs should be accompanied by clear documentation of assumptions, priors, transformations, validation approaches, uncertainty and limitations, without requiring disclosure of proprietary code or client-specific results.

→ **System transparency**: Advertisers and their partners should be able to understand how MMM outputs are used within planning, optimization and automated decision systems, including where human oversight, override and escalation mechanisms apply.

→ **Commercial accountability**: Data, documentation, validation, audit and AI-safeguard expectations should be translated into RFPs, contracts, data-sharing agreements and supplier review processes.

These areas are interdependent. Better data quality improves model usability. Methodological transparency improves interpretation. System transparency supports oversight of how outputs are applied. Commercial accountability turns guidance into practice by embedding expectations for data, documentation, validation, auditability and AI safeguards into procurement, contracting, audit and data-sharing mechanisms.

The practical shift is from treating MMM as a specialist analytical exercise to treating it as a decision process that depends on disciplined inputs, documented assumptions, credible validation evidence and clear accountability for how outputs are used. This does not require a single governance regime for MMM. It requires a clearer operating framework for the shared inputs and practices on which private MMM systems increasingly depend.

Progress will be constrained by real market conditions. Incentives are not fully aligned: platforms, media owners, advertisers, agencies and measurement providers do not all benefit from the same level of transparency, standardization or comparability. The costs of improvement are also unevenly distributed. Data standardization, documentation, validation and auditability create operational burdens that fall differently across large platforms, smaller media owners, agencies, advertisers and vendors. Finally, institutional capacity is fragmented. No single body currently has the mandate, authority or funding to coordinate across the full ecosystem.

Progress is unlikely to be centrally directed. It is more likely to emerge through voluntary alignment, commercial adoption, technical standardization and practical experimentation. The most realistic starting point is not a comprehensive governance regime, but a set of bounded steps that can be tested without requiring disclosure of proprietary models, confidential advertiser results or commercially sensitive business data.

The next section sets out six practical steps for strengthening those shared foundations.

7. Six Practical Steps for Strengthening MMM Inputs and Evidence

As MMM becomes embedded within decision systems, differences in model inputs — including data, priors and validation evidence — become more consequential. The practical focus should therefore shift from model construction alone to the quality, documentation and validation of the inputs on which private MMM systems depend.

The six steps below translate that shared-foundations approach into practical workstreams.

Step 1: Develop an MMM-ready Media Data Specification

A practical first step would be to develop a common specification for media data used in MMM. The specification should define the minimum fields, metadata and reporting structures required to make TV, CTV, streaming, digital video and related media more consistently usable within MMM workflows.

The specification should address campaign identifiers, publisher and platform identifiers, media type, format, placement, creative, geography, audience definition, exposure definition, reach, frequency, spend, timing, delivery status, reporting cadence, data provenance and known limitations. Its purpose is to create structured, machine-readable media inputs that can flow more reliably from publishers, platforms, agencies and measurement providers into advertiser MMM systems.

To be credible, the specification should be technically usable, commercially practical and capable of being referenced in data-sharing agreements, RFPs and supplier onboarding processes.

Step 2: Create a Standard MMM Model Factsheet

Advertisers should be able to require a standard disclosure template from MMM providers, agencies and internal analytics teams. This should not require disclosure of proprietary code, confidential client results or commercially sensitive budget strategy. Instead, it should document the information required for informed interpretation: data sources, transformations, aggregation levels, priors, adstock assumptions, saturation curves, excluded variables, validation methods, uncertainty ranges, refresh and retrain cadence, known limitations and conflicts of interest.

The purpose of the factsheet is to make MMM outputs more interpretable, auditable and comparable at the level of process, while preserving methodological diversity. It should help senior decision-makers understand how much confidence to place in model outputs, what assumptions matter most, where uncertainty is material and when additional validation is required.

Step 3: Establish an Experimentation and Validation Playbook

A useful next step would be to develop practical guidance for geo tests, lift tests, calibration studies, sensitivity analysis, out-of-sample validation and model stress-testing. The playbook should specify when evidence is strong enough to inform model calibration, when results should be treated as directional and how uncertainty should be represented.

This workstream should emphasize experimentation as a calibration anchor, not as a universal replacement for MMM. It should also define how experiments are translated into priors, response curves, confidence ranges or validation benchmarks. The goal is to make validation evidence more consistent, better documented and more usable across private MMM systems.

Step 4: Build an Independently Overseen Premium Video Evidence Library

A practical next step would be to develop an anonymized and independently overseen evidence library focused on premium video effects. The library would synthesize evidence on carryover, long-term brand effects, reach and frequency dynamics, co-viewing, search and retail halo effects, and cross-channel synergies.

7. Six Practical Steps for Strengthening MMM Inputs and Evidence

The library should not create fixed priors that all models must adopt. Instead, it should provide evidence ranges, confidence levels, applicability notes and quality ratings. The purpose is to improve the evidence available to MMM practitioners, not to predetermine the answer that any model should produce.

To be credible, the evidence library should be independently overseen, use transparent inclusion criteria and distinguish between experimental evidence, modeled evidence, case studies and expert interpretation.

Step 5: Create a Contractual Adoption Toolkit

The data specification, model factsheet and validation guidance should be translated into practical tools for RFPs, contracts and data-sharing agreements.

This toolkit should include sample RFP language, data provision requirements, documentation requirements, audit rights, change-control expectations, data latency commitments, AI and automation safeguards, escalation procedures and supplier portability provisions. These tools would allow advertisers, agencies, media owners, platforms and measurement providers to embed good practice directly into commercial relationships.

Step 6: Engage with Agentic Advertising Protocol Developers

As agentic planning and buying standards develop, MMM-informed evidence should be represented in machine-readable form. This does not mean making MMM the only feedback signal for automated buying agents. It means ensuring that agents do not default solely to short-term, platform-specific or deterministic conversion signals because richer evidence is unavailable or poorly structured.

Engagement with relevant standards bodies and protocol developers could help define how automated systems should ingest MMM-derived response curves, confidence ranges, priors, validation evidence, data provenance and known limitations. These signals should be accompanied by sufficient context to prevent probabilistic estimates from being treated as deterministic truth.

Conditions for Success

These steps would need to be credible to the organizations that use, build, evaluate and contract for MMM in practice. They should be designed around usability, neutrality and confidentiality: useful to advertisers and agencies, technically workable for MMM providers, practical for media suppliers and platforms, and capable of being referenced in commercial workflows without requiring disclosure of proprietary business results or model outputs.

Better shared foundations improve advertiser decision quality, reduce false precision and make MMM outputs easier to explain to finance and executive leadership. Sell-side participation remains necessary because many relevant inputs originate with media owners, platforms and intermediaries.

These steps will only be useful if they are designed around real market constraints. Advertisers must see them as improving decision quality, not as an attempt to influence MMM outcomes in favor of any channel. Confidentiality protections must be explicit: no practical step should require advertisers to disclose sensitive sales, profit, customer or business outcome data. Any standards should begin with practical input, documentation and validation requirements before attempting more ambitious forms of coordination. Adoption should be supported through commercial incentives, including RFP language, contract clauses, audit rights and data-sharing requirements.

A practical pathway would be staged rather than comprehensive. The first stage would define a minimum viable set of materials: common media input fields, a model factsheet template, evidence-quality criteria and sample RFP language. The second stage would test those materials with live or retrospective use cases to determine whether they improve usability, interpretation and documentation. The third stage would translate the tested materials into voluntary adoption guidance, contract templates and machine-readable documentation requirements. This staged approach would allow the market to learn what is useful before attempting broader institutionalization.

7. Six Practical Steps for Strengthening MMM Inputs and Evidence

From Models to Market Infrastructure

As MMM becomes embedded in AI-driven systems, its outputs increasingly shape how capital flows across the market. The integrity of MMM is not simply a technical issue. It is a matter of market design.

The industry does not need a single model or a single answer. It needs better shared inputs, stronger documentation, more credible validation evidence and clearer commercial expectations. These interventions are modest compared with the scale of the challenge, but they address the point at which collective action is most feasible and most valuable: the common evidence base that private MMM systems use to represent media value.

For premium video, this is particularly important. If TV and video inputs remain fragmented, delayed, inconsistently classified or weakly documented, their contribution may be harder for MMM systems — and future buying agents — to detect, validate and act upon. Improving those inputs is not a defensive exercise. It is a practical step toward a more accurate, trusted and accountable outcome-based marketplace.

8. Conclusion: MMM in the Age of AI

MMM is no longer simply a measurement tool. It is becoming embedded within the systems that determine how capital is allocated across the media ecosystem.

This transition changes the nature of the challenge. The question is no longer only how to improve individual models, but how to improve the conditions under which MMM outputs are interpreted, documented, validated and used in decisions that shape the allocation of marketing capital.

Because MMM outputs are model-dependent estimates, their integration into AI-driven systems raises the stakes for data quality, methodology and transparency. Limitations that once affected analysis can be propagated through automated decision-making and buying systems, with direct effects on budget allocation and media valuation.

Addressing this does not require a single industry model, a common MMM methodology or disclosure of proprietary advertiser results. The focus is on shared inputs and evidence, not on standardizing advertiser-specific models. The practical question is how to strengthen the shared foundations that make MMM more reliable, interpretable and usable in automated decision environments.

This agenda is practical because it targets the parts of the MMM ecosystem where collective action can improve quality without compromising confidentiality or methodological diversity. It recognizes that MMM will remain advertiser-specific and model-dependent, while also acknowledging that inconsistent inputs, opaque assumptions and weak validation create market-level consequences as MMM becomes embedded in automated decision systems.Ultimately, the future of MMM will be determined less by advances in modeling techniques than by the strength of the data, standards, and institutions that support it.

As MMM becomes embedded within shared tools and AI-driven systems, influence over market outcomes increasingly shifts upstream — from model outputs to model inputs. Data, priors, and validation evidence become the mechanisms through which value is defined and operationalized.

As adoption scales, widely used tools, priors and data pipelines may become de facto definitions of media value — not because the market has agreed on them, but because they are operationalized at scale.

Improving the quality, documentation and validation of these inputs is therefore not a technical refinement. It is a requirement for transparent, accountable and evidence-based decision-making. The transition from analytical tool to decision infrastructure is already underway. The question is no longer whether MMM will shape the market, but how reliably, how transparently and under whose assumptions.

Appendix A: Technical Methods and Model Components

A1. Purpose and Role of Marketing Mix Modelling

Marketing Mix Modelling (MMM) is a statistical framework used to estimate the relationship between marketing activity and business outcomes, and to inform forward-looking budget allocation decisions.

MMM operates on historical data — typically spanning one to three years — to model how variations in media investment and non-media factors (e.g. pricing, distribution, macroeconomic conditions) are associated with changes in outcomes such as sales or revenue.

MMM should be understood as a **decision-support system under uncertainty**, not a deterministic forecasting tool. Its outputs are directional estimates designed to inform trade-offs, scenario planning, and strategic allocation.

A2. Model Architecture and Inputs

MMM models are typically constructed using aggregated time-series data at a weekly or daily level. Inputs fall into three broad categories:

1. **Media Inputs:** Spend, impressions, or exposures across channels.
2. **Non-Media Drivers:** Pricing, promotions, distribution, seasonality, macroeconomic variables.
3. **Transformations:** Functional adjustments to reflect real-world effects (e.g. diminishing returns, lag effects).

MMM is not a single model but a multi-stage system in which assumptions, transformations, and data choices materially shape outputs.

Figure 8: Anatomy of an MMM System: From Inputs to Decisions

Stage	Components	Description/Role in the System
1. Input Data Layer	• Media Inputs: TV, CTV, Digital, Search, Social. • Non-Media Drivers: Price, Promotions, Distribution, Seasonality, Macro. • Data Conditioning: Aggregation, Normalization, Data Cleaning.	• Core marketing activity data used to explain variation in outcomes. • External and business factors influencing outcomes beyond media. • Preparation of raw data into consistent, model-ready formats.
2. Transformation Layer	• Adstock (lag/carryover effects). • Diminishing Returns (saturation curves). • Interaction Effects (optional). • Priors (external assumptions / constraints).	• Captures how advertising effects persist over time. • Models decreasing marginal impact at higher spend levels. • Captures interplay between channels. • Introduces external evidence to guide and stabilize model outputs.

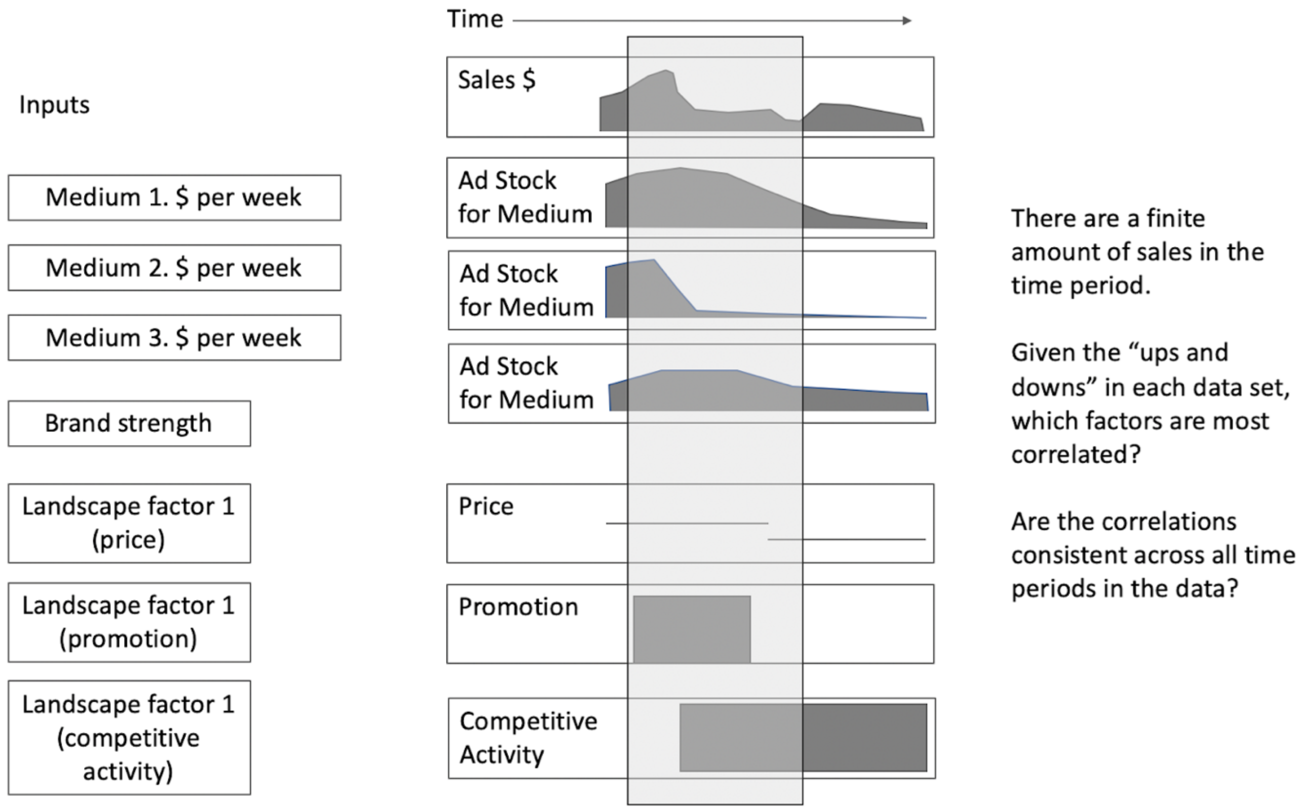
Appendix A: Technical Methods and Model Components

Stage	Components	Description/Role in the System
3. Estimation Layer	• Statistical Modelling (regression/Bayesian approaches). • Parameter Optimization. • Model Diagnostics (e.g. R^2, residuals).	• Estimates relationships between inputs and outcomes. • Fits model coefficients to best explain observed data. • Evaluates how well the model explains historical variation.
4. Output Layer	• Channel Contribution. • ROAS / Marginal Returns. • Response Curves. • Scenario Simulations ("What-if" analysis).	• Estimated impact of each channel on outcomes. • Efficiency of spend and incremental value. • Relationship between spend levels and outcomes. • Forecasts impact of alternative budget allocations.
5. Decision Layer	• Budget Allocation. • Channel Mix Strategy. • Strategic Planning. • Performance Evaluation.	• Optimizing investment across channels. • Determining optimal media balance. • Informing long-term marketing decisions. • Assessing effectiveness of past activity.

The modeling process estimates the contribution of each input to observed outcomes, subject to statistical constraints and assumptions.

Appendix A: Technical Methods and Model Components

Figure 9: Basic Data collection and processing for a Market Mix Model



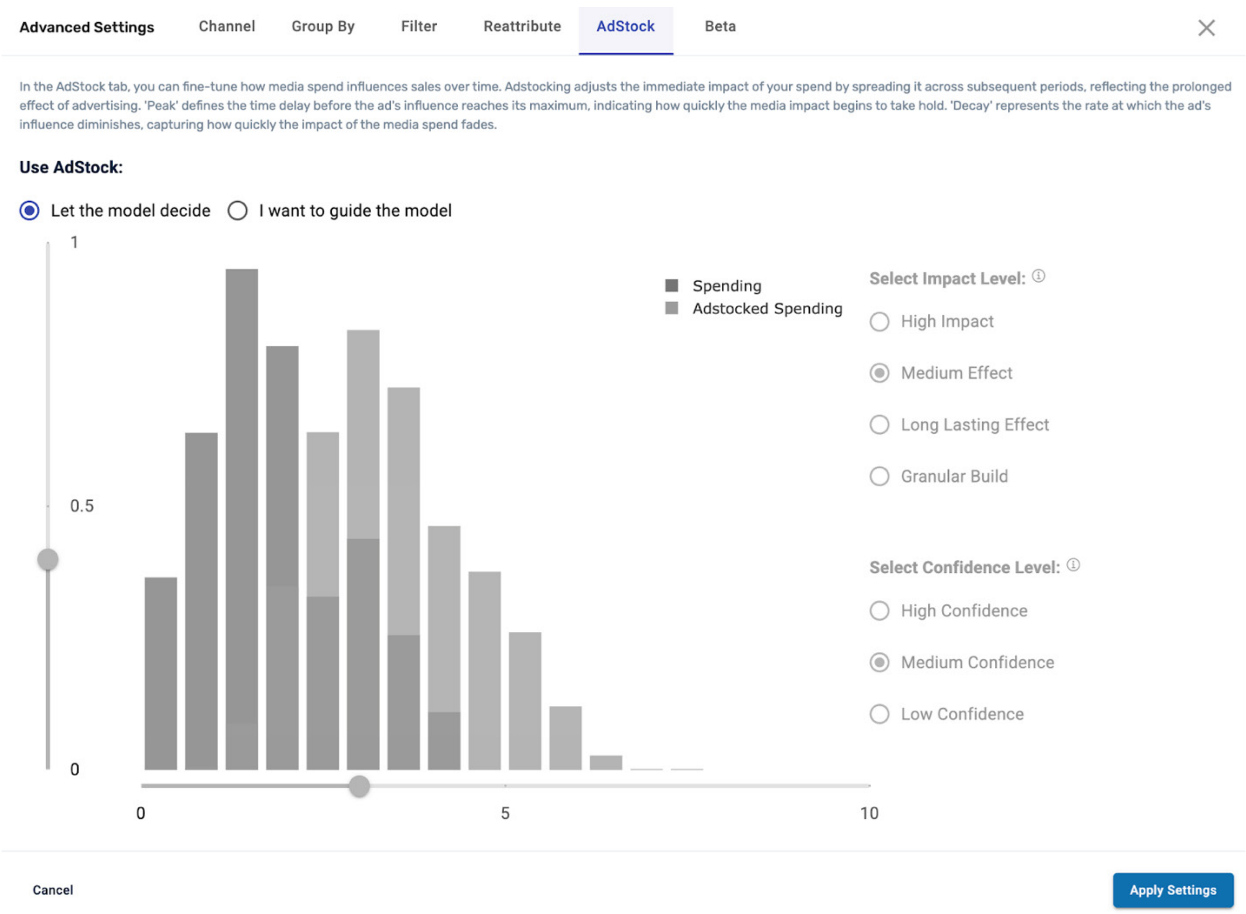
A3. Core Model Components

Adstock (Carryover Effects)

Adstock captures the persistence of advertising effects over time. Rather than assuming that media impact occurs only in the period of exposure, adstock functions distribute impact across subsequent periods using a decay rate.

Appendix A: Technical Methods and Model Components

Figure 10: Adstock Influence over Outcome Allocation



Source: Arima Data (2025)

Different channels exhibit different decay profiles, reflecting variations in attention, memorability, and purchase cycles.

In practice, adstock parameters may be estimated directly from the data or constrained using external evidence (priors).

The specification of adstock has a material impact on attribution and should be treated as a **key modeling assumption requiring scrutiny and validation**.

Diminishing Returns (Saturation Effects)

MMM typically incorporates non-linear response curves to reflect diminishing marginal returns to advertising investment. At higher levels of spend, incremental impact decreases, affecting optimal allocation decisions.

Priors and External Evidence

Priors are externally derived assumptions — often based on experimental evidence, meta-analysis, or historical learnings — used to guide model estimation.

They serve two critical functions:

1. **Stabilization**: Reducing volatility in model outputs.
2. **Calibration**: Embedding external evidence into model structure.

However, priors can also introduce bias if poorly specified. Their selection, justification, and sensitivity should be transparent and documented.

Appendix A: Technical Methods and Model Components

A4. Model Outputs and Validation

MMM produces several key outputs:

- **Channel Contributions**: Estimated impact of each channel on outcomes.
- **Return Metrics (e.g. ROAS)**: Ratio of incremental outcomes to investment.
- **Response Curves**: Relationship between spend and outcomes.
- **Scenario Simulations**: Forecasts under alternative budget allocations.

Model validation typically includes:

- **Goodness-of-fit metrics** (e.g. R^2), which assess how well the model explains historical variation.
- **Out-of-sample testing (backtesting)**: Comparing predictions against held-out data.
- **Sensitivity analysis**: Testing robustness to changes in assumptions.

No single validation metric is sufficient. Robust validation requires **multiple complementary approaches**. While statistical diagnostics and backtesting provide important indicators of model performance, they are insufficient on their own. The most robust validation occurs when model-generated forecasts are tested against real-world outcomes, particularly through controlled interventions such as geo experiments. A model may fit historical data well yet fail to predict future outcomes accurately.

An example of a typical model output is shown below.

Figure 11: Channel Effectiveness

Source: Mutinex (2026)

A5. Limitations and Interpretation

MMM provides a structured analytical framework but does not eliminate uncertainty or fully resolve causal inference challenges.

Figure 12: Sources of Uncertainty in MMM — A Layered Risk Framework

Layer of Uncertainty	Key Sources of Uncertainty	Implications for MMM Outputs
1. Data Uncertainty	• Incomplete or inconsistent datasets. • Measurement error (e.g. impressions, reach, identity resolution). • Misalignment across data sources. • High noise / entropy in behavioral data.	• Model outputs may reflect data gaps rather than true effects. • Misstated exposure leads to biased attribution. • Distorted relationships between inputs and outcomes. • Reduced signal clarity and model stability.
2. Model Uncertainty	• Choice of functional form (linear vs non-linear relationships). • Adstock and decay assumptions. • Variable selection and feature engineering. • Multicollinearity between channels.	• Different specifications produce materially different results. • Alters timing and magnitude of attributed impact. • Inclusion/exclusion of variables shifts contribution estimates. • Limits ability to isolate independent channel effects.
3. Assumption Uncertainty	• Use of priors and external constraints. • Stability of historical relationships. • Omitted variables (e.g. competitor activity, distribution shifts). • Structural change in market dynamics.	• Can stabilizes outputs or introduce systematic bias. • Past patterns may not hold under changing market conditions. • Missing drivers distort estimated contributions. • Model becomes less predictive over time.
4. Interpretation Risk	• Over-reliance on point estimates (e.g. ROAS). • Confusion between correlation and causation. • Ignoring confidence intervals and variability. • Over-optimization based on unstable outputs.	• Creates false precision in decision-making. • Misinterpretation of model outputs. • Underestimation of risk. • Poor budget allocation decisions.
Resulting Impact	• Compounding uncertainty across all layers. • Translation into business decisions.	• Final outputs should be treated as probabilistic, not deterministic. • Introduces risk in budget allocation and strategic planning.

Source: the authors

Appendix A: Technical Methods and Model Components

Key limitations include:

- **Aggregation Bias**: Use of aggregated data obscures variation at the audience, creative, and placement level.
- **Multicollinearity**: Correlated media activity limits the ability to isolate independent effects.
- **Omitted Variable Risk**: Unobserved factors (e.g. competitor actions) may bias results.
- **Structural Change**: Historical relationships may not hold in evolving market conditions.
- **Model Instability**: Outputs are sensitive to model specification, priors, and input data.
- **Causal Ambiguity**: MMM estimates associations, not definitive causal effects.

Uncertainty compounds across layers — MMM outputs should be interpreted as probabilistic, indicative signals, not precise or definitive answers. MMM outputs should be used in conjunction with experimentation and other measurement approaches.

A6. Data Quality and Model Sensitivity

The reliability of MMM outputs is fundamentally dependent on data quality.

Key considerations include:

- **Data completeness and consistency**
- **Measurement accuracy (e.g. impression validity, exposure definitions)**
- **Identity resolution and deduplication**
- **Temporal alignment across datasets**

High levels of noise or inconsistency increase uncertainty and reduce model stability. MMM outputs should therefore be evaluated in the context of underlying data integrity.

A7. Operational Considerations

MMM implementation typically involves:

- **Data engineering and integration**, often the most resource-intensive phase
- **Model estimation and tuning**
- **Ongoing refresh and recalibration**

Advances in automation and SaaS platforms have reduced model runtime, but **data preparation remains the primary bottleneck.**

Appendix A: Technical Methods and Model Components

Figure 13: From Model Output to Decision Risk — Moving Beyond Point Estimates

Part 1: Example of MMM Output Interpretation

Metric	Value
Reported ROAS (Point Estimate)	3.2
Lower Bound (Plausible Range)	1.8
Upper Bound (Plausible Range)	4.1
Confidence Level	Moderate

Part 2: Interpretation of Results

Observation	Implication for Decision-Making
Point estimate suggests strong performance.	Channel may appear highly efficient.
Wide plausible range (1.8 — 4.1).	True performance may be materially lower or higher.
Uncertainty is not visible in single ROAS figure.	Risk of overconfidence in planning decisions.
Results depend on model assumptions and data quality.	Outputs should be stress-tested before action.

Part 3: Decision Framework Based on Confidence Levels

Confidence Level	Characteristics of Output Range	Recommended Action
High Confidence	Narrow range, stable across model variations.	Proceed with allocation decisions.
Moderate Confidence	Moderate range, some sensitivity to assumptions.	Validate with experiments or additional data.
Low Confidence	Wide range, high model sensitivity.	Avoid major reallocation; prioritize further testing.

Source: the authors

Increasingly, MMM outputs are integrated into planning and optimization systems, enabling faster scenario analysis. However, this also raises risks of over-automation without sufficient governance or interpretation.

A8. Role Within a Broader Measurement Framework

MMM should be positioned as one component of a broader measurement ecosystem, alongside:

- Controlled experiments (e.g. lift studies)
- Attribution models
- Incrementality testing

Effective decision-making requires **triangulation across methods**, recognizing the strengths and limitations of each.

Figure 14: MMM in the Measurement Ecosystem — Complementary Methods, Not Substitutes

Dimension	MMM (Marketing Mix Modelling)	Experiments (e.g. Lift Tests)	Attribution Models
Primary Question	What drove outcomes? (historical, aggregate)	What causes incremental lift? (causal)	What drove this specific action? (user-level)
Data Type	Aggregated time-series data.	Controlled test vs control groups.	User-level journey / event data.
Core Strengths	• Holistic view across all media and factors. • Incorporates non-media drivers. • Supports strategic planning and budgeting.	• Strong causal inference. • Clear measurement of incrementality.	• Granular, real-time insights. • Enables tactical optimization.
Key Limitations	• Limited ability to establish causality. • Aggregation masks audience-level variation. • Sensitive to model specification and assumptions.	• Limited scalability and coverage. • Can be costly and operationally complex.	• Susceptible to bias (e.g. last-touch). • Often constrained by platform data silos.
Best Use Cases	• Budget allocation and channel mix optimization. • Long-term strategic planning.	• Validating key channels or tactics. • Testing specific hypotheses.	• In-flight optimization and short-term tuning.

Source: the authors

The highest-confidence decisions occur when insights from MMM, experiments, and attribution models are directionally consistent. No single method is sufficient in isolation.

Appendix A: Technical Methods and Model Components

The Limitations of MMMs — Interpreting Model Outputs

MMM provides a structured way to estimate the relationship between marketing activity and business outcomes, but it does not eliminate uncertainty or fully resolve causal inference challenges.

Several well-established limitations should be considered when interpreting results:

- **Aggregation bias:** MMM typically operates on aggregated time-series data, which can obscure variation at the audience, creative, or placement level. Important effects may be diluted or misattributed.
- **Multicollinearity:** Media channels often move together (e.g. coordinated campaigns across TV, digital, and search), making it difficult for models to reliably isolate the independent contribution of each channel. Research has shown that correlated media investments can significantly limit the ability of MMM to distinguish individual channel effects (Jin et al., 2017).
- **Omitted variable risk:** Not all relevant drivers of outcomes — such as competitor activity, distribution changes, or macroeconomic factors — can be fully observed or included, which can bias results.
- **Structural change:** Consumer behaviour, media consumption, and market conditions evolve over time. Models trained on historical data may not fully capture future dynamics, particularly during periods of disruption.
- **Instability of estimates:** Metrics such as return on ad spend (ROAS) can vary significantly depending on model specification, time period, and input assumptions, and should not be treated as fixed truths. Both academic and industry implementations of MMM highlight the sensitivity of results to model configuration, priors, and data inputs (Meta Robyn; Google Meridian documentation).
- **Causal interpretation:** While MMM can incorporate experimental priors and testing data, it does not inherently establish causality in the same way as controlled experiments. Results should be interpreted as indicative rather than definitive.

These limitations reinforce the importance of combining MMM with other measurement approaches, including experimentation and attribution, and of applying informed judgment when translating model outputs into business decisions. MMMs should be interpreted as a decision-support framework rather than a deterministic system, requiring triangulation with complementary measurement approaches.

Appendix B: Reference and Sources

This report draws on a combination of academic research, industry studies, platform documentation, and practitioner perspectives to provide a comprehensive view of the evolution of Marketing Mix Modeling (MMM) and its role in AI-driven media decision-making.

Key Themes Across Sources

The body of research referenced in this report reflects several consistent themes:

- MMM is becoming operationalized within planning, optimization, and AI-driven systems
- Data fragmentation and inconsistency remain core structural challenges
- Model outputs are highly sensitive to assumptions, priors, and input quality
- Open-source MMM tools increase accessibility, but introduce standardization risks
- AI amplifies existing model limitations, rather than resolving them
- Governance, transparency, and validation are emerging as critical requirements for market-scale deployment

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