Unified Marketing Measurement

The Power of Blending Methodologies

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Abstract

In an increasingly complex marketing landscape, marketers need to prove the business impact of their activities more than ever. But measuring this impact remains one of the core challenges in the industry. Recent changes, such as the deprecation of third-party cookies, as well as the rising amount of channels, complex user journeys, and data availability, reduce the usefulness of traditional measurement methods. As such, marketers are collectively looking for alternatives.

To solve these challenges, this paper proposes a rethinking and merging of traditional measurement methods. One approach that successfully does so is Unified Marketing Measurement (UMM), which measures the impact of marketing activities by utilizing computing and alternative statistical frameworks. To help marketers better find their way in the complex world of marketing measurement, this paper examines how UMM compares to other methods and why it could be beneficial.

The paper elaborates in three parts. The first part discusses the central ideas of UMM and how it compares to other methodologies. Following the comparison, the paper discusses a few applications of UMM. According to this study, the ideal UMM approach combines multi-touch attribution (MTA), experiments, and MMM to form a holistic approach. Moreover, it calls for adding business knowledge and experiments to the equation. The third part of the paper presents a case study, showcasing what the examples mentioned above look like in practice. By the end of the paper, readers will be able to identify the main shortcomings of traditional measurement methods and how they can be tackled with the UMM approach.

This paper is, can, and should be, read by anyone with an interest in Marketing Effectiveness. It does not rely on you having a statistical background but is designed to take you through the principles and give you a basic understanding of some of the most modern and powerful new approaches being employed in the field currently.

Unified Marketing Measurement

The Power of Blending Methodologies

This study showcases how a unified measurement approach results in more accurate budget decisions, when compared to multi-touch attribution (MTA), leading to a 40% increase in expected uplift

Traditional marketing measurement methodologies are not sufficient.

- Traditional methodologies such as MMM, MTA, and experiments often exist within organizational silos, creating a flawed framework for measuring impact and sacrificing accuracy.
- Instead of combining insights from different models, measurement accuracy can be gained by blending the data and methodology at a technical level.

Unified Measurement Framework rethinks the traditional methods to remedy the aforementioned shortcomings.

- Unified marketing measurement is not a model, but rather a methodology or approach that maximizes the use of available data sources and techniques to create a single truth suitable for actionable steering.
- Bayesian modeling within the unified framework allows us to create new interaction models that incorporate MTA, MMM, and experiment learnings as prior principles.
- At the heart of a unified framework there should be a clear and common goal, upon which you can build an advanced modeling layer and develop a flexible, adaptive, and continuous learning framework.
- Advantages:

Accurate	**Holistic**	**Feedback loop**
Flexible	**Reliable**	**Granular**

If you are interested in more details, the paper deep dives into three topics:

- How to blend MTA and MMM
- Bayesian estimation and how it differs from the more common frequentist approach
- Working with probability distributions and expected uplift

Introduction

Traditional marketing measurement methodologies often exist within organizational silos, creating a flawed framework for measuring impact and sacrificing accuracy

More and more, marketers are required to prove the business impact of their work. With enormous yearly budgets, culminating in a staggering global advertising spend of over $600 billion dollars in 2019, this should come as no surprise. Measuring this impact, however, remains one of marketing's biggest challenges.

Marketing measurement has become increasingly complex. Consumers move faster, interact with on- and offline media touchpoints, and buy products across multiple sales channels.

Meanwhile, many organizations still work in silos focused on a part of the customer journey and have different teams responsible for the different sales channels. There is often a lack of transparency, communication, and exchange of wisdom between silos. Traditional measurement methodologies, including marketing mix modeling, multi-touch attribution, and experiments, exist within these silos, creating a flawed framework for measuring marketing impact.

Traditional marketing measurement methodologies are not sufficient.

Marketing mix modeling (MMM) is part of every marketing effectiveness toolbox, providing a holistic view on marketing performance. The term MMM covers models ranging from relatively simple to extremely advanced in complexity and application. There are huge variations in granularity, speed, and impact contribution, but most lack tactical detail and are built on outdated methodologies.

Multi-touch attribution (MTA) addresses the tactical shortcomings of MMM. It has proven to be a powerful method for gaining a deeper understanding of digital touchpoints. It provides insights at the user level but often ignores offline activities and external factors, resulting in an incomplete view. It is also increasingly challenged by data limitations and privacy regulations.

Experiments, if properly set up, generate extremely accurate insights into the incrementality of campaigns or ad executions. However, experiments are only scalable to a limited amount of insights and results are rarely structurally integrated in MMM or MTA models.

Although MMM, MTA, and experiments in isolation might suffice to answer questions within silos, holistically they result in biased recommendations and budget decisions. Lack of consistency across silos means each department steers on different insights.

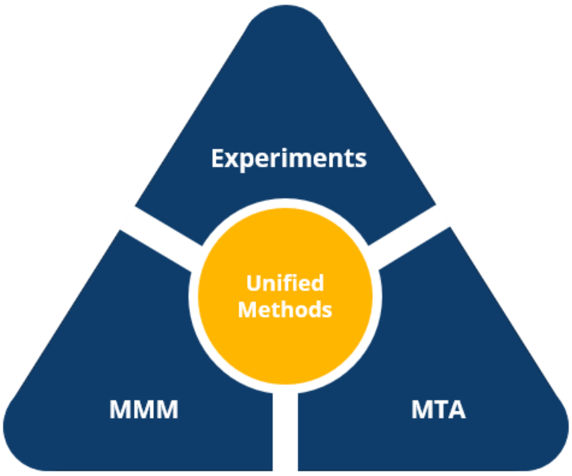
Marketers often blend insights from the different models in an attempt to create consistency, but this is like comparing apples and oranges, and sacrifices accuracy.

The need for Unified Marketing Measurement

Instead of combining insights from different models, measurement accuracy can be gained by blending the data and methodology at a technical level

To optimally use all available data of different granularities from different sources, marketers need a measurement framework that connects data at a technical level. This allows marketers to analyze the direct and indirect effects of media channels at the most granular level possible and without losing valuable information. A unified marketing measurement framework results in more accurate, granular, unbiased, and holistic estimates.

By using advanced modeling techniques within this unified framework, including Bayesian statistics, we can transfer knowledge from one model to another. As a result, marketers get a grip on unreliable modeling results and they have consistent, more accurate insights available that are comparable across different departments.



In this paper, we discuss how UMM overcomes the challenges of common measurement methodologies and its best practices. Moreover, we explain that UMM is not only a technique but a way of thinking; about how we can use a continuous feedback loop to learn from previous campaigns; and how, by being open to improving current models and blending techniques, we can increase accuracy and consistency.

Comparing Unified Marketing Measurement to Traditional Measurement Methods

Unified marketing measurement is not a model, but rather a vision or approach that maximizes the use of available data sources and techniques to create a single truth suitable for actionable steering

UMM provides a modeling framework for maximizing the use of available data sources. It applies the strengths and addresses the weaknesses of the different methodologies, but does not replace them completely. Also, it ensures that marketing measurement is consistent and aligned over different departments.

To blend multiple methodologies into one unified approach requires the individual techniques to be in place and, preferably, in use for day-to-day decision making. Each methodology has a unique objective applicable to different data types and use cases:

	MMM	MTA	Experiments	Unified
OBJECTIVE	• High-level budget planning • Cross-channel budget allocation • Assess the value of marketing at channel level	• Day-to-day steering of online campaigns and channels • Assess the value of specific marketing executions • Select tactics within online channels	• Measurement of the incremental impact of a channel, campaign, or creative	• All-encompassing measurement and budget allocation • Get a grip on unreliable results • Combine strengths of individual models • Incorporate available knowledge (e.g., results from experiments or analyses)
REQUIRED DATA	• Aggregated KPI and media data on a weekly/daily basis	• User-level data of individual online (media) touchpoints	• The data for analysis is gathered during the experiment	• All information that is available from digital and non-digital sources, experiments, and existing analyses
STRENGTHS	• Measure all media activities • Measure all KPIs, including branding • Include business dynamics and external factors	• Near real-time performance tracking • Measures impact of every customer interaction • Allocates business value to touchpoints proportional to their contribution	• Highly detailed and accurate measurement	• Comprehensive measurement of all channels • Harness strengths of individual models • No loss of information or granularity • Adaptive to the level of granularity in the data
WEAKNESSES	• Not possible to include much detail • Large amounts of historical data required	• No insights into offline media • Requires cookie-level data • No insights into branding KPIs	• Reliability depends on many factors • Requires extensive planning, time, knowledge, and resources • Difficult to scale	• Requires both aggregated and user-level data • Implementation is more difficult and time-consuming • Organizations have to be ready to adapt unified measurement

Unified Measurement Framework: Applications

Bayesian modeling within the unified framework enables us to create new interaction models that incorporate MTA, MMM and experiment results as prior beliefs

The unified measurement framework has many structural advantages over common methodologies. It makes use of all information that is available, blends different data streams and methodologies, making use of their core strengths, and creates more accurate and actionable measurement.

Many of the aforementioned benefits of UMM are made possible by the use of Bayesian statistics; an advanced statistical method that has major advantages over traditional estimation methods. The role and benefits of this method are explained widely throughout this paper.

In this chapter, we will dive into the blending of different models, and we share some best practices and our vision on a structural marketing measurement setup that continuously learns and improves.

Blending MTA and MMM

The individual results of MTA and MMM form important building blocks for the unified framework. These results are merged to model the cross-effects between on- and offline channels and offer a holistic view over all channels. Modeling the outcomes of the aggregated data against the attribution results from MTA allows us to gain insights into the proportion of lower-funnel activity that is affected by activities in upper-funnel channels.

For example, a peak in Paid Search attribution right after a YouTube commercial could indicate an interaction between the two channels, and that the commercial strengthened Paid Search results. They both receive a share of the attributed conversion to account for the cross effects. These cross effects are measured for all online and offline channels. The resulting insights show both the total channel impact on the KPI and the interaction effects with other media channels:

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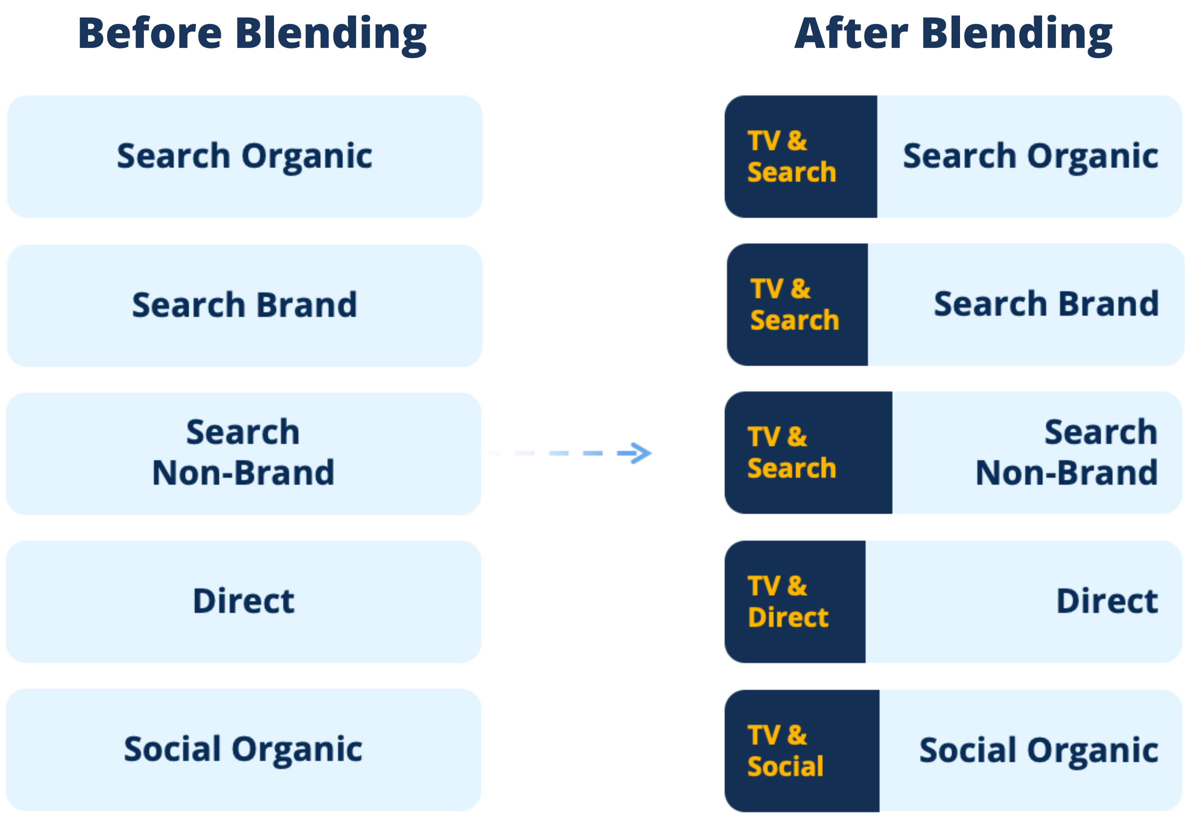


Bayesian statistics play a big role in the estimation process. The existing MMM model estimates the effect of aggregated channels on online channels. Bayesian statistics allows us to blend this prior knowledge into new interaction models.

Rather than merging the model results coming from MTA and MMM, we are able to create new interaction models that incorporate MTA and MMM results as prior beliefs.

Deep Dive

Blending MTA and MMM in 4 steps

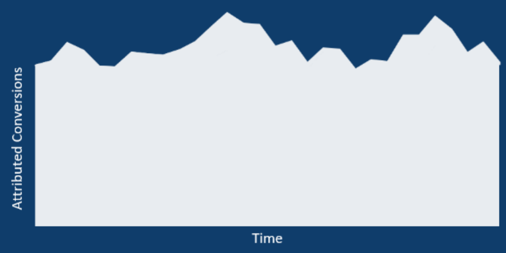
Note that a prerequisite for blending MTA and MMM models is having both models in place. If not, this is a crucial first step. Moreover, Bayesian optimization of the MMM model is highly recommended.

1. ### Create a common understanding

Often separate teams have different definitions of KPIs and media channels (e.g., net sales vs gross sales). Define a common understanding on which KPI should be evaluated by the models. Bundle all existing information from experiments, analyses, and experience to create common prior beliefs and knowledge.

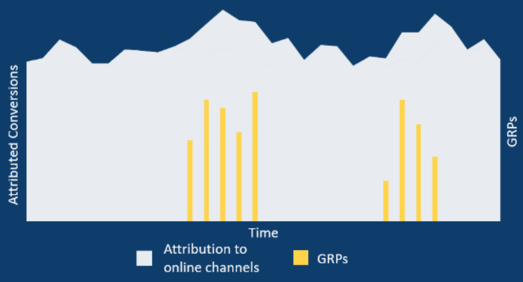
2. ### MTA: Measure the impact of online channels on your KPI

Measure the impact of all online interactions on sales using an MTA model. Note that tracking pixels enable marketers to measure impressions on a user level and thus provide very valuable information.



3. ### MMM: Measure the impact of aggregated channels on online attribution

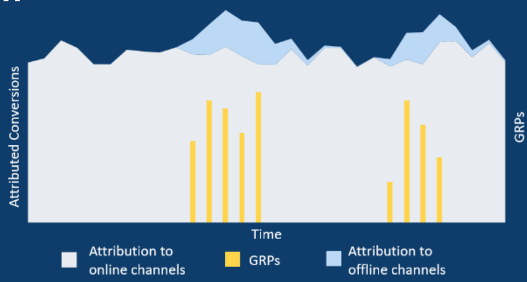
Model the impact of aggregate data channels on online channels using the MMM model. We build a new model for each combination of aggregated and online channels. The dependent variable in this regression is the attributed sales for a specific online channel and the independent variable is the weighted sum of all efforts in an aggregated channel.



Practical example: if we observe a peak in direct visits shortly after a TV commercial, our models understand that the TV commercial might have contributed to this peak. They calculate this interaction effect.

4. ### Unified: Reattribute part of the online attribution

After we have determined the fraction of attributed sales to an online channel that were caused by the interaction with aggregated channels, this amount is redivided over both types of channels according to their contribution. These final outcomes are the unified results.



Use Experiments to Finetune Outcomes of Unified Measurement

Experiment outcomes are the next important building block in the unified framework and are incorporated in unified measurement as prior beliefs. Results from experiments can also be used to effectively finetune the outcomes of unified measurement. An overview of various possibilities can be found in the table below:

Action	When
Do nothing	The experiment results align with current attribution outcomes, or the experiment results are not trusted more than the current models.
Correct attribution only for this experiment	The experiment results are trusted to be more accurate than current attribution outcomes in this experiment, but they are not generally applicable.
Extrapolate the experiment results to correct channels/campaigns in general	The experiment results are trusted to be more accurate than current attribution outcomes, and they are generally applicable to the channels or other campaigns.
Use the experiment results to create more detail in attribution	The experiment results contain more detail than the current attribution outcomes. For example, experiments on banner size, regions, or creatives that are not part of current models.
Integrate experiment outcomes structurally in your attribution models	The experiment results are trusted to be more accurate than current attribution outcomes, so they are used to improve the current model structurally.

If you want to find out more, head to the deep dive section on the next page.

Deep Dive

Bayesian estimation and how it differs from the more common frequentist approach

As we have seen many benefits of Bayesian Statistics in marketing measurement and especially in blending methodologies, we will deep dive to explain the differences and benefits of this concept compared to the more common frequentist approach.

For statistical inference, the most used method is the frequentist approach, the classical view on statistics and hypothesis testing. It is typically easy to implement and its intuitive principles are easy to understand. The frequentist approach estimates the parameter value that is most likely given the observed data. The parameter values represent the 'true' media effects and are considered as fixed and constant, while the data is seen as random. Given these 'true' and fixed parameter values, one looks at whether the observed data is plausible, while infinitely many realizations would have been possible.

As computation power increased over the years, Bayesian inference has rapidly gained popularity. The Bayesian method is the exact opposite of the frequentist approach in some respects, as can be seen in the table below.

	Frequentist approach	Bayesian approach
PARAMETER VALUES	The parameters are fixed and unknown constants. The estimated parameter values are equal to the true media effect.	The parameters are stochastic variables. One defines a prior distribution representing a prior belief of the effects.
THE OBSERVED DATA	The observed data is used to estimate and check the validity of the postulated model, by comparing data with an infinitely large, hypothetical dataset.	The observed data is used as evidence to update the state of mind: data transforms the prior into the posterior distribution by the likelihood.
CONCEPT OF PROBABILITY	Frequency concept of probability: a probability is the fraction of occurrences when a process is repeated infinitely. It should be noted that although the frequentist approach is often used in non-experimental sciences, repeating the process is only possible in experimental situations.	Subjective concept of probability: a probability is a degree of belief that an event occurs. This degree of belief is revised when new information becomes available.
ESTIMATION OF THE EFFECTS	Use the maximum likelihood estimator as a gauge for the media effects.	Use Bayes' theorem to obtain the posterior distribution of the media effects. Use the posterior mean or mode as an estimator of the media effects.

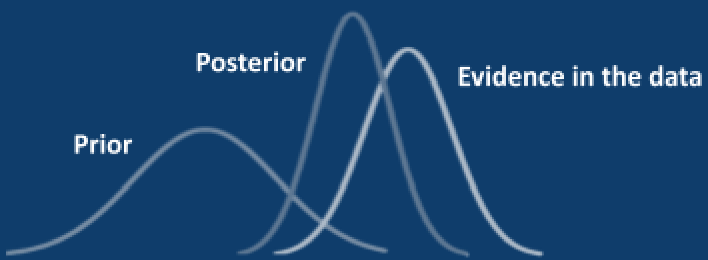
From a Bayesian perspective, the data is fixed. The parameter values are conditional on the data – random variables that all have their own probability density function. So, we need to check whether the value assigned to the media effects is plausible, given the data. The Bayesian approach also looks at probability as a subjective concept: a probability is a degree that an event occurs at, which is updated when new information becomes available.

Three crucial components of the Bayesian approach are:

- **The Prior**
  Prior to observing the data, the Bayesian approach enables us to specify a belief (a minimum or maximum impact that could realistically be expected from a certain channel or campaign) about the distribution of the parameters, such as the media effects. This prior belief can be based on knowledge from experiments, other models, and/or analyses carried out in the past.

- **The Data**
  The observed data is used as evidence to update the prior beliefs. The more data is observed, the stronger the evidence will be.

- **The Posterior**
  Updating the prior beliefs with evidence in the data will result in a final belief. This final belief is called the posterior. The mean or median of the distribution is typically used as an indicator of the estimated effect, and the shape of the distribution represents the level of uncertainty in our final belief.



Bayesian estimation can provide reliable results when little data is available.
Bayesian methods outperform the frequentist approach with just a small amount of data. Less data just means less evidence will be found in the data and will result in a smaller deviation of the posterior from the prior beliefs.

Also, the inclusion of a prior has the advantage that marketers can **get a grip on final results and correct unreliable outcomes**. For example, channels that are consistently heavily underestimated by models can be corrected by increasing the prior. One could argue that this allows marketers to manipulate their analyses and steer the outcomes in a certain way, and that a prior belief is subjective. Although this is true, it is at least transparent and shows how final estimates are obtained.

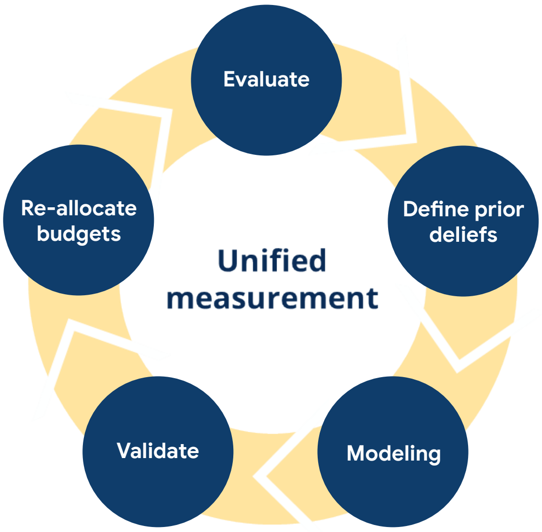
Best Practices of Unified Measurement

At the heart of your unified framework you need a clear and common goal, upon which you can build an advanced modeling layer and develop a flexible, adaptive, and continuous learning framework

In this section, we will provide some best practices that we defined from applying unified measurement in practice.

Setting a clear goal is essential for the success of marketing measurement within organizations. It is important to create a common and transparent understanding of which KPI should be used for media optimization and what the media steering hierarchy should look like. Different measurement methodologies can use different KPIs. The MMM team uses net sales from the CRM system, for example, and the MTA team uses gross sales from the engagement platform. When blending these techniques, it is important to decide which of these KPIs should be used for the final budget decisions.

Continuous Learning is crucial for any measurement approach to stay on top of the game. When new and valuable information becomes available, the measurement framework should be adaptive and flexible enough to include this information. We therefore aim for a structural setup: a continuous learning game. In practice, marketers often focus on short-term model improvements. Many fail to focus on a structural setup in which existing methods are continuously challenged, improved, and/or adapted according to changing business dynamics and needs. The Bayesian setup can easily and effectively include new conditions and information.



A continuous feedback loop in which the unified measurement framework is constantly kept accurate, up to date, and relevant can be found in the figure below:

- **Define prior beliefs**
  Prior beliefs about media effectiveness can be based on many different types of information such as experiments, analyses, experience, or outputs of other measurement methodologies. This belief can also be based on results of unified measurement from the (near) past, possibly in combination with several experiments that have been performed recently.

- **Modeling**
  The prior beliefs will be updated with the data that has been observed, resulting in a posterior estimation of the media effects. In-depth insights are obtained by keeping as much granularity in data and modeling techniques as possible.

- **Validate**
  Validate the modeling results with stakeholders and challenge if they are reliable. Be aware to include changed business dynamics and events, for example, Black Friday, to effectively measure the marginal effects of media efforts.

- **Reallocate budgets**
  Based on the modeling outcomes, we accurately and effectively reallocate budgets over all channels, resulting in a significant increase in sales.

- **Evaluate**
  Evaluation of unified measurement will potentially offer new learnings and ideas to further improve the current measurement setup. Moreover, the outcomes can be used as a basis for new prior beliefs or might suggest some cases that need to be validated by experiments.

Advantages of Unified Marketing Measurement

Combining the strengths of individual methodologies without loss of information and granularity leads to highly advanced marketing measurement. Some of the advantages of unified marketing measurement include:

Accurate
Precise measurement of the effectiveness of marketing efforts and other factors that affect KPIs such as sales, leading to improved budget allocations and increased revenues.

Feedback loop
Existing knowledge, serving as a reservoir of knowledge, can be updated when new data becomes available. Outcomes can be used again as input for future models.

Holistic
Measure marketing effectiveness over all available channels, including cross-effects between upper and lower funnel channels. Include non-marketing factors.

Reliable
Bayesian statistics allows marketers to get a grip on unreliable results and correct them during the modeling process to obtain reliable and accurate results.

Flexible
Handle and incorporate data with different levels of granularity from various sources.

Granular
Combine data from many different sources on the deepest level, without losing valuable information.

A Case Study: Blending MMM and MTA

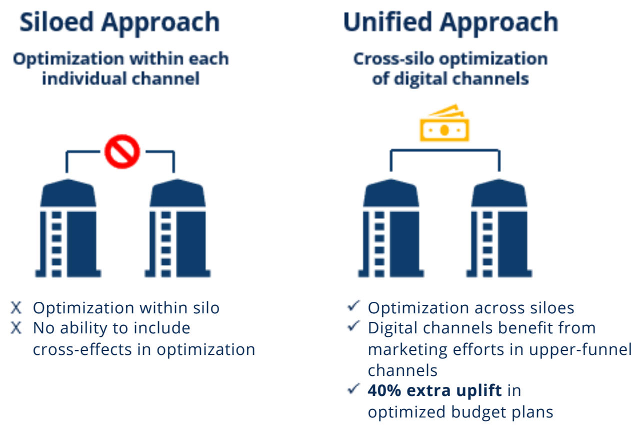
In this case study, we calculated that our UMM results in more accurate budget decisions when compared to multi-touch attribution, leading to a 40% increase in expected uplift

This case study provides a calculated proof of the added value of blending methodologies. This study was performed with a leading Dutch e-commerce retailer. This company worked with separate MTA, MMM, and experiment methodologies. They then applied corrections to the results to blend insights from the three methodologies. After shifting to UMM, they broke the silos by blending methodologies at a technical level into one unified framework.

When comparing the outcomes of both measurement methodologies, we will compare the expected uplift. This is interpreted as the expected amount of additional sales resulting from proposed budget allocation decisions driven by a model.

The Case Study

Before working with a unified model, the measurement and budget decisions were made using a siloed approach where the performance and branding departments had their own measurement solutions. The online department worked with an MTA model measuring their online investments towards online performance. The brand department was more focused on reaching the right audiences while measuring sales impact with MMM models.



Case Study Results

Implementation of the unified framework enabled the online department to measure the effects of marketing efforts in upper-funnel channels (such as radio and TV) on their owned channels (such as organic and direct). As upper-funnel channels are branding-heavy, they could now measure how much every euro spent on branding campaigns yielded in their owned channels, which helped them find a balance between branding and performance. At the moment of writing, the online department found their performance and owned channels were saturated, resulting in lower effectiveness of spend.

The unified framework revealed that the performance KPIs in their own channels would benefit from investments higher up in the funnel, in channels such as TV, radio, and YouTube.

It is possible to distinguish three interaction effects: with branded lower-funnel channels, non-branded lower-funnel channels and upper-funnel channels. The chance a consumer sees an ad in one of these channels remains the same. We are looking at whether the chance of a consumer converting via one of these other channels after seeing a TV, radio, or social media ad increases.

	TV	Radio	Social Media
Branded Lower Funnel	●●●●	●●	●●●
Non-Branded Lower Funnel	●●●●●●	●●●	●●●
Upper Funnel	●●●	●●	●●

The dots represent the magnitude of the interaction effects between TV, radio, and social media, and both lower-funnel and upper-funnel media

Branded lower-funnel channels include branded Paid Search, organic Search, and direct. The interaction effect between TV and these channels is quite strong. People might search for the specific brand after seeing a commercial. This interaction occurs less strongly with social media and to an even lesser extent with radio.

We see the strongest interaction effect between TV and non-branded lower-funnel channels. These include non-branded Paid Search, affiliate, and referral channels. Consumers may have been looking for a specific product, but not specifically looking for the brand.

The weakest interaction effects occur with upper-funnel channels such as display.

As a result, the unified model suggested shifting approximately 9% of the performance budget to upper-funnel channels. The budget shift was expected to result in an additional sales uplift of 40%. The upper-funnel channels can thus be used to create more potential in the lower-funnel channels.

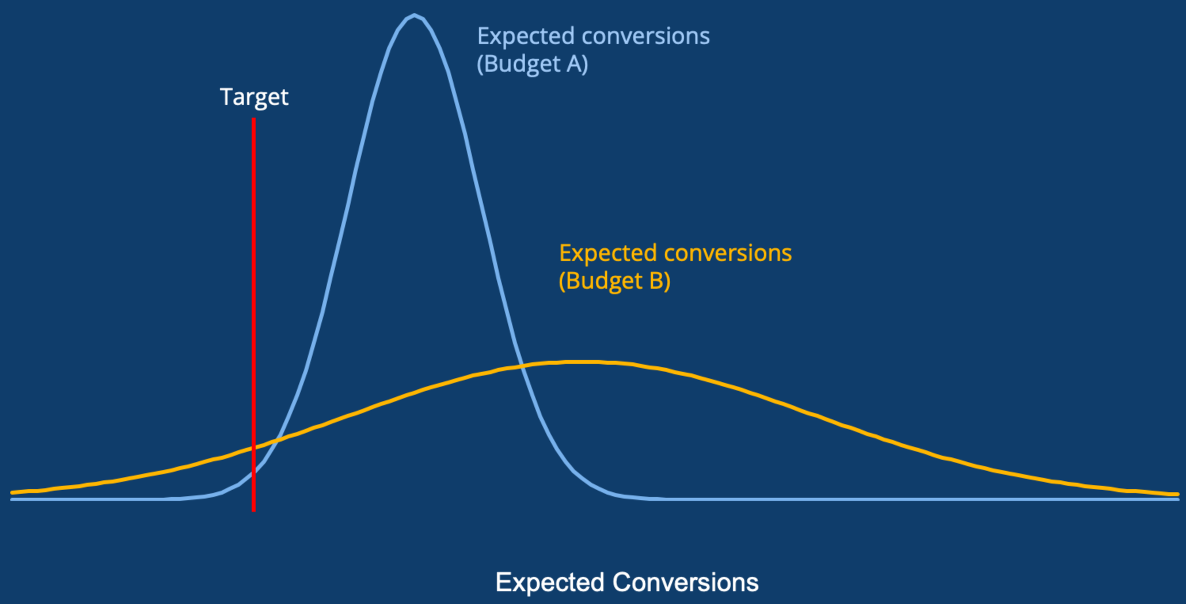
As the framework is also granular, channel marketers can determine how to be more efficient within the performance channels. Some campaigns may be over-invested, but some still have potential. Channel marketers can shift budgets across campaigns, while taking into account cross effects with other channels, external factors, and seasonality.

Note that this captures a single moment in time. It is unlikely that all campaigns in the lower funnel are permanently saturated. The unified framework allows you to compare campaign performance over time while constantly adapting your media investments.

Deep Dive

Working with probability distributions and expected uplift

The Bayesian methodology considers the estimations to be probability-density functions. To compare models, we can look at the unified expected uplift as a distribution, and the MTA expected uplift is expressed as a single number. See the figure below for an intuitive graphical representation:



Our case study results show the expected uplift of following unified budget allocations is 1.4 X higher than when following MTA budget allocations. With a probability of 50%, unified measurement will result in an uplift that is expected to be at least 40% higher than the expected uplift of the MTA model.

Taking a deeper look at the expected uplift distribution, budget allocations from unified measurement outperform suggestions based on the MTA model with a probability of 74.8%. We even find that there is a 25% chance that its uplift is 80% higher, and a 16% chance that the uplift is at least twice as big.

The distribution functions of expected sales have another major advantage: they enable marketers to make more informed decisions. By taking the probabilities into account, they can base their budget allocation on the shape of the distribution. Fat-tailed distributions show higher uncertainty in their forecasts than light-tailed distributions. For example:

A marketing manager might find the probability of reaching their sales target with a given budget is 70%. That probability might increase to 93% if the budget is spent on channels and campaigns with higher certainty (and less volatility). This enables the manager to weigh the extra budget against the higher probability of reaching their target.

They can now make informed decisions about whether they prefer a budget allocation that, on average, results in lower expected sales but has a higher probability of reaching those sales. An intuitive illustration can be found in the figure below where Budget B is (on average) expected to result in more sales. However, Budget A is more likely to reach this target as it is narrow.

Conclusion

To summarize, a unified marketing measurement framework aims to maximize the use of available data sources and address the shortcomings of isolated measurement methodologies.

By blending MMM, MTA, and experiments at a technical level, the unified framework is holistic and flexible. It can handle data from various sources and thereby measure marketing effectiveness over all available channels, including non-marketing factors, without sacrificing granularity.

Bayesian estimation within this framework has drastically changed the measurement game. It is much more reliable than common effectiveness techniques when little data is available and provides a feedback loop in which outcomes can be used again as input for future models.

It is possible to achieve a significantly higher increase in sales following budget recommendations from unified measurement, in comparison to isolated MTA or MMM plans. Moreover, marketers can take the probabilities of achieving a certain uplift into account and make more informed decisions about following up on recommendations.

And one final thought: always approach marketing measurement as a journey. Measurement constantly changes, your business dynamics change, and the media landscape is constantly evolving, which means that you must continuously develop and adapt your models. The perfect model doesn't exist.

About the Authors

Arno Witte, Senior VP Data Science
Arno has a background in econometrics and consulting and has a thorough understanding of marketing measurement. He plays a leading role in developing innovative marketing measurement models, keeping a close eye on market developments and adapting our approach to keep our models ‘best in class’. Arno also teaches guest lectures at Emerce, the University of Amsterdam and Erasmus University Rotterdam.

Marc Baardman, Lead Data Scientist
Marc has a deep knowledge of Bayesian statistics stemming from his study in econometrics and his work as a consultant in the data science field. Within Objective Platform, he is responsible for the implementation of many clients from a data and modeling perspective, and has extensive understanding of the best practices within marketing measurement.

Willem van der Weide, Co-Founder
With an extensive background in the media landscape, Willem is passionate in all new developments and innovations in the field of media. After having experiencing major disruptions in the landscape from conventional to digital media consumption, mobile, and data analytics, Willem decided to found Objective Platform to offer transparency and data-driven decision making in the media landscape.

If you want to discuss this report, please contact us at:
willem.vanderweide@objectiveplatform.com

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Head Office
Kabelweg 57
1014 BA Amsterdam

UK Office
123 Buckingham Palace Road
London SW1W9SH

Singapore Office
30 Bukit Pasoh Road
Singapore 089844

info@objectiveplatform.com