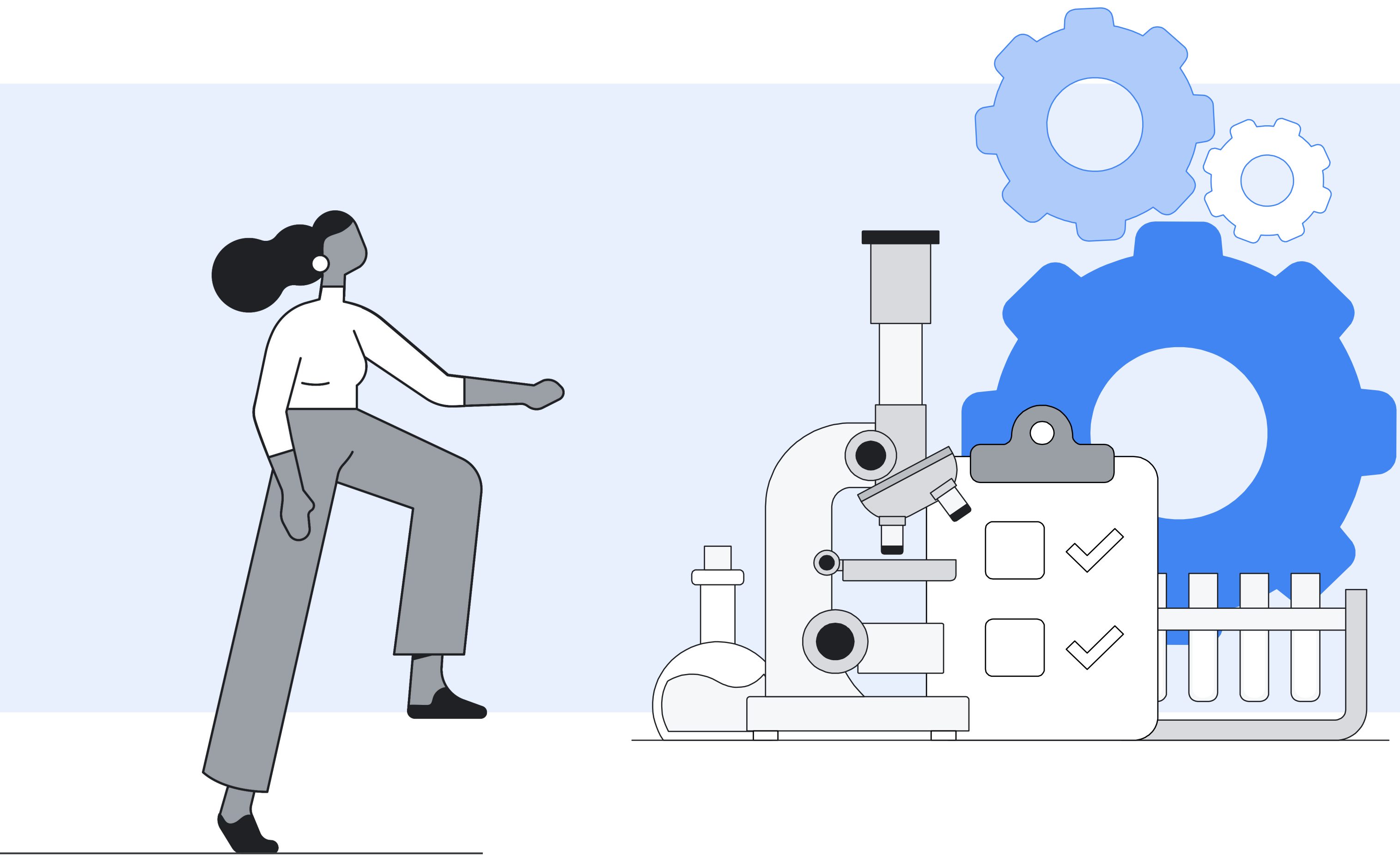
Modern Measurement Playbook

How to use media effectiveness measurement to **make better business decisions**

2024 edition



Foreword

In recent years, we have collaborated with advertisers, agencies, and third-party providers from various industries, platforms, and countries. Through these partnerships, we have witnessed first-hand the tremendous impact that media effectiveness measurement can have on driving business growth when utilised correctly.

Our broader perspective has also revealed that no single party holds the key to modern measurement nor is there a one-size-fits-all solution that can work for all advertisers. While this playbook may not have all the answers, we aim to share the insights we've gained over the years and provide a comprehensive overview. It's packed with best practices for every advertiser to consider when developing media effectiveness measurement strategies.

We are excited to embark on this journey with you and work towards improving your media effectiveness measurement.

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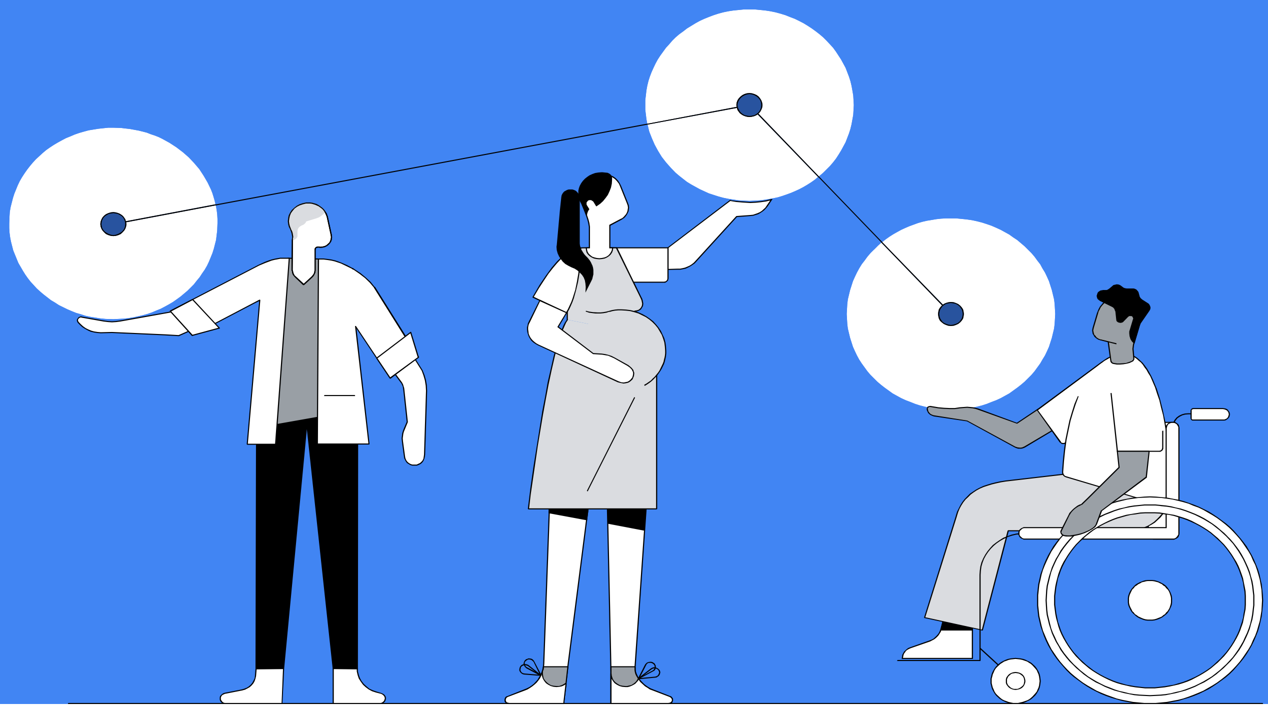
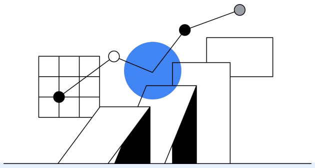


Why should you care about media effectiveness measurement?



Measurement can be a driver of growth by helping organisations understand and improve the effectiveness of their media investments.

83% of CEOs agree with this statement, but 45% of CFOs revealed they have either declined or not fully funded marketing proposals previously because they didn't demonstrate a clear line to value.* This disconnect shows that to position media effectiveness as a driver of growth, there needs to be a change in mindset. Media effectiveness must be representative in your media investment efforts in a clear and compelling manner — and one that can be trusted across an entire organisation.

**Source: McKinsey*

Media effectiveness supports business growth by answering two key questions

1 What is the full impact of my media investments?

Capture the full impact of your media investments by measuring:

- All sales (online — including app — and offline).
- All media channels (digital and offline).
- The short- and long-term impact on both sales and brand KPIs.

Key decisions:

- Cross-media mix budget allocation.
- Start/stop channel investment.
- Target goals per channel.

Stakeholders: Media director, CMO, CFO.

2 How can I best optimise my media investments?

Explore the relative value of different channel and campaign-level strategies to enable frequent optimisations that continuously improve performance.

Key decisions:

- Channel and campaign tactics.
- Budget allocation within a channel.
- Target goals per campaign.
- Testing of new formats and tactics.

Stakeholders: Channel specialists.

The goal of this playbook is to give you the **tools and knowledge to build your own media effectiveness measurement (MEM) framework** that answers those two questions. Before we go any further, it is essential to understand that even a perfect framework, leveraging advanced measurement tools, will be useless without a clear definition of success and available quality data. Check for these prerequisites before you apply the knowledge shared in this playbook to create your MEM framework.

Step 1: Foundations

Identify the right outcomes **(KPIs and metrics)** to evaluate your progress. Embrace a data-driven culture with measurement owners, test-and-learn agendas, and accessible dashboards.

Step 2: Data collection

Invest in a **durable measurement setup** with privacy-centric measurement tools that maximise observed data and leverage first-party data.

Still need to complete Step 1 or Step 2?
Read: A media effectiveness guide for CMOs (and CFOs).

Not covered in the playbook but crucial for success

Step 3: MEM framework

Define and create alignment within the organisation on a **framework that maps the available media effectiveness measurement tools** to your strategic business decisions and optimisation decisions.

Focus of this playbook

What has changed in the media effectiveness measurement toolbox?

The measurement toolkit is evolving to become more privacy-centric. Marketers can no longer expect to observe and attribute all conversions via tags, stitch user journeys, or fully rely on user-based MTAs. Advances in modelling will preserve robust attribution for the foreseeable future. Data-driven attribution is here to stay and will retain a key role in your measurement toolkit. However, where attribution alone was sufficient in the past, today's marketers require other tools such as incrementality testing and media mix modelling (MMM). **No single tool has all the answers any more — you will need a combined approach that uses each tool's strengths and fills in the gaps.**

What are the key changes that you should know about?

- **Attribution** has reinvented itself to **continue to provide real-time data** by relying on modelling to cover tracking gaps.
- **Incrementality experiments are becoming more accessible** and popular among advertisers, thanks to more open source resources and increased availability to run experiments in platform.
- **MMM is living a renaissance** with its future-proof nature (it relies 100% on aggregated data), increased ability to show granular results, and improved frequency of updates.

Overview of media effectiveness measurement tools

	What is it?	Benefits	Challenges	Frequency	Best used for
Data-driven attribution	The process of assigning credit to the different touchpoints that are found on the path to a conversion.	**Fast and easy to scale.** Gives real-time insight into drivers of performance, fuelling better automated bidding and optimisations at campaign, channel, and cross-channel level.	Limited to digital channels and best suited for measuring short-term impact. Modelling-reliant. Requires large-scale experiments to calibrate accurately.	Ongoing, real time.	Daily channel and campaign optimisations.
Incrementality experiments	Uses randomised controlled experiments to compare the change in consumer behaviour between groups that are exposed or withheld from marketing activity while keeping all other factors constant.	The gold standard to **measure causality**, so it gives the most rigorous view of the incremental value brought by the marketing investment.	It gives a snapshot of a concrete strategy at a concrete point in time. Can be difficult to scale.	Quarterly.	Adding an extra level of incrementality awareness for your attribution and MMM efforts.
MMM	Top-level modelling that utilises advanced statistics to understand what drives sales. It measures media investment efficiency on top of base sales and other external factors that impact sales (e.g. seasonality, pricing, economy).	Gives a **holistic overview** of all channels, sales, and external factors. It can also provide a longer-term view of media impact. It doesn't require user-level data, making it more future-proof.	Requires modelling with causal inference assumptions and at least two years of historical data. Can be expensive to run.	Twice a year. *However, some advanced advertisers do it quarterly.*	Cross-channel budget allocation.

Pro tip! Include Brand Efficiency measurement tools to capture the full impact of your media beyond sales (Practical advice: Chapter 6).
A note on experiments: AB experiments are a strongly recommended tool for optimisation purposes, but they are outside the scope of this playbook. Make sure you understand the difference between AB and incrementality experiments by reading Appendix 1.

Resources available to learn more about the tools: Measure the full value with attribution | Incrementality fundamentals | MMM explained | Brand efficiency measurement | AB experiments

Differences between attribution, MMM, and incrementality

When using a media effectiveness framework with multiple measurement tools, differences in the output results can be expected. While this is normal, these differences may raise questions from stakeholders. Therefore, **it's essential to understand them and be able to explain them.**

Why discrepancies in results are expected and ok

Data-driven attribution gives credit to the eligible touchpoints that can be linked to a conversion and it is able to differentiate high-impact touchpoints from low-impact touchpoints. This is useful for understanding how different marketing channels contribute to sales, but it does not take into account whether the sale would have happened without any marketing intervention.

For example, let's say that a customer clicks an ad, checks the website, and then leaves. This same person then gets a recommendation from a friend and is convinced to return and purchase. In this case, attribution would credit the digital ad because it preceded the sale, but the actual driver may have been the recommendation.

This example is relevant to any media investment. **From all the sales a business measures, some will be driven directly by a media touchpoint and would not have happened otherwise (AKA incremental sales)**. Some will result from loyal customers, word of mouth, and seasonality, etc. (AKA baseline sales). Tools such as incrementality experiments and MMM enable you to explore this concept and enrich your understanding of the insights data-driven attribution provides. As the table on the previous page shows, incrementality experiments can determine which sales wouldn't have happened — using control groups and MMM modelling techniques — and which would have occurred anyway. The types of sales, the timeframe of the data, and the number of channels are all variables that will also impact the output results from a tool.

Overview of factors impacting differences in results outputs:

	Ability to assess causality	Sales scope	Channel scope	Media impact timeframe	Output metric
Data-driven attribution	Partially, through modelling	Digital conversion tracking	Digital only	Short-term (usually 30 days)	Attributed ROAS/CPA
Incrementality experiments	Most rigorous	User-based (digital conversion tracking) Geo-based (all sales)	Depending on the test	Short-term (test duration)	Incremental ROAS (iROAS)
MMM	Partially, through modelling	All first-party sales	All channels	Mid-term (usually two years)	MMM ROAS (accounts for incrementality)

How do these factors affect the total volume of sales reported by each tool?

- **Attribution** provides attributed sales, not incremental, for shorter periods and only for digital scope. For digital click-based channels, we expect to see the biggest volume of sales.
- **Incrementality** experiments provide results for incremental sales at a specific point in time. We expect the volume of sales to be the most conservative.
- **MMM** provides modelled results for incremental sales for longer periods. We expect the volumes to be higher than for incrementality experiments.

How to deal with discrepancies: View each tool's output to set the upper and lower bounds of performance. For digital click-based channels, in-house attribution typically represents a generous view of that strategy's contribution (i.e. the upper-bound), and incrementality represents the most conservative view (i.e. the lower-bound). Your MMM's assessment should fall within the range of these bounds. If you see drastic discrepancies between outputs, revisit the foundations of the tool to ensure the correct setup (i.e. conversion tracking, model assumptions) and apply the best practices from this playbook.

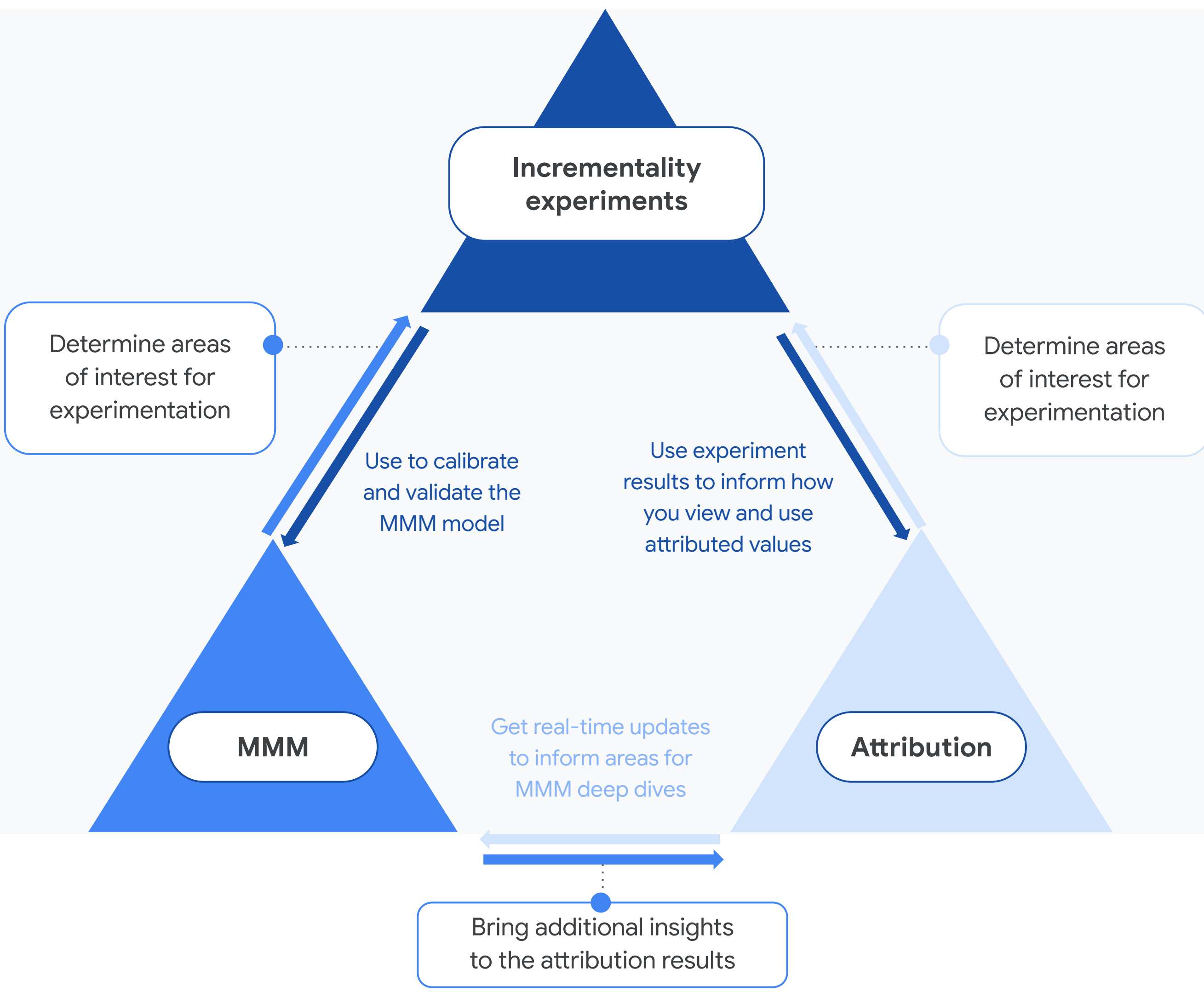
How can MEM tools work together?

The list of ways attribution, incrementality, and MMM can be combined is almost endless and sometimes overwhelming, but that's why we're here to help.

To help you build your media effectiveness measurement framework, we have compiled a comprehensive list of how these tools can work together, along with the considerations and best practices to implement them (jump to **Practical advice**).

The objective is to help you comprehend the best practices and factors to consider when combining tools. With this knowledge, you can choose the most effective tool combinations to enhance the insights required for making informed business decisions. The choice of tool combination will vary based on your level of experience and available resources. This playbook will help you make that decision.

Overview of some of the many ways in which attribution, incrementality experiments, and MMM can work together to strengthen each other:



Maturity stages for media effectiveness measurement frameworks

The maturity of your media effectiveness framework will depend on what measurement tools you use and how you plan to incorporate their outputs to assess your media.

Typically, most mature frameworks use all three tools (attribution, incrementality, and MMM). However, this should not be the end goal. The end goal is to answer the key media effectiveness questions while striking the right balance between rigour and available resources, and applying best practices. Using two tools well is better than using three without a clear purpose.

Early stage

Compare results from different tools

- **Goal:** If you have one tool as your main source of truth (e.g. data-driven attribution), start by understanding what you might be missing and decide which other tools you could use to fill those gaps. Once you have the first results from your complementary tool (incrementality or MMM), look at them side by side and use the additional insights to inform your business decisions.
- **Focus on:** Developing a clear framework for which tool will take priority for which key decision. Educate yourself on the scope and methodology behind each tool. Define hypotheses based on the main source of truth, and be deliberate about which channels or campaigns you want to compare first.
- **Pitfalls to avoid:** Drastically reducing or increasing budgets based on channel comparisons when you do not yet have an overview of each channel's performance, e.g. if you have only conducted an incrementality experiment in one channel.

Intermediate stage

Introduce calibration when possible

- **Goal:** Once you have some data points from different tools and understand what they can offer, in addition to the comparisons you're already doing, start calibrating certain tools based on results.
- **Focus on:** Using experiments and/or attribution results to calibrate MMM. In some cases (Practical advice: Chapter 2), use results from experiments to calibrate your attribution reports.
- **Pitfalls to avoid:** Using results from a single experiment to calibrate a full channel. Calibration should be done continuously and across as many channels as possible to be representative.

Advanced stage

Create an ongoing loop between tools

- **Goal:** Develop an annual test-and-learning plan, where insights from each tool are used to continuously improve and complement each other. For example, new experiments can be built to calibrate and validate MMM, and MMM can be used to complement attribution results. This stage incorporates the best of qualitative comparisons and calibrations within a structured plan.
- **Focus on:** Adjusting the framework on which tool takes priority for which key decision as needed. Map the key moments where you need to make business decisions and plan your experiments and MMM reads accordingly.
- **Pitfalls to avoid:** Aiming to create a new single source of truth.* Even at this stage, there won't be a single tool that can answer all business questions. Instead, aim to improve the data provided by each tool while still using each of their strengths. For example, even with a world-class MMM, attribution is the best tool for day-to-day optimisations.

***Reflection on the search for a "single source of truth": Technically**, we could create a new source of truth by forcing the MMM and attribution model results to agree imposing strong regularisation assumptions and then calibrating the MMM to match each new incrementality experiment. **In practice**, each of these methodologies has different scopes and strengths. Aiming to get the MMM, attribution model, and experiments to fully match will force you to ignore nuances and use strong assumptions that decrease the accuracy of the results.

Practical advice:

MEM guidelines and best practices

1 Transform your knowledge of media effectiveness into actions

Having a comprehensive media effectiveness measurement framework and toolkit will help you better understand the impact your media is having. However, this **knowledge will only lead to business growth if it's bridged into actions and better decisions**.

- We can split the types of actions and decisions you can take using media effectiveness insights into two categories:
  1. **Planning strategy and portfolio budget allocation**
  2. **Channel and campaign optimisation**

- In both cases, to ensure the actionability of the results you have, you will also need:
  1. Clear KPIs and targets based on your business objectives.
  2. A clear plan that covers the actions you will take based on the KPI results and target attainment. "If I hit the target for KPI x by date y, I will do this. Otherwise, I will do that."

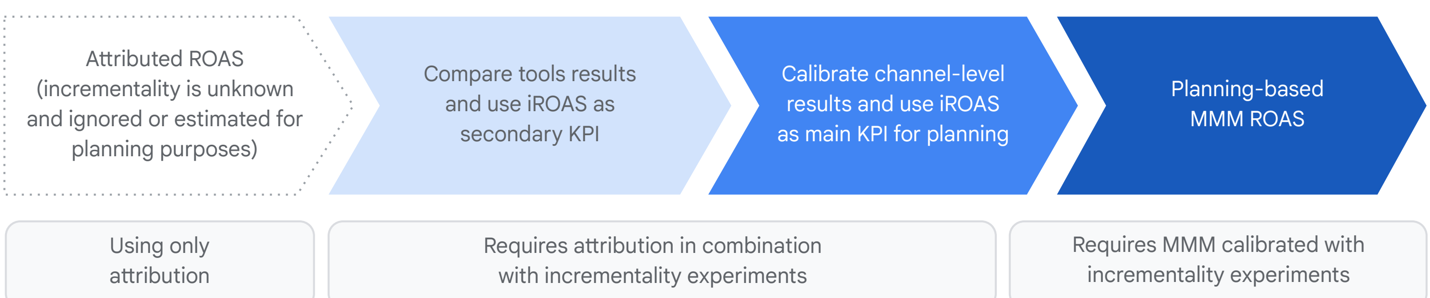
Setting KPIs and targets

If you are able to run incrementality tests at scale and/or an MMM for your company, we recommend setting **incrementality-based targets at the channel level. This ensures that you are planning and optimising your media investments towards the most incremental growth.**

You can start your journey by including incrementality KPIs as secondary KPIs to understand what decisions would be different when using incrementality-based targets compared to attribution-based targets. Once you get buy-in from stakeholders, you can focus on adjusting your media effectiveness measurement (MEM) framework and tools to switch to incrementality-based KPIs as your primary KPI.

Notice that **incrementality-based targets are best for planning, but for day-to-day optimisations, your attribution-based KPIs will still be the most useful**.

See what a KPI and target-setting journey could look like below:



Planning strategy and portfolio budget allocation

Media effectiveness measurement can facilitate business growth by providing the necessary insights during the media planning and strategy phase. This helps you identify which channels will most likely help you achieve your goals, enabling you to invest accordingly.

To utilise these insights for planning, it's essential to have a framework that organises the required insights and decisions and a clear understanding of any gaps in the results of your current measurement tools. By identifying what might be missing, you can explore additional tools that enhance your planning capabilities.

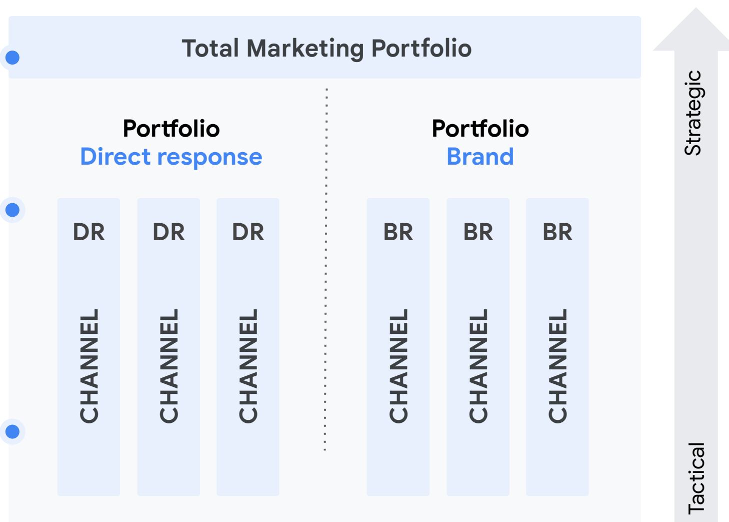
One way to organise your media effectiveness measurement framework is to categorise your marketing portfolio and business decisions into three different levels, as demonstrated below. In this proposed framework, most strategic planning occurs at the cross-channel level, while optimisations occur at the channel and campaign levels.

Example marketing portfolio framework for planning:

LEVEL 3: Total Marketing Portfolio Measurement
- Decision: Inform cross-channel budget allocation
- Key audience: C-suite.

LEVEL 2: Separate Direct Response or Brand Measurement
- Decision: Inform cross-channel budget allocation within brand or direct response portfolio.
- Key audience: Media director, channel practitioners.

LEVEL 1: Channel Measurement
- Decision: Inform in-channel optimisations.
- Key audience: Channel practitioners.



In the upcoming sections, we will cover how to use a combination of tools for different maturity stages to make better planning decisions:

Attribution and incrementality experiments:

- [Early stage] Run incrementality experiments only for specific channels or campaigns
- [Intermediate and advanced stage] Calibrate attribution results based on incrementality experiments
- [All stages] Use attribution results to build experiments hypotheses

Attribution and MMM:

- [Early stage] Use the attribution results to rule out versions of your MMM model

MMM and incrementality experiments:

- [Intermediate and advanced stage] Design incrementality experiments based on insights that improve the model over time
- [Intermediate and advanced stage] Validate MMM results based on incrementality experiments
- [Intermediate and advanced stage] Calibrate MMM results via incrementality experiments (Bayesian and non-Bayesian MMM)

Campaign and channel optimisation

Always strive to optimise your campaigns and adopt a test-and-learn mindset.

Regardless of the maturity stage or the number of tools you are using, when it comes to optimising campaigns and tactics, **attribution will be the best tool to prioritise since it allows you to monitor relative changes in the performance of your chosen KPI in real time**.

When optimising your campaigns, there are two foundational best practices we recommend you have:

DDA and AI-powered bidding:

DDA optimises towards the most incremental touch points, and when paired with AI-powered bidding, it will help you improve your channel-level efficiency over time.

Test-and-learn optimisation agenda:

To discover and validate the most effective optimisation levers for your campaigns, develop a structured approach. AB experiments can be a great tool at this stage. Some proven impactful levers are creatives, audiences, frequency, formats, and targets.

That said, to ensure you hit your incremental targets and optimise your campaigns towards incrementality, you can use strategic check-in moments to look at the results of attribution together with experiments and/or MMM. From there, you can decide whether to change your bidding strategy or budget allocation across tactics and campaigns to reach the overall channel target.

In the upcoming sections, we will cover how to use a combination of tools for different maturity stages to make better optimisation decisions:

Attribution and incrementality experiments:

- [Intermediate and advanced stage] Use incrementality experiment results to set new target bids
- [All stages] Validate whether optimisations are improving incrementality over time

Attribution and MMM:

- [All stages] Use attribution to provide speed and granularity not available in the MMM
- [Intermediate and advanced stage] Use MMM to calibrate the attribution outputs

2 Combine incrementality experiments results with data-driven attribution

Incrementality experiments are widely regarded as the gold standard for assessing media effectiveness. However, such experiments are conducted at a slower pace and only for certain pockets of media at a time. Therefore, **incrementality cannot replace the real-time insights provided by data-driven attribution at a channel and campaign level. Instead, incrementality serves to periodically confirm that your media investments are driving incremental business value** (read the introduction for full context).

This section describes the different ways these two tools can be combined. These scenarios assume that you are not using MMM.

4 ways in which these tools can work together:

1. Use incrementality to complement data-driven attribution insights
2. Use incrementality experiment results to set new target bids
3. Validate whether optimisations are improving incrementality over time
4. Use attribution results to build experiment hypotheses

1 Use incrementality to complement data-driven attribution insights [Goal: Planning]

Google's data-driven attribution uses incrementality to inform where credit is assigned within the customer journey, providing a greater picture of which campaigns and strategies are more effective relative to each other. However, it cannot tell which conversions would have happened anyway, and sometimes conversions can be missed.

For instance, conversions could be lost due to tracking gaps that are not covered by modelling or privacy-centric tools or because they are outside the conversion-tracking scope, such as offline conversions. Third-party attribution models might also miss non-click-based conversions. **This means that attribution alone may not reveal the full value of certain channels and campaigns. Incrementality experiments can help bring new insights on that value, which you can use for better planning.** We provide two approaches depending on your maturity stage.

Run incrementality experiments only for specific channels or campaigns [Early stage]

Detect which channels might be underrepresented in the attribution model and plan experiments to confirm the value they're driving. Use the additional insights to look at the attribution results side by side when assessing the performance of each channel for budget planning.

Example: View-based channels such as YouTube may seem more effective within data-driven attribution due to their ability to measure engaged views — but they may perform poorly in third-party MTA or CRM. Video campaigns can also generate valuable brand exposure, with higher CPAs if they result in incremental sales. To get this additional insight, you could plan a Conversion Lift Study before your next planning round.

When running your experiment, you must first decide what represents a successful outcome. This could be as simple as a significant lift in conversions (regardless of the size of the lift) or a target incremental ROAS (defined based on business return rather than comparison with attributed ROAS). In the example below, there is a significant lift in conversions that drove $1.5 iROAS — going above the target of $1.3 — so a decision could be made on whether to maintain or increase investment.

	ROAS in DDA attribution	ROAS in 3P MTA (clicks only)	iROAS goal	iROAS conversion lift	% conversion lift
YouTube Video Action Campaign (VAC)	$3.1	$1.1	$1.3	$1.5 [$1.2 - $3.1]	8% [3% - 10%]

Calibrate attribution results based on incrementality experiments [Intermediate and advanced stage]

You can run incrementality experiments consistently across your portfolio to understand if the relative performance differences seen in your attribution reports are consistent with the incremental value those channels are driving.

One limitation of this approach is that experiments for different channels may not be conducted simultaneously or at a consistent frequency. By creating a calibration multiplier, you can use the results from the experiments you have been running and create a comprehensive view of your channels' estimated incremental value for a specific period.

How to calculate a calibration multiplier

Incremental impact ÷ **Attributed impact** = **Calibration multiplier**

Incremental impact: Estimated from a rigorous incrementality experiment. Geo Experiments are the best approach.

Attributed impact: Reported in attribution for the same set of campaigns and during the same time period as the incrementality experiment.

Step 1: Run experiments to create an informed iROAS per strategy type	ROAS Attribution	iROAS Geo Experiment
Channel 1	$5	$3.5
Channel 2	$5.5	$3
Channel 3	$8	$12

Step 2: Calculate calibration multiplier — Calibration Multiplier	
0.7	= 3.5 ÷ 5
0.54	= 3 ÷ 5.5
1.5	= 12 ÷ 8

Step 3: Use multiplier to evaluate periods between experiments — iROAS Goal	Q2 ROAS Attribution	Q2 Estimated iROAS
$3	**$4.5**	**$3.1**
$3	**$5**	**$2.7**
$8	**$7.5**	**$11.25**

Example: In this case, Channel 1 and 2 are performing at similar attributed ROAS, with Channel 2 outperforming Channel 1. However, when accounting for the calibration multiplier based on the experiment we ran, we see that actually Channel 1 is performing better.

*We recommend using ROAS for this approach, but it would also work with CPA values.

Best practices when using a calibration multiplier

- **Have incrementality tests for all or almost all relevant channels:** Experiment results from only one channel or campaign lack a view of the baseline incrementality of other channels and your overall portfolio. This makes it impossible to know if that result is better or worse compared to another channel.
- **Deal with missing data points:** One option to handle them is to use results from other channels to estimate a multiplier. Look at the relative lift of different channels across the funnel and assign a similar value for channels in similar steps. When using this data to make decisions, make sure to be clear about the strength of the evidence. A channel that has been tested and proven incremental has much stronger evidence and should get priority on budget allocation compared to a channel that hasn't been tested and is using a hypothetical relative lift.
- **Look at drastic differences between incrementality experiments results and attribution:** Investigate potential causes (conversion-tracking issues, attribution rules, or experiment errors) and retest. Instead of making a drastic change, use a guardrail. For example, if your multiplier is 0.20 and you know another channel in the same funnel space is 0.80, you could adjust the first channel by 0.40 until a second experiment validates the large discrepancy.
- **Design incrementality experiments for maximum comparability:** When the goal is calibration across channels, we recommend using the same experiment methodology (Geo Experiments), using the same timeframe, and ensuring parity of KPIs between the incrementality experiment and the attribution results (find more recommendations in Chapter 5).

2 Use incrementality experiment results to set new target bids

[Goal: Optimisation] [Intermediate and advanced stage]

Once you have an iROAS goal and have used incrementality experiments to understand a strategy's incremental contribution to your business, you can start setting bids (tROAS/tCPA) based on the strategy's estimated incrementality. **While the theoretical implementation of this approach may seem straightforward, some risks should be considered before applying it. Keep these important factors in mind:**

- Bid changes have many implications. More aggressive targets could improve your efficiency but lead to less conversion volume. Ensure the new target you set balances efficiency and volume goals — following optimisation guidelines for the channel — and adjust bids by no more than 20% at a time
- Significant changes can also impact who your campaign targets, resulting in changes in incrementality. If you see the nature of your campaign change due to your bid adjustments or another optimisation, you may need to retest incrementality again to keep your calibrations accurate.
- Ensure channel parity. You should have incrementality-based targets for all channels and platforms (both Google and non-Google).
- Incrementality changes over time. Keep your calibration multiplier fresh by retesting every three to six months.

Step 1: Run experiments to create an informed iROAS per strategy type

	ROAS Attribution	iROAS Geo Experiment	Calibration Multiplier
YouTube VAC	$7.5 ROAS	$5.25 iROAS	0.7

Step 2: Adjust bids

iROAS Goal	Original tROAS in Platform (Google Ads)	New tROAS in Platform (Google Ads)
6	$7.5 tROAS	$8.57 tROAS = 6 / 0.7

Example: Since your iROAS experiment shows lower iROAS than your iROAS goal, you could increase the tROAS in your bids.

3 Validate whether optimisations are improving incrementality over time

[Goal: Optimisation] [All stages]

Thanks to its connection to AI-powered bidding and its ability to offer real-time insights, attribution is the best tool for day-to-day optimisations. However, as **you gain an understanding of incrementality, you can build and test hypotheses about which optimisations are improving a channel or campaign's incrementality**. When using this approach, keep in mind the overall portfolio's incrementality may have changed since you ran the first test. If you have a view of other channels' incrementality, you can make this call, but if you're only applying this approach to a single channel, factor in all the possible changes that might have occurred between experiments. We also recommend comparing confidence intervals instead of point estimates.

Example: You have the hypothesis that a new creative and audience expansion will improve your YouTube VAC's incremental ROAS. However, you believe the audiences selected may decrease the strategy's attributed ROAS. To explore this, you use iROAS as your measure of success. You run a Conversion Lift to find the baseline incrementality for YouTube VAC in Q1. Then, you implement your optimisation and run a second Conversion Lift study to assess the impact of the change. The second study shows that the strategy's incremental ROAS has improved, offering evidence that the new creative and audiences have improved the incrementality of the strategy.

Step 1:
Decide on an optimisation to improve incrementality.
Run an experiment to create a baseline and decipher what to evaluate it against

	Q1 ROAS Attribution	Q1 iROAS Geo Experiment	Optimisation
YouTube VAC	$7.5 ROAS	$2.25 iROAS	New creative New audiences

Step 2:
Run a second incrementality experiment to evaluate if the optimisation has improved the incremental contribution

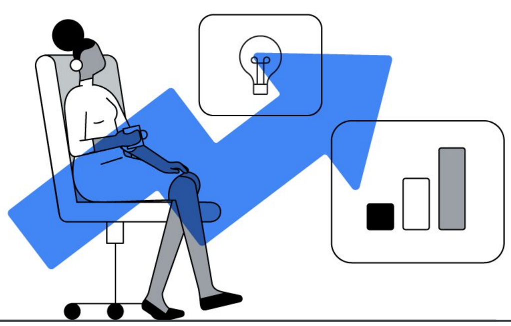
Q2 ROAS Attribution	Q2 iROAS Geo Experiment
$5.5 ROAS	$3.25 iROAS

Evaluation: Despite decreasing attributed ROAS, this optimisation improved iROAS by 44%.

4 Use attribution results to build experiment hypotheses

[Goal: Planning] [All stages]

This recommendation is similar to the one in Section 1.1. The key takeaway is to use all the knowledge you've gained from your attribution reports to build strong incrementality experiment hypotheses. More on this in Chapter 5.



3 Combine attribution results with MMM

While MMM shines as a planning tool, attribution remains the best for real-time insights and optimisations. Data-driven attribution provides fast and granular feedback on which channels and tactics are more likely to contribute to a conversion within a customer journey, which is useful for day-to-day optimisations. However, this view is limited to digital channels and the constraints of your conversion tracking.

For key strategic planning moments, you need to know the incremental value of each of your channels, taking into account potential interactions between them, external factors that may affect performance (e.g. seasonality), and all your sales, regardless of their origin. MMM enables you to gain this view of performance by using non-PII data to create their models, making them the best tool for obtaining planning insights.

With third-party cookie deprecation, MMM has seen a renaissance as a future-proof tool since it relies on non-PII data. **The phrase "attribution is going away" has also become popular among marketers. A more accurate description would be "attribution is evolving to become more privacy-centric and durable".**

While our ability to record observed conversions may decrease in the coming years, combining modelling and privacy-centric measurement solutions will allow advertisers to continue assigning value to ads' touchpoints. Data-driven attribution will remain the most effective measurement tool for optimising day-to-day activity within ads. This is because the measurement is granular, incrementality-calibrated, and directly connected to AI-powered bidding.

3 ways in which these tools can complement each other

1. Use attribution to provide speed and granularity not available in the MMM
2. Use MMM results to calibrate the attribution outputs
3. Use the attribution results to rule out versions of your MMM model

1 Use attribution to provide speed and granularity not available in the MMM [Goal: Optimisation] [All stages]

MMM runs at a slower cadence, usually one to four times a year, and contain more aggregated data than what's needed by channel specialists in their day-to-day jobs. One way to combine the two tools is to separate the business questions they answer when creating your MEM framework (Read more at "Put it into practice").

Example: Use MMM for overall cross-channel budget allocation and attribution to allocate that budget across campaigns and tactics. For levels of granularity, where you have information in the MMM, prioritise MMM (e.g. a split between Brand and Generic Search). Use attribution to understand which tactic brings more value relative to the others for granular levels not covered by the MMM (e.g. creative and audience) and inform AI-powered bidding.

2 Use MMM results to calibrate the attribution outputs [Goal: Optimisation] [Intermediate and advanced stage]

MMM is great at providing insights into the value of each channel. However, its results are typically provided at an aggregated level (e.g. total online video, or YouTube vs. other online video), which makes it challenging to implement optimisation changes at the campaign, strategy, or audience level.

To bridge this gap and merge insights from MMM and those from attribution, create a calibration multiplier — at a level where attribution and MMM converge. Then, apply that multiplier to the attribution report.

Step 1: Pull attribution report

	In Platform (DDA) Attribution ROAS	
Search Generic – campaign A	1.2	2.32
Search Generic – campaign B	3.5	
Search Brand – campaign A	5.3	4.39
Search Brand – campaign B	3.5	
Display general	2.05	2.05
Display customer match – campaign A	9.4	5.22
Display customer match – campaign B	1.0	

Step 2: Calculate multiplier by comparing same timeframe and level of aggregation

	DDA ROAS	MMM ROAS	Calibration Multiplier
Search Generic	2.32	2.12	0.91
Search Brand	4.39	3.0	0.80
Display general	2.05	1.5	0.73
Display customer match	5.22	5.5	1.05

Step 3: Evaluate ROAS post-reweighting

	Estimated DDA iROAS
Search Generic – campaign A	1.09
Search Generic – campaign B	3.17
Search Brand – campaign A	3.62
Search Brand – campaign B	2.39
Display general	1.5
Display customer match – campaign A	9.9
Display customer match – campaign B	1.1

Example: In this case, we see that, after applying the multiplier, the estimated DDA iROAS offers a slightly different picture. Before calibration, Search and Display had similar attribution results. However, after calibration, we can see that Search is driving a higher iROAS than display.

3 Use the attribution results to rule out versions of your MMM model

[Goal: Planning] [Early stage]

Given the ability of MMM to model for incrementality, the iCPA they provide should generally be higher than the CPA provided by the attribution model. This means we can use attribution results as a simple heuristic to discard versions of the MMM model that give estimates with iCPAs higher than the CPA observed in the attribution reports. Ensure the strategy's value can be attributed before applying this logic. Some impression-based strategies don't feature an attributable event and may be under-credited by attribution models.

Step 1:
Pull attribution report

Channel attribution CPA	
Channel 1	N/A: offline
Channel 2	$55
Channel 3	N/A: offline
Channel 4	$140

Step 2:
Compare attribution report results and iCPAs from different MMM versions

	MAPE*	C1 iCPA	C2 iCPA	C3 iCPA	C4 iCPA
Model 1	3.6%	$20	**$12**	$16	**$24**
Model 2	2.5%	$69	$52	$50	$148
Model 3	3.1%	$48	$65	$41	$130

Example: After completing all the modelling work, you may have several model versions that appear to have similar levels of accuracy based on their MAPE values (MAPE is a commonly used metric to measure the accuracy of media mix model predictions). However, when analysing the attribution results, you may notice that digital click-based channels, such as Channel 2 and Channel 4, have lower iCPAs in Model 1 than the attribution results. This indicates that Model 1 can be ruled out.

4 Use results from incrementality experiments to enrich MMM

4 ways in which these tools can complement each other

1. Design incrementality experiments based on insights that improve the model over time
2. Validate MMM results based on incrementality experiments

3 & 4 Calibrate MMM via incrementality experiments (Bayesian and non-Bayesian MMM)

MMM is a great tool for measuring and comparing effectiveness across a variety of media channels over longer time periods. However, since MMM is based on correlations, their accuracy depends on the scale, timing, and variation of historic media spend. As a result, MMM can still fall short in precisely measuring effectiveness, especially for smaller media channels, always-on channels, or pull media (e.g. Search). Incrementality experiments can address some of these drawbacks and improve the accuracy of your correlation-based MMM. This section outlines four ways MMM and incrementality experiments can be used together. Consistent with the rest of the playbook, A/B experiments unrelated to incrementality are outside the scope of this section.

1 Design incrementality experiments based on insights that improve the model over time

[Goal: Planning] [Intermediate and advanced stage]

Use your MMM results to design experiments to evaluate the robustness of the MMM or to calibrate it using priors. We suggest exploring the following three use cases:

- **Check confidence/credible intervals of media channel ROAS:** Channels with wide intervals should be validated using incrementality experiments.
- **Validate MMM forecasts:** As MMM uses historical data, they can be inaccurate at predicting future performance. When using MMM forecasts for budget shifts, we recommend adjusting only up to 20% of a channel's spend at a time. And if you are making more than a 10% change, validate with an incrementality experiment if feasible.
- **Run regular incrementality experiments for accurate Search representation:** Search as an always-on pull media is notoriously difficult to measure in an MMM. As Brand Search is often strongly correlated with outcome KPIs, it limits the ability to measure incrementality. We recommend running incrementality experiments for Search regularly to validate the MMM.

2 Validate MMM results based on incrementality experiments

[Goal: Planning] [Intermediate and advanced stage]

You can specifically design an incrementality experiment to explore your MMM results or you can use the results from previous incrementality experiments to validate the model during the production phase.

When using previous incrementality experiments to validate the MMM you are building, make sure they meet these criteria:

- They must have the same level of aggregation (e.g. channel level) and the same metric under measurement.
- They must have run during a specific time period or season, representing business as usual — since MMM results evaluate channel effectiveness over longer time frames.

If the results are not comparable, plan a new incrementality experiment tailored towards MMM comparability. If the incrementality experiment is deemed fit for validation, you can compare the results from the experiment and the MMM for that channel. You can expect two outcomes:

1. **New MMM results vs. incrementality experiment result discrepancy is <10%:** There's no immediate need for extra validation since you shouldn't expect a 100% match; differences in the range of 5% to 10% are acceptable. Once you refresh your MMM, consider running an updated incrementality experiment and use that one to calibrate your MMM refresh.
2. **New MMM results vs. incrementality experiment result discrepancy is >10%:** Calibrate your MMM based on the incrementality result (see Sections 3 and 4 on calibration below). Once you refresh your MMM, consider running an updated incrementality experiment and use it to validate your MMM refresh.

3 Calibrate MMM via incrementality experiments (non-Bayesian MMM)

[Goal: Planning] [Advanced stage]

Unregularised non-Bayesian MMM only allows for calibration after the fact. There are two main ways in which you can use the results from incrementality experiments to calibrate a frequentist MMM:

1

Create a multiplier:

Divide the iROAS from the incrementality experiment by the MMM ROAS and apply the resulting multiplier to the initial MMM ROAS.

This is similar to the approaches described in Chapters 2 and 3, where you can find an example of how to approach a calibration multiplier calculation.

2

Use incrementality experiment results to choose the best version of your MMM:

During the building phase of the model, you will need to make important decisions on which assumptions you utilise, e.g. representing carryover and shape effects within your model. The assumptions you choose will impact the results of the model. When faced with different models of comparable statistical quality, you can check the proximity of the MMM ROAS and the incrementality experiment iROAS. Use the least similar results to rule out some models (a similar logic to Chapter 3, Scenario 3).

4 Calibrate MMM via incrementality experiments (Bayesian MMM)

[Goal: Planning] [Advanced stage]

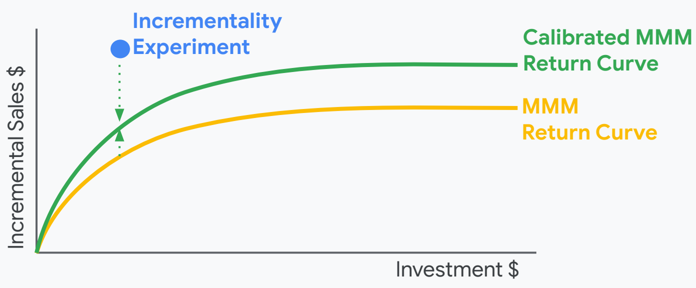
Modern MMM often uses Bayesian modelling approaches, which offer several advantages. One key benefit of Bayesian MMM is that it allows modellers to incorporate their prior domain knowledge or beliefs about the effectiveness of various media channels. This can be particularly valuable when dealing with limited or noisy data for specific channels.

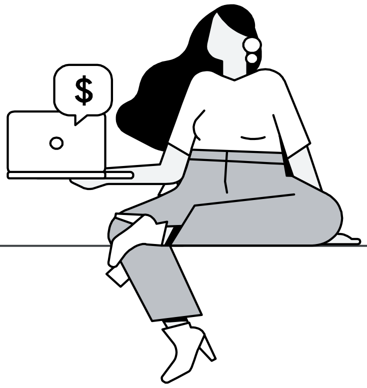
Incrementality experiments provide excellent opportunities to use priors and enhance the model's accuracy. By leveraging these experiments as priors, you can ensure a closer alignment between the model's outputs and the actual incremental value of the channels.

To use experiments as priors, you will need to take the following steps:

1. **Equate and compare outputs:** Ensure experiment and MMM output are aligned across metric, media and time.
2. **Engage technical experts:** Adjust the prior distribution of model parameters to ensure that the prior ROI distribution aligns with the experiment

Example: As mentioned previously, Search as an always-on pull media is notoriously difficult to measure in an MMM. By running an incrementality experiment, you could measure the true incremental impact of the channel and use the result as a prior in your model. By introducing the prior, you could bring the MMM return curve closer to the experiment result.





FAQ and considerations when using incrementality experiments as priors:

1. **How should I aggregate multiple experiments for the same channel?** If you have multiple experiment results for the same channel, you can take the mean of the various ROAS estimates. You can also use the experiment intervals (uncertainty) and draw from the combined distribution of experiment results. The latter is better, as the prior has a mean and a variance. If you have too many disparate experiments, you can remove the outlier ones or upweight more recent results.
2. **How many experiments do I need before I start calibrating the MMM?** This heavily depends on how representative your experiment is for calibrating the media channel in the MMM (see case #2 for some example criteria). Assuming there is little variation in how you execute a media channel across time and assuming your business is not affected by strong seasonalities, a single experiment might already be a good source for a prior.
3. **Where do we need more experiment evidence?** MMM and experiments should form a loop where MMM results inform the next experiment and vice versa. Channels with large posterior variance (uncertainty) are the ones that should get the next experiment. Over time, we want to reduce uncertainty.
4. **How should we treat channels that don't allow experiments?** It may not be possible to measure every channel with an incrementality experiment. To prevent penalising less testable channels, we advise using wider (flatter) priors for non-experiment channels (e.g. high variance, uncertainty). Priors can be adjusted to achieve model fit and results that align with expectations. Bear in mind that strong regularisation (lower variance) may be necessary to obtain a reasonable model fit, in which case the choice of the prior may heavily influence the result.

Two critical factors to consider when using incrementality experiments to improve MMM

1) You cannot use the same incrementality experiment to validate and to calibrate a model: Incrementality experiments can both validate a model (use case 2) or calibrate a model (use cases 3 and 4). However, never use the same incrementality experiment for both purposes simultaneously. For instance, let's consider an example of an MMM that used data from 2018-2020 and an incrementality experiment conducted for YouTube in 2020.

1. Correct: When refreshing the MMM in 2021, the 2020 incrementality experiment result is used as a prior for YouTube. A new experiment is planned to validate the 2021 MMM since the 2020 experiment was already used for the prior and, therefore, can't be used for validation. The MMM is built without using the incrementality experiment results. The YouTube ROAS from the MMM is compared to the iROAS from the experiment to check that they align.

2. Incorrect: The incrementality experiment yields a YouTube iROAS of 1.8, which is used as a prior in the 2018-2020 MMM. The MMM produces a YouTube ROAS of 1.9. The experiment is used to validate the MMM, and both show close agreement (1.8 and 1.9). The error here was the experiment informed the MMM and shouldn't then be used as an independent validation.

2) Don't be blinded by iROAS: Getting the MMM ROAS right does not guarantee that other aspects of the model are accurate. For example, the response curves could be inaccurate, ROAS estimates for other media channels could also be inaccurate, and media interactions effects could be modelled incorrectly. The bottom line is even if the ROAS is correct, this does not guarantee accuracy of other model outputs, such as spend optimisation recommendations.

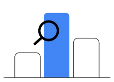
5 Design incrementality experiments following best practices

Incrementality experiments are the gold standard and the most rigorous method in the media effectiveness measurement toolbox to demonstrate the incremental value of a channel at a specific point in time. This makes them a perfect tool for uncovering new insights to complement your attribution (Chapter 2) or to enrich, validate, and calibrate your MMM (Chapter 4).

When planning to introduce incrementality experiments to your toolbox, it's essential to consider their rigour comes at a cost. These experiments require time to run and can disrupt your campaigns as you will need to hold out a portion of your investment. Therefore, **the preparation work before you run the experiment is crucial to ensure success**. You will need to prioritise the experiments that will prove most impactful for your business — and apply best practices for each experiment's design and implementation.

Choose impactful experiments

Impactful experiments provide insights that would only be available by running them. Therefore, each experiment should aim to answer a business decision that is relevant enough to warrant designing an experiment. The meaning of "impactful" and "relevant" may vary depending on your business, so it's up to you to make that determination.



Start by examining the insights from your current attribution and/or MMM, and identify the most pressing questions they don't answer yet. Some examples:

- **Test the value of new campaigns/channels:** Getting a read on the impact of a new channel in your MMM might take several months, while an experiment can give insights as soon as the campaign and analysis are finished.
- **Test budget strategy changes:** The incremental value of a channel can change when budgets are decreased/increased, and neither attribution nor MMM can predict those changes. When planning big budget shifts, consider running an incrementality experiment to test the impact.
- **Enrich and validate insights from your attribution and MMM:** Identify potential knowledge gaps, such as the underrepresentation of view-based channels in attribution (Chapter 2) or the misrepresentation of Brand Search in MMM, and plan experiments accordingly (Chapter 4).

Checklist for experiment design

1 **Business question and hypothesis:** Your experiment should have a clear hypothesis based on evidence (from your attribution and MMM insights and/or industry research) and defined actions if the desired outcome is achieved or not. Features of a thorough hypothesis include:

- Media strategy under investigation.
- Ad spend opportunity — based on your goals and the available ad inventory.
- The response metric we believe will be influenced by the media investment.
- Action to take if expectations are met or not.

An example hypothesis: "YouTube VAC drives an iROAS of 3. Our budget is $150,000 for a four-week experiment. If we reach our ROAS threshold, we will move the campaigns to always-on to capture the efficient, incremental revenue they drive. If iROAS is below the threshold, we will continue testing to improve efficiency before scaling investment."

2 **KPI parity:** When running experiments to compare or calibrate results for a specific metric, it is essential to ensure comparability of the chosen KPI. First, consider whether the channel you're evaluating is intended to drive such a KPI (if the answer is no, proceed to the next page). The second step is to understand how that metric is captured in each tool so that you can make an apples-to-apples comparison once you obtain the results.

- **Attribution:** The amount of sales will be determined by the attribution model used, the lookback window, and whether you are improving your conversion modelling with PCM tools (Enhanced Conversions, Consent Mode).
- **MMM:** Has visibility to all realised sales and revenue without gaps and usually takes into account at least two years of historical sales.
- **Incrementality experiment:** The amount of sales captured depends on chosen methodology (see table below).

Scope of conversions captured by different incrementality experiments methodologies:

	Conversion Lift Based on Users	**Conversion Lift** Based on Geographies	**Geo Experiments** Open Source
Tracking Coverage	Subject to tracking gaps (ITP, ETP, in-app). Modelling and Enhanced Conversions can account for some of those gaps	Unattributed Floodlight or conversion actions	Representative of all realised conversions
Accurate Performance Value	Depends on value being passed in conversion tag	Depends on value being passed in conversion tag	Representative of actual realised value

3 **Experiment design:** Designing a good experiment starts by choosing the right methodology for the question you want to answer. Then, you will need to give your experiment enough power to detect a statistically significant lift if it occurs (the channel should have enough investment and sales volume) and ensure a clean holdout group (e.g. avoid creating experiments on overlapping audiences). Regarding the chosen methodology, there are specific recommendations to consider when the goal is to compare or calibrate MEM tools:

- **Geo Experiments — conversion lift based on geography (Google Ads UI):** These Geo Experiments run through the Google UI using raw conversion value. Compared to open source Geo Experiments, they are less resource-intensive and implement all best practices for Geo Experiment designs — which means they can provide effective designs for smaller campaigns. They are an optimal method to use for calibration since the results are 100% comparable for digital and app campaigns. They will soon be available for offline conversions. In the meantime, you can apply estimations, as explained in Appendix 6, to account for offline conversions.
- **Conversion lift based on users (Google AdWords UI):** Feasible for smaller campaigns and tactics due to reduced noise. They are the least comparable across MEM tools and channels since they face measurement gaps and capture only digital conversions. We recommend proceeding with caution if the goal is to compare/calibrate. You can address the gaps using assumptions to extrapolate the total conversions (see Appendix 6). Create a learning agenda that includes Geo Experiments once a year to get the most rigorous read, complemented with additional Conversion Lift studies to run more frequently at other times.
- **Geo Experiments (open source code):** Uses first-party data and can be applied equally to any channel, publisher or format, allowing for apple-to-apple comparisons. The drawback is that they are resource-intensive and subject to noise, making them more feasible for bigger investments and channels.

4 **Scope of the test:** There should be parity between the scope of the experiment and the corresponding granularity from the attribution model or MMM. This means running the same campaign with identical settings at the same point in time. For instance, you need to ensure that you can view the MMM results with the same level of granularity as that obtained from the incrementality experiment, such as distinguishing YouTube VAC from the overall YouTube group.

Final reflection: Regardless of how well-designed an experiment is, it's important to remember that the experiment will reflect the performance of a point in time. The specific context of that time includes other channels running, promotions, or external factors like seasonality, extreme weather, and competitors — and the specific settings for that campaign. If results from the experiment deviate heavily from attribution/MMM results, re-run the experiment.

Resources available to learn more about the different incrementality experiments designs:
Conversion Lift | Geo Experiments (open source) | Skillshop training

Incrementality experiments are not always the best option

We have been talking about incrementality experiments in the context of a MEM framework where the aim is to compare the results with the attribution/MMM outputs or to calibrate those tools. In those instances, the best use case will be Geo Experiments with sales outcomes as the primary KPI. However, there are some instances where short-term sales are not the right metric to measure or where your business question doesn't need an incrementality experiment. **See some common scenarios below and what to do instead:**

1. Your business question doesn't require an experiment: Strive for simplicity. If your question can be answered with an observational analysis from available data or a pre-post test, prioritise them over an experiment. For cases where you already have a significant change in spend, try running a Causal Impact study to get a first view into the impact. Use that analysis to set targets for future tests and/or compare with MMM results.

2. Your business question requires an A/B experiment instead: If your question is about how many additional conversions (visits, clicks, etc) a certain strategy will bring compared to the one you're currently using, then look at A/B experiments. For example, how many additional conversions will you get using Broad Match compared to your current strategy?

3. The channel's marketing goal is awareness: Within your brand marketing portfolio, you need to look beyond sales to capture a channel's full value. Running incrementality experiments based on short-term sales won't be the right option. See Chapter 6 for a full view of how to measure brand outcomes most effectively.

One option within incrementality experiments is to run Brand Lift studies (user-based incrementality experiments available on YouTube that measure lift in upper funnel metrics) and compare the outputs side by side with your attribution or MMM outputs (early stage in the MEM maturity framework).

Example: When assessing the effectiveness of YouTube campaigns, you can complement your attributed CPAs with a brand metric, such as Cost Per Lifted User. In this case, Brand Search has more efficient CPAs, but YouTube campaigns can lift awareness for a low cost, so they still have value in fuelling the funnel, suggesting that continued investment is important for future growth.

	CPA in Platform Attribution (DDA)	Cost Per Lifted User (Brand Lift)
YouTube Select	$37.0 CPA	$5.8 CPLU
Brand Search	$6.8 CPA	N/A
YouTube Reach Campaign	$17.6 CPA	$6.5 CPLU

4. An experiment is not possible due to the technical limitations of the channel: Sometimes, it's not possible to split a channel by regions (e.g. TV or OOH buys are not available at that granular level). In those cases, you can use Causal Impact studies to find the incremental impact of the channel on sales. Causal Impact studies also allow synthetic controls with a combination of covariates — for example, other countries' baseline sales or keyword trends. You will still need a period of no advertising vs. a period of advertising, so this doesn't work with always-on campaigns (see open source package and web app interface).

5. It is not possible to get a feasible incrementality experiment design: To get an experiment with enough statistical power, you need a high volume of sales. However, you might not reach the required volume for several reasons:

- **The channel is not meant to drive sales:** See point 3 above.
- **You have long sales cycles and/or high-value items:** When running incrementality experiments, we can only capture the sales that occur within the timespan of the experiment, and this might be too short in some cases (e.g. automotive or finance). You can measure incrementality with micro-conversions instead. Use correlation analysis to find out which micro-conversions are best at predicting sales.
- **There is small investment in the channel:** Reassess whether you need an experiment. Use a pre-post test or "validate as you grow" approach until you reach enough volume to warrant an experiment.

6 Integrate brand measurement within your framework

Strong brands deliver superior shareholder returns, providing resilience during times of crisis and delivering a quicker recovery after declines in performance. Get tracking performance for brand media investments is still not always part of the media effectiveness measurement framework, making it difficult to have a unified view of the effectiveness of the total media portfolio. In this chapter, we address measurement practices to help you understand **the value of and how to report, plan, and optimise your brand marketing investments**.

**Source: BCG*

Understanding the value of brand investments

Step 1 **Start by defining the KPI that will track your brand performance and a set target:** Your chosen KPI should have a clear link to business outcomes. As one example, you may use industry research benchmarks (see below), although we encourage you also to find your own ratios between brand KPIs and commercial impact. Understanding the link to business outcomes allows you to set a target for your chosen KPI — setting yourself up for success with brand marketing and maximising its contribution to your business outcomes.

Benchmarks of advertisers from different industries and brand-equity levels

- Share of Search has 0.83 correlation with market share (IPA).
- +1 pts in awareness/consideration yields +1 pts in sales and decreased CPA by -1 pts (Nielsen).

Step 2 **Decide which measurement tool you want to include in your framework to track your chosen KPI.** We outline three options and recommend using at least Options 1 and 2. Option 3 will only make sense if you have an MMM.

3 useful brand measurement tools

1 Actively collected data: Surveys [All stages]

Brand growth requires a shift in consumer behaviour. To measure attitudinal outcomes, use surveys in two ways:

- **Third-Party Brand Trackers:** Implement continuous survey tracking of attitudinal KPIs measuring long-term effects. Conduct an overarching brand measurement survey not specific to media/campaigns. Typically, an upper funnel metric (awareness/consideration/favourability) is tracked over time on a quarterly/annual basis.
- **Brand Lift Studies:** YouTube measurement surveys that identify lifts in attitudinal KPIs on a campaign level. Use Brand Lift surveys consistently across all eligible campaigns to understand the baseline performance of your campaigns over time, allowing you to see progress and optimise results.

2 Observed data: Share of Search (SoS) [All stages]

Share of Search helps you understand **how your brand is positioned compared to competitors** by calculating the share of active consumer interest (see formula below). Brand media investments will impact the result but also other factors. The better you understand your competitive landscape, the more relevant SoS will be. Unlike surveys, SoS can be used easily over time and across markets, making it a great tool to detect trends and patterns.

Share of Search calculation

Searches for your brand ÷ (Searches for your brand + Searches for **relevant** competitor brands) × 100 = **SoS**

This is the tricky part

Further resources: Les Binet on SoS

3 Full-funnel MMM [Advanced stage]

Traditional MMM is designed to account for short- and mid-term impact of the marketing spend on lower-funnel KPI. **To estimate long-term impact of brand marketing over months and even years, you can build a brand-equity MMM (nested model) to see how brand media drives the baseline (brand equity and market share).**

The goal is not to modify the existing lower-funnel MMM but to run an additional nested brand-equity model in parallel to measure the long-term brand effects. Combining both models will give you a full-funnel MMM that will capture the full value of media in the short- and long-term.

Lower-Funnel MMM

Brand media spend ⟶ Sales relationship

Lower-funnel MMM (more traditional MMM) typically undervalues brand media by only measuring the direct impact of media on sales.

+

Nested Brand-Equity MMM

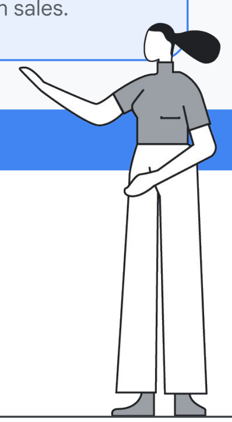
Brand media spend ⟶ Awareness ⟶ Sales relationship

The nested brand-equity MMM uses brand KPI as a mediating variable (e.g. brand survey, search data or website visits)

›

Full-Funnel MMM

The nested brand-equity MMM extends from lower-funnel MMM to a full-funnel MMM with a second equation. Full-funnel MMM allows us to measure brand media's direct and indirect effect on sales.



Read more about this approach and download our MMM guide **here**.

Planning for brand KPI outcomes

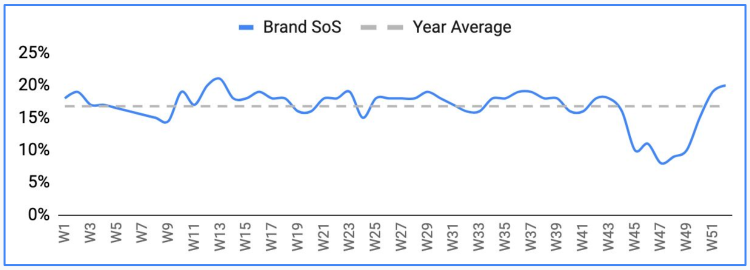
Establish which brand KPIs and tools you want to use, and start using the results you obtain for the planning phase. That way, you ensure your portfolio works for both brand and performance KPIs. We present you with two options, some recommended for any advertiser, regardless of maturity stage, and one for more advanced advertisers.

1 Plan towards brand KPIs outcomes [All stages]

- **Define optimal budget mix:** Decide on the overall **Brand vs. Performance marketing portfolio investments**. Combine the results from your media effectiveness performance measurement tools and those obtained from SoS, Brand Lift surveys, and other Brand KPIs measurement tools.

- **Use the insights from SoS to plan key investment moments for your brand:** SoS will provide a yearly trend that can help put your brand investments into context with peers and seasonality. Use these insights to adjust budgets throughout the year.

Example: The SoS plot on the right would indicate a decrease in brand strength in Q4. During the planning phase, consider increasing brand investments to be more competitive during that period.



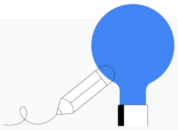
- **Connect your baseline brand performance to your growth target to set budgets.** Using the baseline for your brand (either based on SoS or your survey brand tracker), calculate the investments needed to reach your goal. This approach helps supplement reach planning and considers the effectiveness of your media activation. This is a three-step process:
  1. **Calculate the target needed to achieve success:** Based on your understanding of how the brand KPIs interact with your commercial metrics. For example, you ran a correlation analysis and found that to reach a goal of +3% in sales, you need to lift awareness by 5% in a specific high-intent demographic.
  2. **Quantify the ambition in consumer numbers.** Using public demographic statistics, you can estimate how many actual incremental consumers need to be made aware of your brand to reach the 5 ppts increase in your goal.
  3. **Calculate the cost.** Based on your Brand Lift studies, you can use the **cost per lifted user** metric to estimate The investment needed to reach your goal. The more Brand Lift studies you conduct, the more robust your metrics will be. However, keep in mind that past performance does not guarantee future results.

2 Use the insights from your full-funnel MMM for planning [Advanced stage]

In addition to the practices described above, if you have a full-funnel MMM, you are best positioned to use its insights for planning. You can also explore the budget shift recommendations from the model (see Chapter 4 for considerations on using MMM's budget shift recommendations).

Optimise towards brand KPI outcomes

Optimising towards brand outcomes, similar to performance outcomes, will be a cyclical process that should be captured within your test-and-learn agenda. Testing should go hand in hand with the implementation of best practices, which will accelerate the achievement of your brand objectives.



When building your test-and-learn agenda and optimisation, keep these best practices in mind (ordered by share of effect[1]):

- **Creatives** are responsible for nearly half of the average sales effect, and this percentage increases to nearly 60% in digital marketing. Our ABCD guidelines can help you boost your long-term brand contribution by 17%, as well as your short-term sales by 30%.[2]
- **Media tactics** account for about 36% of the effectiveness of a campaign. We've found that running ads 3+ times a week instead of once, targeting intent signals instead of demographics alone, and mixing long and short formats instead of using only one, increases the effect of a campaign between 1.5 and 2 times.[3]
- Your **brand associations** and relevancy account for 15% of the total effect of a campaign. To create a strong brand, you need to consistently evoke an emotional response, a need to belong, and aspirations that only your brand can fulfil.[4] You also need to use distinctive assets that will make your brand stand out from the competition.

All industries and advertisers are unique, so it's crucial to customise your advertising strategy to suit your specific needs. As you enhance the baseline performance of your brand, you'll find that achieving the next percentage point of improvement will be significantly more challenging. The above-mentioned best practices are an excellent starting point for most advertisers, but you may need to adapt them based on your specific circumstances.

Each campaign presents an opportunity to A/B test various creatives and media tactics. With a robust test-and-learn approach, you can collect yearly insights from experiments and run meta-analyses. These provide even stronger evidence to questions such as: "What unites the best-performing campaigns?" or "Did the creative adjustments increase favourability over time?". With all of these insights, you can develop your own best practices for your business and ensure the most effective use of your media.

Sources: 1. Nielsen, "When it comes to advertising effectiveness, what is key?" 2017 | 2. Kantar, "Validating Google's ABCD framework", 2021 | 3. Google Brand Lift Survey, Internal meta studies 2017-2020 | 4. Kantar, Brand equity guide, 2022

Put it into practice:

Build your own MEM strategy

Build your own framework

In this section, we will give an example template to create your media effectiveness measurement framework and put into practice all the theories you've learned in this playbook. We encourage **getting buy-in from all stakeholders across the organisation — this pre-work on alignment will be key for success**. Getting buy-in from relevant stakeholders will ensure they understand the purpose of the MEM framework and how it's used. Your framework should be clear, concise, easy to use, and flexible enough to accommodate changes in the organisation's goals and objectives.

The first step to structuring your framework will be organising your marketing portfolio according to the levels presented in Chapter 1 (adjusting the levels to your needs). The next step to making the framework actionable will be to link it to business questions, KPIs, and methodologies. We recommend including some use cases and interpretation tips to pre-empt any discussion that could arise when deciding which tool should take precedence for which business decision.

Illustrative example of what your framework could look like

Level	Channel	Business question	KPI	Methodologies used	Use cases	Interpretation tips
Level 1	YouTube Direct Response	1) Are YT campaigns driving incremental sales?	1) iCPA/iROAS	1) Conversion Lift based on users (Quarterly)	1A) Confirm hypothesis 1B) Set channel targets	1) Check regularly incrementality of the channel and evolution over time. Conservative.
Level 1	YouTube Direct Response	2) How should YT campaigns be optimised for a short-term impact on sales?	2) Attributed CPA/ROAS	2) UI attribution reports (real-time) + Video experiments (Monthly)	2) Tactical optimisation: format, audience, bidding, etc.	2) Relative impact, not absolute, offers the most actionable insight.
Level 1	YouTube Brand	Are we generating future demand for our products?	Lifted users Cost per lifted user	Brand Lift surveys (always-on)	1) Planning brand media investment based on target Lifted Users 2) Optimise media tactics	Results represent channel specific audiences.
Level 1	Complete with all portfolio channels					
Level 2	Direct Response Portfolio	What is the impact of my DR channels together and individually?	1) iCPA/iROAS 2) MMM ROAS	1) Geo Experiments 2) MMM	1) Confirm hypothesis 2) Cross-channel budget allocation	Experiments iROAS should directionally align with MMM ROAS but will not be identical. For hard-to-measure channels (such as MMM), experiment will take priority.
Level 2	Brand Response Portfolio	What is the impact of my brand channels together and individually?	1) Percent Point lift 2) MMM ROAS	1) Brand trackers 2) Nested MMM with Brand KPI or SoS	1) Establish baseline 2) Cross-channel budgets	Sparse data will hide response to media campaigns. Include in total MMM ROAS calculation as a long-term effect.
Level 3	Total Marketing Portfolio	What is the full value of my media investments across all channels (online and offline)?	1) MMM ROAS 2) Share of voice 3) Share of sales	1) MMM 2) and 3) Competitive analysis	1) Size media budget as a strategic investment based on business goals 1) and 2) and 3) Cross-channel budget allocation	MMM results are informed and compared with incrementality and attribution results but, when in doubt, MMM takes priority.

All content in this table is shared for illustrative purposes. You should decide what is most relevant for your business. We have also limited the amount of information for simplicity purposes, but you can consider including additional information to bring the message across the organisation. One recommendation is to include information about the goal of the channel and the frequency of updates.

Thought-starters to decide which tools to incorporate in your MEM framework and how best to utilise them

There is no universal solution for measuring media effectiveness. To build an effective framework for your business, start with your core measurement questions and then explore how a combination of tools can provide answers at each portfolio level. As you learn about each tool, weigh the value of it against the costs of adding it to your toolkit. Some tools may not make sense and won't win a place in your media effectiveness framework.

<table>
<tr><th colspan="2">Level</th><th>Goal/question</th><th>Media effectiveness measurement recommended approaches</th></tr>
<tr><td rowspan="2">Level 1</td><td>Direct Response</td><td rowspan="2">Channel specific performance and optimisations
What strategies/ campaigns are delivering value within a specific channel?</td><td rowspan="2">Regardless of maturity level, within each performance channel:
• Data-driven attribution is informing AI-powered bidding within each campaign to maximise performance.
• Day-to-day campaign and channel optimisations are fuelled by attribution reports.
• Budgets are being allocated to campaigns based on channel-level data-driven attribution.
Relative differences in strategy and campaign performance for planning purposes can be measured via incrementality experiments, but we recommend limiting tests to the most impactful changes, e.g. key new campaigns or drastic changes in campaign budget allocation.
Advanced and granular MMM might reach an aggregated strategy or campaign level of detail. If aiming to reach this level of detail, make sure the model is calibrated with attribution and incrementality experiment insights. Optimise for brand outputs by incorporating Brand Lift experiments in every eligible campaign.</td></tr>
<tr><td>Brand</td></tr>
<tr><td rowspan="2">Level 2</td><td>Direct Response Portfolio</td><td rowspan="2">Budget allocation between channels with the same KPIs
What was each channel's individual contribution?</td><td rowspan="2">MMM represents each channel's value in a way that factors incrementality. This provides a more robust view than data-driven attribution and allows you to evaluate both performance and awareness channels. Calibrate your MMM with incrementality experiments to improve accuracy.
When MMM is not possible or to supplement MMM, cross-channel data-driven attribution informs channel-level budgeting for performance strategies. Complement insights from channel-level attribution for planning with incrementality experiments. Decide if you will run fewer experiments and use the information side by side in a qualitative manner (starting stage) or if you are going to plan a comprehensive testing plan to cover every channel and fully calibrate results (more complex).
Capture the value of brand investments by implementing brand tracking tools such as Share of Search and Brand Lift studies.</td></tr>
<tr><td>Brand Response Portfolio</td></tr>
<tr><td>Level 3</td><td>Total Marketing Portfolio</td><td>Strategic planning and budget allocation
What was the value of my performance and awareness portfolios?</td><td>MMM is the best tool to measure portfolio-level contribution, informing portfolio (i.e. performance vs. awareness) budget allocations. Calibrate the MMM with the channel-level incrementality experiments to improve accuracy. Capture the long-term impact of brand investments by including a nested MMM with brand metrics such as Share of Search.
When MMM is not possible, use cross-channel data-driven attribution in combination with industry knowledge to plan a full-funnel budget.</td></tr>
</table>

Create a test-and-learn programme

What is a test-and-learn programme? A programme with a defined **learning agenda**, a pipeline of **hypotheses** to test, a suite of **measurement solutions** to apply to each hypothesis, and a set **group of stakeholders** who make business decisions based on the outcomes of each test.

The scope of this programme can vary. The optimal scenario is to have a holistic programme where you capture all measurement-related activities for all channels — including analysis, optimisation experiments (A/B tests), incrementality experiments, causal impact studies, attribution reads, MMM reads, and any other relevant checks. Holistic test-and-learn programmes involve the whole organisation and require great coordination and **commitment across all teams. Tests will only succeed if there is a culture of experimentation supported by leadership** (read what other experts say here and here). This should be part of your pre-work on fundamentals mentioned at the start of the playbook.

This section explains how to create a plan where the different MEM tools (attribution, incrementality, MMM) work together. You can use the output of this exercise to build on your optimisation test-and-learning plan, including other tools such as A/B experiments and pre-post tests.

3 steps to build your learning agenda

1 Assess the situation

Begin by identifying **key pieces of information related to your business situation:**

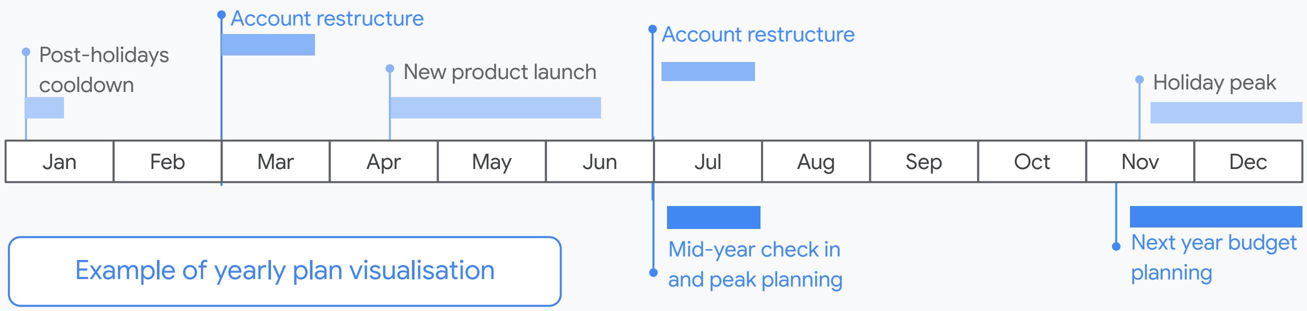
- The MEM framework you developed using the previous section's guidance.
- The stage you are in on your media effectiveness measurement journey (find out here).
- A realistic view of the resources you have available.

Once you have collected the necessary information, **review your marketing and business plans for the year and provide answers to two questions**:

- Which key moments in the year require data to support your business decisions?
- What are the crucial periods for media investments throughout the year? Consider major promotions, product launches, and seasonality.

Combine your answers to these questions with any other relevant plans that may impact media performance, and create a visual map to help you plan your measurement activities effectively. For instance, you should ensure that you have the required results before budget planning periods or be aware that you won't be able to conduct experiments while restructuring your Search accounts.

Visualising these "guardrails" will enable you to identify potential conflicts or overlaps in your plans and adjust your measurement activities accordingly.



Example of yearly plan visualisation

2 Align on the updates and cadence

Based on your situation assessment, prioritise the MMM, attribution updates, and incrementality experiments you will run. The required cadence will depend on the way you plan to use the tools:

Complement [Early stage]:

When the goal is to read results side by side to complement potential gaps, you can focus on running a limited amount of tests directed specifically to certain channels and moments.

Calibration and loop [Intermediate & advanced stage]:

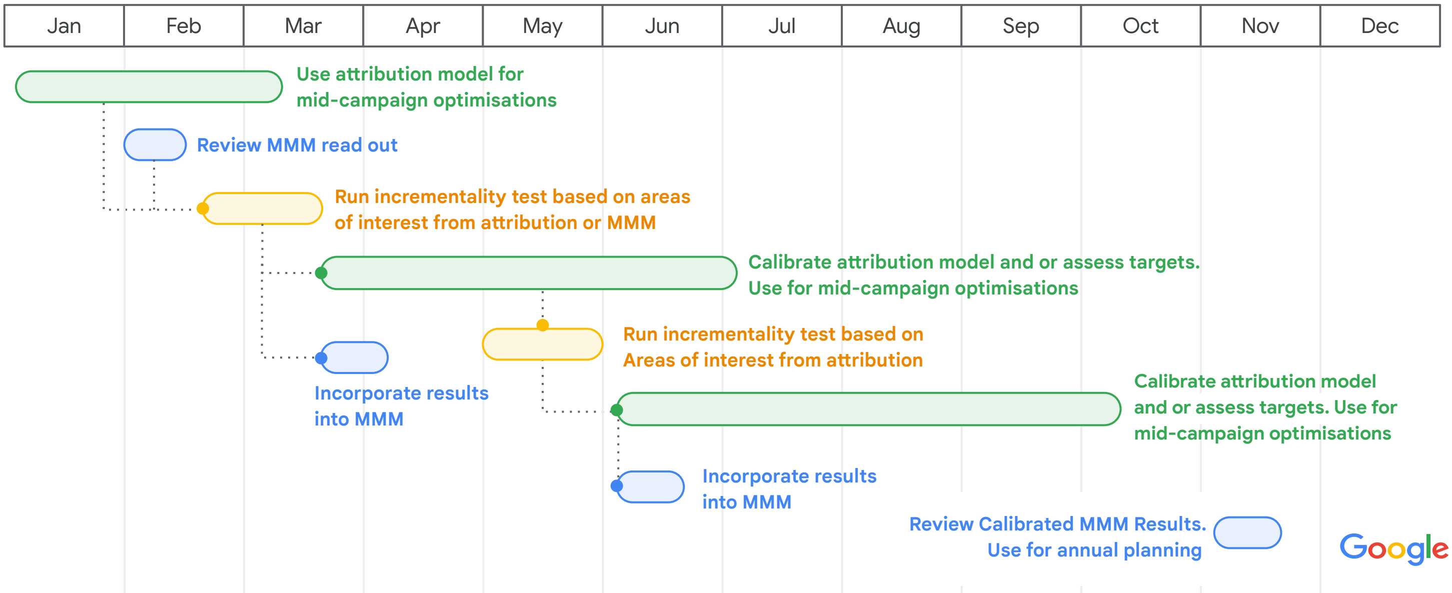
You will need a structured testing approach that produces an incrementality result for each testable channel, plus additional guidelines and alignment on what to do with channels that are not testable (see Chapter 5). Here are some common questions on cadence and their answers, but we recommend you read Chapters 2, 3, and 4 for full context:

- **How many experiments do I need to plan to start calibrating?** We recommend running one experiment per channel before starting to calibrate your model. For MMM using Bayesian models, one test can already be used to improve the model, but having a fair representation will yield better results.
- **Can I calibrate attribution results if I only have an experiment for one channel?** Calibrating attribution results based on one single test on a channel can be misleading since you don't have a reference of what is your baseline incrementality on other channels. Our recommendation is to work with qualitative comparisons until you have more data points.
- **What should I do if my company operates in several markets?** You will have attribution data for every market, but experiments and MMM are resource-intensive and expensive to run for every market and/or brand. You can cluster markets, use extrapolations from the MMM, and experiment with results from one representative market to the rest of the markets in the cluster.

3 Plan, execute, and apply learnings

Hopefully, by now, you will have a clear understanding of yearly plans and a list of key moments annually where you will need to read results from your attribution model, experiments, and MMM. Combine those with any special requirements for certain tests (e.g. high/low season) and draft your schedule.

Sample schedule for illustrative purposes



Google

Appendix

Clarifying key concepts: Analysis vs. Experiments vs. Incrementality

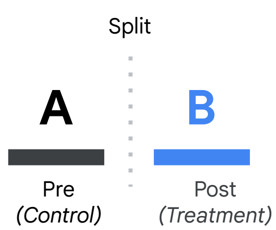
Analysis vs. Experiments

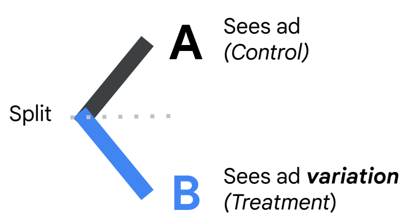
- **Analysis:** a detailed examination of anything complex in order to understand its nature or to determine its essential features.
- **Experiment**: a planned activity used to investigate the validity of a hypothesis in a scientific manner.

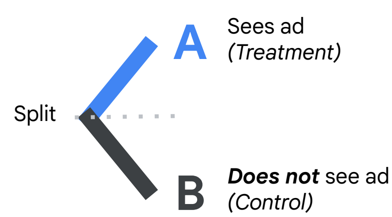
Prefer an analysis when…	Prefer an experiment when…	Comments
The burden of proof is **low**	The burden of proof is **high**	If you need a randomised controlled study to test a hypothesis, use an experiment.
Time is **limited**	Time is **not limited**	Experiments should be planned ahead of time so that all parties can be aligned on goals and methodologies.
Coordination is **challenging**	Coordination is **feasible**	Experiments require getting people aligned while analyses can be performed independently. Make sure your client is willing to coordinate on an experiment.
Examining the **past**	Looking to the **future**	Experiments cannot be applied retroactively, but analyses can.
Cost is **a concern**	Cost is **not a concern**	In an experiment, you need to either hold back or increase spend. This is not required in an analysis.
You need to **generate opinions**	You want to test **existing opinions**	An analysis is best for discovery and forming initial observations/opinions about a situation. Experiments should test existing opinions and hypotheses.

Pre-Post vs. Optimisation vs. Incrementality

All analyses/experiments compare scenarios (shown as "A" & "B"), but they use different methodologies. Incrementality experiments are A/B experiments that measure true causal impact by removing the ad from one arm but not the other.







Pre-Post Analysis

A and B happen **sequentially**. Best for **directional analyses**; does not control for confounding factors.

Optimisation

A and B happen **simultaneously**. Best for **optimisation testing**; does not demonstrate causality.

Incrementality

A and B happen **simultaneously**. Best for **proving causality** since it compares presence of ad to no ad.

For all study types, attribute the difference in values (e.g. conversions) between A and B to the ad difference between A and B.

A: Value before change
B: Value after change
B - A: Directional impact

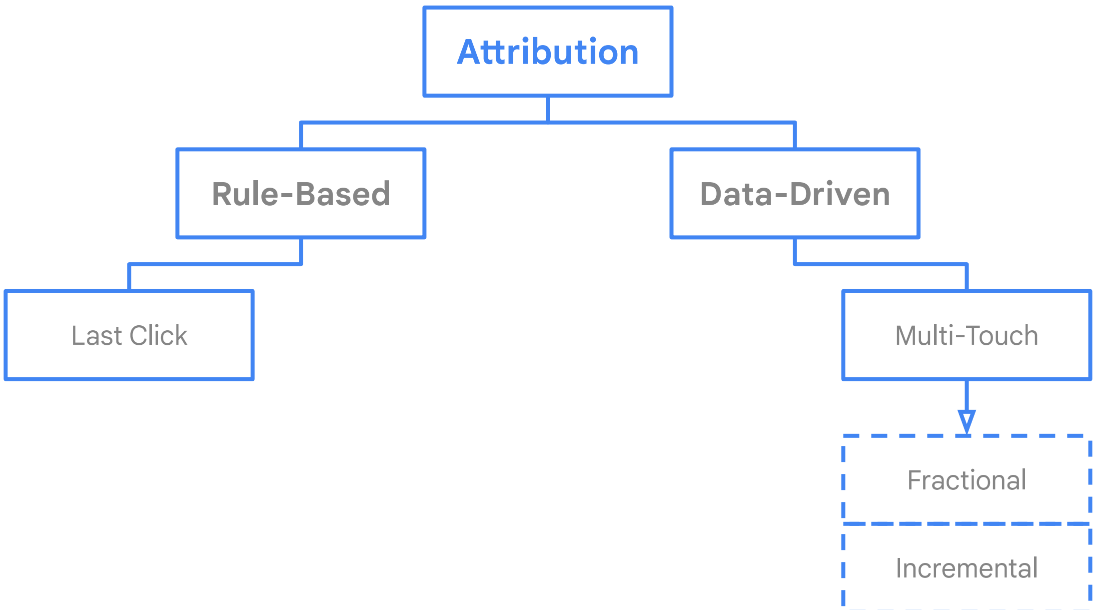
A: Value with ad
B: Value with ad variation
B - A: Impact

A: Value with ad
B: Value without ad
A - B: Causal impact

Clarifying key concepts: Analysis vs. Experiments vs. Incrementality

Type	Definition
Pre-Post Analysis	Compares data from before a change was made (pre-period) to the data after a change was made (post-period). This approach **does not control confounding factors**, but it is still incredibly useful for making directional observations. **Google's solutions:** Causal impact (open source package, web app interface)
A/B ("Optimisation") Experiment	Compares data between two scenarios (test and control) that happen simultaneously but vary in one aspect. A/B experiments are a statistically rigorous way to determine the impact of account changes. **Google's solutions:** Google Ads Campaign Experiments, Google Ads Video Experiments, DV360 A/B Experiments
Incrementality Experiment	An A/B experiment where the test group is shown an ad and the control group is *not* shown an ad. **We can infer the incremental impact of the ad** since the only difference between the two arms is the presence of the ad. This means the ad must be the cause of the difference in performance. **Google's solutions:** Conversion Lift, Geo Experiments

Mapping available attribution frameworks



Checklist of best practices for measurement tool implementations

Measurement model		Solutions/recommendations	Checklist
Attribution	Must have	Ensure you have durable measurement in place	☐
		Ditch the last-click model	☐
		Report and bid to DDA across Google products	☐
	Good to have	Make every marketing dollar count with attribution and lift measurement	☐
		Unlock customer intent	☐
Incrementality Experiments	Must have	A test-and-learn mindset across the organisation	
		A clear understanding of Incrementality Experiments (follow Skillshop training)	☐
		Access to accurate conversion data of the type required by the test methodology	☐
		Ability to maintain strict experiment conditions, including sufficient investment	☐
		Brand Lift surveys connected to *all* eligible YouTube campaigns	☐
	Good to have	Incrementality-based targets	
		Conversion Lift studies to complement attribution	☐
		Geo Experiments to measure full channel incremental value and compare results across channels	☐
		Understanding of when to use Causal impact as an alternative method	☐
		A predetermined plan for the actions that different types of results will lead to	☐
MMM	Must have	Apply MMM best practices	
		Use Google's MMM Data Center for ads data	☐
		Ensure model(s) breaks out YouTube from other online video	☐
		Search broken down into brand vs. non-brand vs. shopping ads	☐
	Good to have	Bayesian MMM (Google's whitepaper)	☐
		Split model into geographical areas	☐
		Split model into product segments	☐
		Build a nested model with brand outputs	

Common questions on experiments cadence

How many experiments do I need?

- We recommend one experiment per channel before starting to make decisions:
    - Why not more? Running Geo Experiments (which are the most suited for cross-channel calibration) is costly, so we don't recommend running them too often.
    - When would you want to run a second experiment?
        - If the results are much better or worse than you expected based on your current source of truth, you may be suspicious of the test results.*
        - Tests are reflective of the performance of a specific point in time — if there was some external unexpected event, this can influence the results.
        - Tests have between 80% to 90% confidence (depending on your choice), so there is a chance that statistically your results are outside the confidence limits.

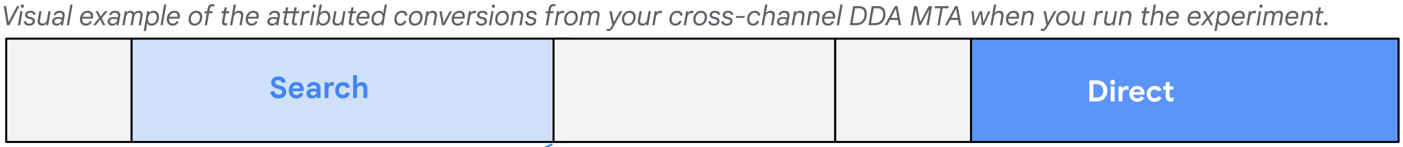
- Once you set a baseline, one or two tests per channel per year are enough to keep validating the models.

***Bonus: What is a normal "incremental" lift to expect?**
Most studies show that channels are between 0% and 25% incremental. 25% is a very high share and only happens for advertisers that are highly optimised for incrementality.

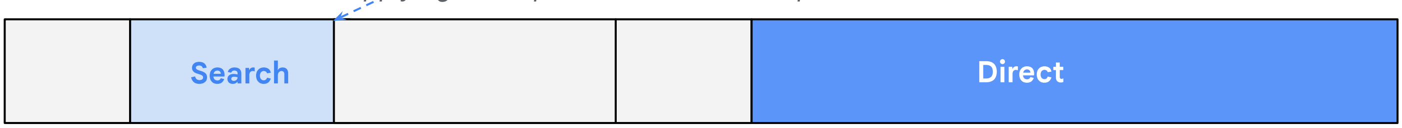
Why is it not recommended to calibrate attribution results based on the experiments results of one channel alone?

Here's an example where you planned a Geo Experiment for Google Search since it was the channel bringing the highest share of conversions in your attribution model. Example test result: From the 200 claimed conversions, 100 are incremental, with a confidence interval of [40,180]. This would give a multiplier of 0.5 [0.2, 0.9].

Visual example of the attributed conversions from your cross-channel DDA MTA when you run the experiment.



Attributed conversions after applying the experiment results multiplier:



From the total 200 claimed conversions, you now count only 100, which are the incremental ones.

If you stopped now, you would be fairly representing search on its own. However, this would not be an accurate comparison with the other channels, since you are comparing incremental conversions for search to attributed conversions for other channels.

Extrapolating gaps from Conversion Lift for users

We know that the absolute lift in conversions provided by Conversion Lift studies is conservative due to measurement gaps. Enhanced Conversions will help recover ITP/ETP and iOS gaps, increasing the number of observable conversions and consequently improving your chances of detecting a significant lift with the study.

One way to estimate the result when accounting for measurement gaps is to apply the known percentage of missed conversions and use it to extrapolate the conversions that are missing.

Here are the step-by-step instructions on how to extrapolate the missing conversions:

1. Collect the share of conversions from known gaps:
   a. Share of offline conversions
   b. Share of ITP/ETP conversions
   c. Share of iOS14+ conversions
   d. Consent rate share
2. Run a Conversion Lift study to measure incremental conversions
3. Calculate adjusted conversions based on assumptions

Example

Conversions for same timeframe	
% offline conversions	20%
% in-app conversions	10%
% of consent	80%

Extrapolations		
	Share	Total
Incremental conversions: Conversion Lift study	-	939
Adjusted for offline conversions	*+20%*	*+186*
Adjusted for in-app conversions	*+10%*	*+94*
Adjusted for consent	*+20%*	*+188*
Total adjusted incremental conversions		***1,407***

Another way to assess the gaps would be to compare the results from a Conversion Lift study to those of a Geo Experiment. Ensure that both tests are comparable and apply a blow-up factor based on the difference in results.