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ABSTRACT

The implementation of the General Data Protection Regulation (GDPR) has posed significant challenges to the digital ad measurement industry, necessitating a shift away from traditional tracking methods such as web beacons, cookies, and browser fingerprinting. With the discontinuation of third-party cookies and increased privacy standards, marketers face obstacles in optimizing ad spending and Attribution models. This paper explores the impact of GDPR on the Ad tech industry and anticipates challenges in adapting to a cookie-less and more regulated data environment.

In the wake of iOS updates and App Tracking Transparency (ATT), Direct-to-Consumer (D2C) companies have witnessed shifts in Ad spending across different channels. The study investigates three main measurement models: Media Mix Modelling (MMM), Multi-Touch Attribution (MTA), and Incrementality for D2C marketers post-GDPR, highlighting Incrementality as the most effective method for analyzing Ad impact and optimizing spending. The key contributions include a proposed triangulation framework that combines data from MMM, MTA, and Incrementality to support a data-driven approach, offering insights for tactical and strategic decision-making. To validate the proposed framework, a mixed-methods approach involving qualitative and quantitative surveys is designed. Targeting experienced advertising professionals, the survey evaluates the implementation of MMM and Incrementality, assessing decision-making attributes such as ease-of-use, accuracy, validation, Robustness, predictiveness etc of measurement models. Results align with existing literature and the proposed framework, demonstrating the efficiency of each technique. The paper recommends the utilization of the Incrementality Randomized Control Trial (RCT) method, providing a road-map for further research in this evolving landscape.

Keywords: ***Marketing Attribution, Incrementality, Multi-touch Attribution, Media Mix modelling***

1. INTRODUCTION

Following the implementation of General Data Protection Regulation (GDPR), the media measurement industry encountered significant challenges due to the constraints on data sharing and heightened privacy standards Rammos and Harttrumpf, 2022 Goldberg *et al.*, 2019. The digital marketing landscape heavily relied on web beacons, tracking pixels, browser fingerprinting and cookies to track user activity and enable marketing attribution models. However, this paradigm is shifting due to changes such as the abandonment of third party cookies by some browsers and upcoming measures like Chrome's discontinuation of cookies by the end of 2024 Cinar and Ateş, 2022; Goel, 2021. With the iOS 14.5 release, apps now require user consent for tracking, further diminishing user-level data availability and impacting ad targeting precision and performance tracking, known as App Tracking Transparency (ATT) O'Flaherty, 2021. Researchers and practitioners are analysing the GDPR's impact on the ad tech industry Cinar and Ateş, 2022; Goldberg *et al.*, 2019; Rammos and Harttrumpf, 2022 and predicting challenges in adapting to a cookie-less and more regulated data environment. First-party data, previously held by major companies, is becoming more crucial as third-party cookie data diminishes, but there are still limitations in tracking the entire customer journey at a granular level necessary for attribution models O'Brien *et al.*, 2022.

First-party trackers represent direct user interactions with websites or applications, are gaining prominence amidst growing concerns over customer privacy Jerath, 2022. Many medium-sized brands are enhancing control by collecting first-party data through in-house data management via pixels on all owned media points, rather than relying solely on platform analytics Cinar and Ateş, 2022. However, challenges persist in tracking the complete customer journey, as evidenced by reduced data collection post-GDPR, hindering online businesses' ability to optimize marketing spending through attribution models Goldberg *et al.*, 2019. This paper will explore alternative attribution approaches, given the limitations of traditional models, to aid performance marketers in optimizing ad spending across multiple channels. Additionally, it will underscore the importance of existing models in meeting decision-making criteria through surveying industry practitioners.

Direct-to-Consumer (D2C) companies are those that bypass intermediaries like retailers or wholesalers, opting to sell their products directly to consumers through channels such as online platforms, social media, or company-owned stores. They rely on digital marketing, e-commerce platforms, and innovative branding to establish direct connections with customers. According to a report by emarketer Feger, 2022, D2C e-commerce sales in the United States are projected to experience double-digit growth, reaching nearly USD 213 billion by 2024, constituting 16.6 percent of all e-commerce sales as shown in the below figure 1.

Following iOS updates, D2C customers have increased spending on Google and offline channels while reducing spending on Facebook, significantly impacting both the e-commerce and D2C industries. In 2021, D2C e-commerce sales were valued at USD 129.31 billion, with a growth rate of 15.9 %, and this trend is expected to continue as more e-commerce brands adopt the D2C model. With the evolving media landscape, performance marketers who heavily relied on conversion attribution must now adapt their strategies to drive profitable and incremental growth. The central question facing D2C marketers is how to best achieve this goal in light of changing market dynamics.

The study explores and investigates three main measurement models (MMM, MTA, and Incrementality) for DTC marketers in the post-GDPR world, offering key insights for guiding ad performance measurement activities. Notably, Incrementality proves to be the most effective way to analyze ad impact and optimize ad spending.The key contribution of the paper can be summarised as follows:

1. A triangulation framework is proposed to overcome the inherent challenges posed by existing methods. This technique combines a benchmark dataset (LTA), covers aggregated data sets (MMM), and suggests validation using Randomized Control Trials (RCT - Incrementality). It aids ad marketers in both tactical and strategic decision-making.

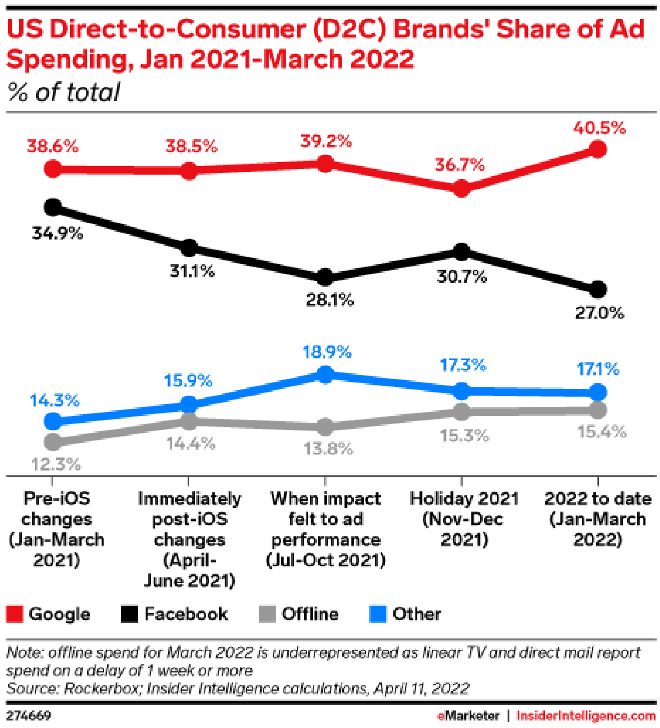

Figure 1 D2C Ad spending shifting pre and post iOS Feger, 2022

2. To validate the argument, a mixed approach of qualitative and quantitative survey questionnaires is designed. Targeting highly experienced advertising professionals, the survey evaluates ease of use, challenges, and the advantages and disadvantages of different models. Results align with existing literature and the proposed framework, demonstrating the efficiency of each technique.

3. Extensive analysis of collected data recommends the utilization of the Incrementality RCT Method. Challenges and opportunities drawn from this analysis provide a road-map for other research to build on this study.

Paper is organised as follows: Section 2 presents the background and discuses the related works. Section 3 evolution of media measurements post GDPR. Section 4.0 Methodology and Section 5.0 Results

2. Background and Related Works

The popular Advertisement experiment studies can be summarised as shown in Table 1 Rigorous causal inferences can be obtained through randomised experiments, which are often conducted through Geo experiments Kohavi *et al.*, 2020; Lewis *et al.*, 2011; Vaver and Koehler, 2011, Ghost Ads G. A. Johnson *et al.*, 2017 and A/B Testing Barajas *et al.*, 2016. Among many RCT based experiment, numerous studies contributed significantly in relation to Ad measurement through incrementality field experiments utilising RCTs Barajas *et al.*, 2016; Blake *et al.*, 2015; G. A. Johnson, 2023; Kerman *et al.*, 2017; Lewis and Reiley, 2008; Sahni, 2016).

Geo-based linear regression models, as proposed by Vaver and Koehler, 2011 can calculate the incremental Return on Ad Spend (iROAS) by assessing the additional impact of advertising within specific geographic regions. Geo-based linear regression models for incremental ROAS analysis enable businesses to assess the localized impact of advertising efforts, allowing for more targeted and efficient allocation of resources across different geographical area. These experiments require high number of Geos to gain statistical power which is not possible in the industry as the Geos are matched and paired in the current Geo-based market tests Brodersen *et al.*, 2015 Bayesian structural Time series-based analysis methodology called Causal can be applied with limited number of Geos to test. Their paper proposes to infer causal impact on the basis of a diffusion-regression state-space model that predicts the counter- factual market response in a synthetic control that would have occurred had no intervention taken place.

Time based Regression (TBR) developed by Kerman *et al.*, 2017 is widely adopted in the industry.TBR is flexible as it is applicable for analyzing experiments with a very low number of Geos (two or more), such as those arising from experiments in smaller national markets, and matched market studies.

Another popular matched-market test is adopted in the industry by Barajas *et al.*, 2020; Gordon *et al.*, 2019the Geos are carefully selected and paired instead of randomised assignment of matching of Geos to test and control group. These tests are popular as they are in expensive and commercially viable as they use small subset of city(Geos) matched although they may not provide the same level of accuracy against any hidden biases as a randomised trial tests. G. A. Johnson, 2023 highlights recent developments and builds on an earlier research primarily addressing the challenges, best practices, and new developments on online display ads experiments. G. Johnson and Lewis, 2015 term this notion Cost per Incremental Action (CPIA), which practitioners are beginning to adopt. The authors argue that CPIA as a pay model solves many incentive problems in the ad industry, in addition to optimizing for the advertiser's desired metric.

Gordon *et al.*, 2021 provides guide to measure Display Ads effectiveness with the focus on challenges such as low statistical power, treatment decisions guided by algorithms and marketplaces, identity fragmentation, and incrementality optimisation. Also discusses two broad solutions to improve inference from Geo based experiments (1st -pretest outcome data to identify baseline differences across diff-difference Blake *et al.*, 2015 or synthetic approaches (Brodersen *et al.*, 2015 – 2nd apply block randomisation by grouping similar regions using past outcomes or regional characteristics (match market tests pair regions together) Kerman *et al.*, 2017; Vaver and Koehler, 2011 discuss design considerations for Geo-based experiments how to narrowly to define regions, test and pretest period lengths and ad spending differences across groups Geo experiments can be applied to measure a variety of user behaviour and can be used with any advertising medium that allows for Geo-targeted advertising. In the United States,one possible set of Geos is the 210 DMAs (Designated Market Areas) 2023, which is broadly used as a Geo-targeting unit by many advertising platforms. Google's DMA (designated market area) is used by researchers for various ad effectiveness not only on display ads, for example Blake *et al.*, 2015 used it for paid search effectiveness.Gupta and Chokshi, 2020 introduce incremental lift as a metric to measure the impact of a marketing strategy. They Use Viewability Lift method for digital marketing strategy planning and campaign optimizations leading to improved campaign efficiency.

3. Evolution of Media Measurement Post GDPR (PGDPR)

These are key areas that have significantly influenced the marketing attribution and media measurement sector in light of data privacy regulations. We discuss these topics and not just the attribution models as these aspects are interwoven and would not be justified to explain without highlighting the relevant data issues.

- **Fragmented Data Sources:** GDPR has led to limitations in data sharing between multiple ad exchanges and platforms. This fragmentation creates siloed data, making it challenging to gather a comprehensive view of consumer behaviour across various channels. There is no Single Source of Truth Data (SSOTD) for identifying the effectiveness of campaign at channel or tactic level.

- **Reduced Granularity:** Restrictions on tracking and collecting user-level data, especially without explicit consent, have reduced the granularity of available data. Marketers and advertisers have less access to detailed user information, affecting their ability to track and target specific audiences effectively. Without the third party cookie tracking soon by Google for example, advertisers will have challenges to target repeat visitors could not be tracked, as the identities of these users will no longer be unique hence the distinction between what constitutes 'unique visitor' and what doesn't will become challenging, leading to a decreased understanding of user uniqueness. The traditional method of reporting impressions will continue, but at a more aggregated level, lacking the detailed insights marketers prefer. Moreover, advertisers will face limitations in attributing user actions, such as clicks and purchases on other sites, resulting in potential challenges in measuring and attributing return on investment Stapleton, 2022

- **Attribution Challenges**: First-party data struggles with limited cross-channel visibility and potential inaccuracies, as siloed information and data quality issues hinder a comprehensive understanding of the customer journey. The user privacy concerns and regulatory limitations on data collection further impact the granularity of available information as there were several content intermediaries. On the other hand, third-party data faces challenges related to reliability, accuracy, and compliance with data privacy regulations. Inaccurate or outdated external data can lead to flawed attribution models, and difficulties in cross-device tracking may introduce gaps in understanding user behavior. Integrating third-party data seamlessly with first-party data also poses challenges, affecting the overall accuracy and effectiveness of attribution models. Addressing these challenges requires a focus on data quality, privacy compliance, integration, and adapting to the evolving landscape of user behavior and regulationsStapleton, 2022. More importantly how can the current existing models (MTA, LTA or MMM, Incrementality) can adopt and support marketers measure ad effectiveness at campaign level and take decisions to optimise ad spending.

- **Impact on Analytics and Insights**: The ability to derive meaningful analytics and insights from fragmented and limited data is hampered. Marketers struggle to gain a holistic understanding of campaign performance and audience behaviour. For example the Media Mix Models (platform) is able support to provide overall channel performance whereas performance marketers require more granular support for tactic level decision making at the campaign level.

- **Compliance and Transparency**: Ad exchanges, Ad revenue models and measurement platforms have had to adapt to GDPR regulations by ensuring compliance and transparency in data collection and usage. This compliance effort can sometimes create barriers in seamless data sharing. Numerous Ad buyers are hesitant to take risks with data-intensive audience targeting methodologies. Instead, the prospect of employing contextual targeting has recently gained momentum due to its perceived enhanced safety and attractiveness. In this approach, advertisements are tailored to individuals based on the contextual content of the web page they are currently viewingDavies, 2018.Ad exchanges may face limitations in enriching their targeting capabilities, leading to a potential decrease in the effectiveness of ad

Table 1 Summary of online Advertising Randomised Control Experiments

Experiment Type	Description	Reference(s)	Pros	Cons
Randomized Controlled Trials (RCTs)	Utilizes randomization to assign participants or regions to experimental and control groups, enabling rigorous causal inferences.	Barajas *et al.*, 2016; Blake *et al.*, 2015; G. A. Johnson, 2023; Kerman *et al.*, 2017; Lewis and Reiley, 2008; Sahni, 2016	- Establishes causal relationships - Allows for precise control over variables	- Can be costly and time-consuming to conduct - Ethical concerns regarding randomization and control group assignment
Geo Experiments	Conducted using geographic regions to assess the additional impact of advertising; often involves Geo-based linear regression models or Bayesian structural time series analysis.	Brodersen *et al.*, 2015; Vaver and Koehler, 2011	- Enables localized impact assessment - Utilizes existing geographic data - Can be applied across various mediums	- Requires high number of regions for statistical power - May overlook regional differences not captured by geographic data
Ghost Ads	Involves the creation of ”ghost” ads to measure the effectiveness of advertising efforts; commonly used in online display ad experiments.	G. A. Johnson *et al.*, 2017	- Provides insight into ad performance - Allows for controlled experimentation	- Can be resource-intensive to implement and manage - May encounter ethical concerns regarding deceptive practices
A/B Testing	Compares two versions of a webpage or app against each other to determine which one performs better; widely used in digital marketing for testing ad creatives and landing pages.	Barajas *et al.*, 2016	- Provides direct comparison between variations - Simple and easy to implement	- Results may be influenced by external factors - Limited to comparing only two variations
Time-Based Regression (TBR)	Employs regression analysis over time to assess the impact of advertising; suitable for experiments with a minimal number of geographic regions.	Kerman *et al.*, 2017	- Flexible and applicable for experiments with few regions - Captures temporal trends	- May not capture localized effects as effectively as Geo experiments - Relies on accurate time-series data
Matched-Market Tests	Involves careful selection and pairing of geographic regions instead of random assignment; cost-effective but may lack the accuracy of randomized trials.	Barajas *et al.*, 2020; Gordon *et al.*, 2019	- Cost-effective and commercially viable - Allows for comparisons between similar regions	- May introduce bias in region selection and pairing - Results may not be as robust as those from randomized trials

campaign.AD revenue models has a significant impact on cross-site tracking without third party cookie tracking, which is fundamental to CPC (Cost-Per-Click) and CPA (Cost-Per-Action) models. Advertisers using these models need to adapt by exploring alternative attribution approach, relying on first-party data, and embracing contextual targeting strategies for example Retargeting revenue. While CPM (cost per Thousand impressions) is less directly affected, advertisers may still need to adjust their targeting and measurement approaches in a cookie-less environment Stapleton, 2022.

- **Innovation and Technology**: GDPR has pushed the industry to innovate in privacy-centric measurement technologies. Companies are exploring new methods like federated learning or differential privacy to derive insights while adhering to privacy regulations.Cookieless analytics are alternative to web analytics explored by marketers example Piwik PRO, Matomo Analytics.

- **Shift in Strategies**: Marketers have had to shift strategies toward more contextual and less personalized advertising to comply with privacy regulations. This shift impacts targeting and personalized ad delivery especially for e commerce business and D2C Direct-to-Customer.

3.1. Resurgence of Media Mix Modelling Post GDPR /iOS

Media-Mix modelling (MMM) has been in several forms from the 1960's and has evolved regularly as and when a new types of consumer data was available with the advancement in the tracking technology (Borden, 1964 Leeflang *et al.*, 2013. MMM is statistical models used by advertisers to measure the effectiveness of their advertising spendBorden, 1964. Several researchers have examined the challenges and opportunities Chan and Perry, 2017; Wedel and Kannan, 2016 with Media-Mix models. The challenges listed below need to be re-examined in light of the latest developments following GDPR.

- **Limited Range of Data available and data aggregation issues** - MMM models rely on historical data to identify patterns and relationships between marketing activities and business outcomes. With a reduced dataset, there's a risk of decreased model performance and less precise estimations of marketing effectiveness. The common forms of data available for MMM modeling has deteriorated post GDPR world whether it is response data, media metrics, marketing metrics or control factors such as seasonality which calls for deeper examination of recent challenges and opportunities.

- **Selection Bias of correlated input variable data** - GDPR emphasizes the need for user consent and transparency in data processing. This can result in selection bias, where the available data may not represent the entire target audience due to consent issues or opt-outs. Advertisers often allocate their spend across Ad channels in a correlated way in a multichannel ad environment. Additionally the platform built MMM models does not have access to competitors dataset

- **Model selection process** - The model selection process becomes critical post-GDPR as advertisers need to choose methods that prioritize data privacy while still providing meaningful insights. The challenge lies in finding models that strike the right balance between accuracy and privacy compliance. Choosing inappropriate models may lead to unintended privacy breaches or inaccurate results especially depending on platform MMM results such as Lightweight (Google) and Robyn (Meta).

MMM model in general requires 3-4 parameters for each channel to evaluate the diminishing returns and optimisation of media budget and minimum number of 7-10 data points per parameter for a stable linear regression which is sparse to find in the industry setting Chan and Perry, 2017 In-spite of all these challenges, the resurgence of MMM in the attribution industry is a response to the evolving marketing ecosystem, where the need for a comprehensive, cross-channel understanding of marketing effectiveness has become crucial for businesses aiming to optimize their marketing spend and strategies. Increasing privacy regulations and limitations in user-level data tracking have made it challenging for MTA (Multi Touch or Last Touch) attribution models to function effectively. MMM, with its focus on aggregated data analysis, is less reliant on individual user level data, making it a viable option in the changing privacy landscape. MMM offers a holistic approach, considering both online and offline channels, to provide a comprehensive view of marketing impact. MMM allows for the integration of traditional advertising mediums, such as TV, radio, and print, with digital channels like online ads and social media. This integration is crucial as brands seek to understand the synergies and interactions between different media types in influencing consumer behavior. Additionally, the availability of extensive datasets and advancements in analytics tools has facilitated more sophisticated MMM techniques,improvements in statistical methodologies, machine learning techniques, and modeling approaches have enhanced the accuracy and applicability of MMM across various industries, making it a valuable tool in contemporary marketing strategies.

3.2. Multi Touch Attribution or Conversion Attribution (Bottom-up approaches))

Post 2005, heuristic models (LTA – Last Touch Attribution model) were first implemented by Google, which opened a new way of calculating Return on Ad spending (ROAS) for online marketing channels. The platform report LTA is widely agreed that is highly biased for either overestimating or under-reporting the tactics/channels directly responsible for sales Lee, 2010 Gordon *et al.*, 2019. However, LTA is still extensively utilized as a benchmark tool despite further depreciation of user level data, because without it there would be no Platform reports for online advertiser's tangible to improve/optimize media spending. In Figure 2, 69.2% respondents of 51 total survey reported they do not believe Last Touch Attribution adequately captures the impact of your marketing efforts and 26% respondents said they partially agree LTA adequately capture the impact and only 4.6% believe LTA adequately captures the impact of marketing efforts in practice.

Self-attributed conversions refer to the actions or conversions that platforms attribute to themselves based on their own tracking mechanisms.This includes MMP (Mobile Measurement Partner) attribution refers to the process of attributing mobile app installs, user actions, or conversions to specific marketing efforts or campaigns. MMPs are third-party platforms or services that help mobile app developers or advertisers track and attribute the source of app installs or in-app actions to various marketing channels or campaigns. For instance, if a user clicks on an ad on Facebook, then later sees the same product in a Google Ad and makes a purchase, both Facebook and Google might claim credit for the conversion. Self-attributed conversions are the conversions that platforms claim based on their own tracking data, often using different attribution models (like Last Click LTA attribution or multi-touch attribution) to determine which touchpoint gets the credit for the conversion.These metrics can be valuable for the platform to showcase the effectiveness of their advertising services. However, discrepancies can arise when different platforms claim credit for the same conversion, leading to challenges in accurately measuring the true impact of each marketing channel.

MTA popular methods are explained in table 2 by Zaremba *et al.*, 2020

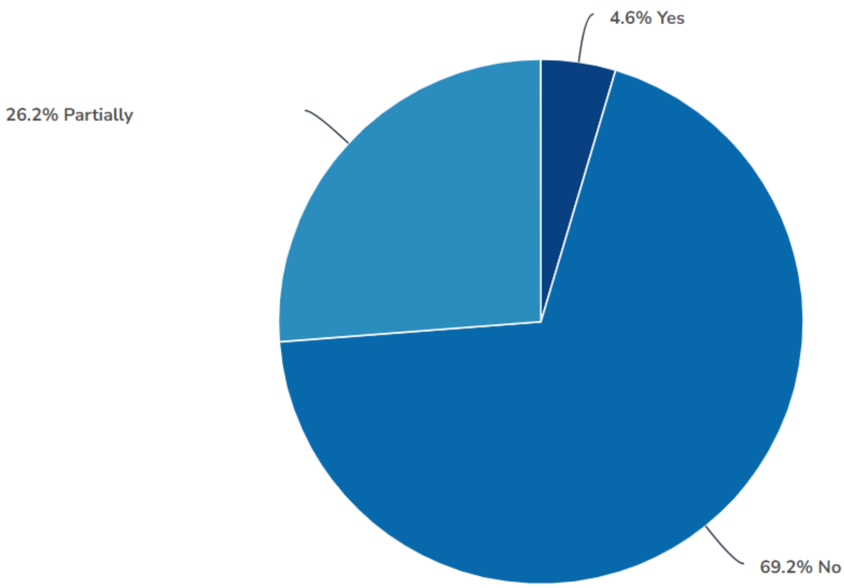

Figure 2 The response for "Does Last Touch Attribution adequately captures the impact of your marketing efforts?"

3.3. Incrementality experiments post GDPR

Running randomized experiments (or Incrementality experiments) is becoming the standard approach to measuring the marginal effectiveness of online campaigns Chittilappilly, 2012; G. A. Johnson *et al.*, 2017. These controlled experiments have gained popularity post GDPR world because they work as validation tool for attribution methods in examining the lifted conversions for platform attribution, MMP report or platform reporting (Google Analytics). The incrementality methods supports in measuring the true impact of marketing efforts, specifically understanding whether a particular marketing channel is genuinely responsible for driving additional sales or conversions. By isolating the difference in behaviour between exposed and unexposed groups, these methods avoid attribution errors seen in traditional models, providing clear insights into the real incremental lift generated by marketing activities and does not depend on user-level data which is depreciating post GDPR. This understanding enables businesses to optimize marketing budgets more effectively, allocating resources to channels that has causal impact than merely coinciding with correlation conversions. While incrementality controlled techniques offer a more accurate understanding of the real impact of marketing activities, implementing them can be complex. The Internet reduced the cost of experimentation, which contributed to the growth of field experiments in the marketing literature however it is still not feasible to run experiments to every single tactic/channel in a multi channel environment. Simester, 2017 recommend various combination in order to compliment field experiments a) a process of looking into explanations to combine a consumer survey with a field experiment.b) Compliment a single experiment with a large number of experimental treatments. In the next section we propose triangulation approach which is more effective way to meet the marketers in industry setting.

Marketing Mix Modelling and Incrementality controlled experiments combined with Attribution (LTA) tracking provides the entropy required to make effective advertisement investment decisions. Implementing controlled incrementality results into MMM and MTA requires a systematic triangulation approach, combining data analysis, model adjustment, validation, and ongoing optimization to derive meaningful and actionable insights for improved marketing decision-making. Triangulation in the context of incrementality refers to the process of using multiple methods or approaches to measure the incremental impact of a marketing campaign accurately. When determining the effectiveness or incremental lift generated by a campaign, triangulation involves employing different measurement techniques or methodologies to cross-validate and corroborate the findings. The results reported by platform LTA/ (Last Touch Attribution) attribution models is cross validated with MMM and incrementality testing (Lift + Inc RCT) results. Repetitive tests/experiments are run to calibrate the 'multiplier' (common denominator) to find true Ad effectiveness primarily for Return on Ad spending (ROAS)Runge *et al.*, 2023 In the endeavor to tackle the existing depleting user-level dis aggregated third party data and attribution challenges, triangulation approach is adopted as there are inter dependencies in the main 3 models. Some of the other main reasons for raise of triangulation approach from the decision-making perspective in the industry setting are

1. **Measuring Causal Impact**: MMM attributes conversions or outcomes to different marketing channels based on observed correlations. Incrementality testing, on the other hand, helps measure the actual causal impact of specific marketing activities by isolating the effects of those activities through controlled experiments.Advertising's causal impact is referred to as "incrementality." G. Johnson and Lewis, 2015. The actions that would not have occurred if the ads had not been displayed are referred to as the incremental actions caused by advertising. Rigorous causal inferences can be obtained through randomised experiments, which are often implemented in the form of Geo experiments Vaver and Koehler, 2011. The common Randomised experiment challenges pre GDPR /iOS 14 were– lost opportunity cost,

Table 2 MTA Popular methods

Model	General Rules
Last Click and First Click	The overall effect on the conversion is attributed to the last activity (source) or the first activity on the path
Last Non-direct click	The overall effect on the conversion is attributed to the recent activity on a path that was not a direct access to a website.
Logistic Regression	The effect on the conversion is studied on the basis of logistic regression based, in turn, on the decomposition of all conversion paths and the binary assignment of the presence or absence of the channel on the path.
Linear	The impact on the conversion is assigned proportionally to each activity on the path.
Position-Based	The effect on the conversion is assigned depending on the position of the activity on the path; ex- Google Analytics assigns a default of 40% of the impact to the first and last source, and the remaining 20% is divided proportionally between other activities.
Customised weights	The effect on the conversion is assigned arbitrarily and subjectively to each source (most frequently on the basis of a previous more advanced analysis)
Markov Chain	The effect of sources on the conversion is determined on the basis of an analysis of the incremental impact of the entire source in the population. Based on all conversion paths, chains are created with the probability of user migration between individual sources assigned. During the analysis, individual sources are removed from the calculation area and probability flows are examined in chains without an excluded source. The resulting difference is an incremental impact that illustrates the real impact of a given source on the final conversion.
Shapley Value	The game theory approach and the Shapley value method are a measure of a channel average marginal contribution to each channel set (coalition, which is a unique path to the purchase scheme). The marginal contribution of a particular channel is an average difference between conversion results of channel sets (coalition) with and without a particular channel.

infeasible to run experiments on all the channels however these experiments are vital post GDPR with worsened data availability and inaccuracy with platform models. Advertisers rely on incrementality results to make tactical decisions about their marketing spend, and adherence to these decision-making criteria enhances the reliability and practicality of the findings.

2. **Validation of Correlation vs. Causation**: MMM relies on historical data and correlations between marketing activities and outcomes. Incrementality online controlled experiments validates whether these observed correlations are indeed due to causal relationships or if other factors might influence the outcomes Kohavi *et al.*, 2020.

3. **Accounting for External Factors**: MMM might not always capture the full effect of external factors (e.g., seasonality, market trends) on outcomes. Incrementality tests can control for these external factors by creating controlled environments, providing a clearer understanding of the true impact of marketing actions.

4. **Platform-Specific Validation**: Different marketing platforms might have unique attribution models and methodologies. Incrementality testing allows for platform-specific validation of MMM results, ensuring that the insights derived from each platform align with the observed incremental effects.By running Incrementality testing to validate MMM and LTA results from various platforms, businesses can ensure a more accurate understanding of the causal impact of their marketing efforts. Simester, 2017 researchers have begun using field experiments as a means of validating marketing models. A perfect validation environment is provided by field experiments, where various policies can be implemented in Treatment and Control settings and their results compared.This offers a ”model-free” basis for validation in addition to a comprehensive test of all the assumptions in the model.This validation process enables better decision-making, leading to more effective allocation of marketing resources and improved campaign strategies. This integrated approach allows for more informed decision-making and optimized resource allocation in marketing strategies. Hence the situation has risen to discuss various RCT (tests)incrementality tests available which can be used in parallel to improve accuracy of models and assist in advertisers' decision-making process. Additionally, decision-making in Geo incrementality experiments is vital for optimizing marketing strategies, improving resource allocation, and ensuring that businesses

operate efficiently in diverse geographic markets. The ability to make informed decisions based on experiment results is key to achieving success in localized marketing efforts Kohavi *et al.*, 2020.

5. **Optimizing Future Investments:** Validating MMM results through incrementality testing helps in making more informed decisions about future marketing investments. It guides marketers in optimizing budgets and strategies by relying on validated, causally linked insights rather than purely correlational data Kohavi *et al.*, 2020.

6. **Adapting to Changes:** As consumer behaviour, market dynamics, and advertising platforms evolve, incrementality testing ensures that MMM remains relevant and adaptable. It helps in updating models to reflect changing consumer responses to marketing actions.

3.4. Competitive advantages of Triangulation approach

The triangulation approach pursued in this study aims not only to approximate the causal value of marketing impact but also to mitigate inherent weaknesses associated with individual methodologies post GDPR. Marketing Mix Modeling, for instance, is adept at providing insights at the channel, source, or tactical level, yet it falls short in addressing campaign-level nuances. For example Google Ohlinger and Nedyalkov, 2023has published MMM excels in cross-channel performance evaluation but may fall short in terms of speed and granularity of results. MMM is best suited for overall budget distribution rather than pinpointing the exact amount of incremental return driven by a specific channel or ad format, which is necessary for establishing its profitability in effectively optimising campaigns. To bridge this gap, Incrementality Testing emerges as a valuable tool, offering a comprehensive understanding of a specific channel's true impact. Incrementality controlled tests (without reliable Attribution models (MTA/LTA)) serves as a crucial validation method for Media Mix Modeling (MMM) results obtained from various platforms. However, due to resource constraints, it is feasible to conduct punctuated measurements intermittently rather than continuously, thereby necessitating strategic selection of channels for analysis. Additionally triangulation approach supports in effective decision-making at tactic level to optimise Ad spending or scale testing the incrementality testing serves as a indicator to carefully analyse several factors associated in calculating Return On Investment for example - Display ads, its critical to check the metrics associated such as CPM, conversion rate, targeted audience conversion probability etc Einhorn, 2022. The integration of these methodologies is imperative to achieve a holistic assessment but the standard metrics may not remain same post GDPR due to ongoing changes. For instance, Incrementality Testing, despite its granular insights, is not always feasible for all channels due to cost and time constraints. Consequently, periodic readings are undertaken, serving as calibration points to refine and validate the Marketing Mix Model. This synthesis ultimately provides a nuanced estimation of the value attributed to platforms such as Facebook, though it remains insufficient in delineating the exact campaigns that contributed to this value.

In addressing the specific challenge of evaluating campaign effectiveness at the campaign level, the utility of Multi-Touch Attribution (MTA) or a combination of Last Touch Attribution (LTA) with platform attribution is advocated.Imagine a scenario where a vendor report claims a 40% conversion rate for a particular metric. However, when more sophisticated attribution methods, such as Marketing Mix Modeling (MMM) or LIFT/Geo testing, are applied, they reveal a different result, specifically a 30% conversion rate.

The difference between the two results is calculated as the vendor report's 40% minus the advanced attribution result's 30%, resulting in a negative 10%. To express this difference as a percentage, it is divided by 2, yielding a multiplier of 0.5%.

In simpler terms, this means that the advanced attribution methods suggest a 10% lower conversion rate compared to what the vendor initially reported. The multiplier of 0.5% serves as a way to adjust or account for this difference when interpreting or using the data from the vendor report in a more accurate manner. For a more granular understanding aligned with campaign objectives, reliance on Multi-Touch Attribution or a combined platform attribution approach is recommended which can determine how much of the £3000 can be reduced/hold at same ration or scale those lower funnel campaign channels, now that there is an idea of the relative Return On Ad Spending in reference to MMM channel level output and true ad effectiveness from Incrementality tests. But as you scale spend upwards, there is likely experience "diminishing returns" or decreasing ROI(i) on your investment.

The re-distributive potential of such methodologies, guided by relative shares determined through platform attribution, underscores the importance of a comprehensive assessment that incorporates the diverse strengths of each modeling technique. It is imperative to note that the outcomes of platform attribution should not be disregarded, as they contribute valuable insights to the overall evaluation This re-distributive conversion Testwuide, 2023 is the multiplier which can be used in future to correct the discrepancies reported by Website analytics attribution or self-attributed conversions provided there are periodic Incrementality controlled tests run to check the true conversion rate for each supplier.

3.5. "Navigating Challenges in Implementing Marketing Decision-Making Models: A Comprehensive Examination of Criteria and Evolutionary Trends"

Although it is evident that the understanding of developing models for marketing decisions has grown significantly, concerns remain regarding the empirical foundations on which this knowledge is based. Brodie and Danaher, 2000 highlights attention be given to the issues associated with model 'Validation and Empirical Testing' which are key decision-making criteria presented by Leeflang *et al.*, 2013. The survey methodology proposed is an effort to bring out the unbiased analysis of decision-making challenges faced by practitioners in implementing Marketing models available in the market with focus on experimentation / testing methodology.

As the use of models grows more widespread in many areas of marketing decision-making, these model-building criteria pertaining to model structure, ease of use, and implementation strategy will become widely acknowledged.These criterion form the foundation for constructing advertisement decision-making models Leeflang *et al.*, 2013 Little, 1970. They aim to guide marketers in making informed decisions, optimizing advertising strategies, and maximizing the impact of their campaigns while remaining compliant and ethical.

Media Mix Modeling (MMM) functions as a pivotal decision-making model for marketers, aiding in the strategic allocation of advertising budgets across diverse media channels. By leveraging statistical analysis, MMM enables marketers to assess historical data, attribute the impact of each channel to business outcomes, and optimize their advertising strategies. In essence, MMM serves as a data-driven tool that enhances the efficiency and effectiveness of marketers' decision-making processes in the dynamic landscape of media advertising. The granularity of the output of MMM models for DTC customers is not satisfactory for optimisation at campaign level which is discussed in later section.

Building a MMM model is supported by leading platforms such as Google Ads, Meta and they do offer some capabilities that align with Marketing Mix Modeling (MMM) principles, but not provide a full-fledged MMM solution in the traditional sense. This new technology is supposed to allow MMM's to be built in a point and click environment with less specialized MMM statistical knowledge required. These solutions offer automated modeling techniques that can be run on an ongoing basis and typically contain optimization planning and simulation modules for forward facing scenario planning. "However, the question remains how easy or difficult it is to implement these models and make budget decisions, highlighting the pressing need for a survey."

As stated in the section 3.3 and 3.2 the advanced legacy Multi-Touch Attribution (MTA) is a bottom-up approach with a phenomenal success in the industry until recent times. The reasons for such widespread use from the beginning of 2004-05 was because of these models' ability to attribute conversions to specific media sources in a cross-channel environment which inturn resulted in making informed optimisation of ROAS (Return On Ad Spending) decisions. Advanced MTA models structure on their own without incrementality RCT testing do not meet some basic decision-making criteria for implementation such as ease to use, model accuracy and interpretability for performance marketers to take ad optimisation decisions Hosahally and Zaremba, 2023. This is probably one of the main reason for MMM and MTA models to evolve to advance attribution 2.0 incrementality based framework Leeflang *et al.*, 2013 Little, 1970.

Both Heuristic and advanced Attribution (MTA) methodology were helpful in day-to-day optimisation and providing key input for AI-powered Ad campaigns, but privacy updates and the phase-out of third-party cookies have made it more difficult to use this method alone for decision-making of budget allocation. Additionally, the marketers need a holistic view of all the characters that may influence in the attribution model and to refer to the framework proposed by Hosahally and Zaremba, 2023. Especially in the current recession times and economic uncertainty requires re-evaluation of channels Return On Ad Spending (ROAS) at frequent intervals as there are significant misrepresentations reported at platform level LTA (Last Touch Attribution) results over estimating or under reporting when compared against incrementality test results. This variance is not only limited to paid media but there is a need to re-examine the earned media and competition media contribution Zaremba *et al.*, 2020 as there's significant change in the consumer behaviour pattern with the changing economic times.

Advertisement decision-making models like MMM, MTA Multi-Touch Attribution / LTA Last touch Attribution or controlled incrementality need to meet the standard decision-making criterion for its successful implementation and usage in the industry. The decision-making criteria for implementing a model in any industry can vary based on the specific needs, goals, and characteristics of that industry. However, there are several common criteria that organizations typically consider when deciding to implement a model.

Little, 1970 a decision calculus will be defined as a model-based set of procedures for processing data and judgments to assist a manager in his decision-making. These are main decision-making marketers criteria for decision-making model to meet.

1. **Ease of use**: The Marketing model needs to be easy to use, easily understood and implemented by marketers.

2. **Easy to control**: Marketer should be able to make the model behave the way he/she wants it to. MMM should guide marketers on where and how to allocate resources effectively. A user should be able to make the model behave the way he wants it to.

3. **Accuracy**: the model is accurate with the results. The model should accurately reflect the impact of advertising efforts on desired outcomes, such as sales, brand recognition, conversion, ROAS Return On Ad Spending, or customer engagement. It needs to provide reliable insights into the effectiveness of different advertising channels and strategies. As stated earlier open source MMM tools partially meet the accuracy criteria as they fail to provide insight for tactical decision making as the data they operate on is restricted to their own platform and lack granularity.

4. **Relevance**: It's crucial for the model to align with the specific goals and objectives of the advertising campaign. It should focus on metrics and measurements that directly relate to the intended outcomes, whether it's increasing conversions, driving traffic, or boosting brand awareness.

5. **Validation** does this model also support in validating the results. Many platform-provided Media Mix Models (MMM) model lack transparency in terms of the algorithms used, data processing methods, and the underlying assumptions. Inbuilt models heavily rely on the data available within the platform, and the data might be limited in scope. Advertisers might not have access to comprehensive cross-channel data, including offline or non-digital touchpoints. Therefore validating the model performance and model data is unachievable with MMM models in general.

6. **Robustness** the model should have great potential to be robust and can handle high volume of data and complexity.

7. **Actionability** Marketers need actionable insights. The decision-making model should provide information that can be translated into practical steps and strategies.

8. **Transparency**allowing users to understand and trust the results. The data processing in the back end of the blackbox models is a high risk in today's time.

9. **Predictiveness**: The model should have predictive capabilities, allowing marketers to anticipate the potential outcomes of different advertising strategies or changes in the campaign. Predictive models enable better decision-making by forecasting how alterations may impact results.

10. **Ethical and Legal Compliance**: With increasing regulations around data privacy and advertising practices, decision-making models must comply with ethical standards and legal requirements regarding consumer privacy, data usage, and advertising practices.

4. Methodology - Mixed-Methods survey research - Survey top measurement marketers

The surveys questionnaire incorporate both quantitative and qualitative elements in what is known as mixed-methods research. These surveys mostly collected numerical data to quantify trends and patterns while also gathering qualitative data to explore the underlying reasons or provide context giving an option of others - please specify. For example 1) -Do you believe Last Touch Attribution adequately captures the impact of your marketing efforts? the options were Yes, No or Partially. 2) Rate the below decision calculus criteria from 1-5 with 5 being the highest for using MMM models (Media Mix models) if this is Robyn. 3) What specific challenges or concerns do you anticipate when implementing RCT incrementality tests? a) Lack of expertise in Designing the experiments (DOE) b) Data privacy issues C) Resource constraints d) Budget constraints e) Others (please specify) The goal is to collect data that can be analyzed statistically to identify patterns, relationships, and trends. Quantitative surveys often use closed-ended questions with predefined response options, such as multiple-choice questions or Likert scales. And "Rate your satisfaction with the product on a scale of 1 to 5 (quantitative). Additionally, please provide comments explaining your rating (qualitative)." Data collected: Both quantitative and qualitative data for a comprehensive understanding.

Mixed methods (Qualitative and Quantitative) research, specifically conducting surveys with expert marketers, proves to be the best approach for identifying challenges in implementing marketing models, particularly in the context of decision-making. The utilization of a survey allows for a comprehensive exploration of perspectives and experiences from a diverse range of expert marketers, providing valuable insights into the challenges faced in the field. By targeting a broad audience of marketing measurement experts, the research gains a holistic view, encompassing varied backgrounds and contexts within the industry. Surveys also facilitate the collection of nuanced and detailed responses, allowing participants to elaborate on specific challenges they encounter in implementing decision-making models. This approach is effective in capturing both common and unique issues, enabling a thorough understanding of the landscape. Moreover, surveys offer a structured means of data collection, ensuring consistency in the information gathered and allowing for quantitative analysis of responses, thereby contributing to a robust and evidence-based exploration of challenges in the implementation of marketing models.

4.1. Survey Design and Implementation

A web-based survey was undertaken using Computer-Assisted Web Interviewing (CAWI) an Internet surveying technique in which the interviewee follows a script provided in a website.

By targeting expert marketers, the research aims to capture the intricate details and real-world experiences related to implementing decision-making models. The post-GDPR setting introduces additional complexities and considerations, making it crucial to understand how these regulations impact decision-making processes.

4.2. Participant selection Criteria

The questionnaires are made in a program for creating web interviews targeting marketing measurement professionals selected through tailored screening of individuals possessing pertinent backgrounds in online advertisement performance marketers. The website is able to customize the flow of the questionnaire based on the answers provided, as well as information already known about the participant. Only 50 respondents who met the specified eligibility criteria were included in the subsequent analysis.The eligibility criteria were determined based on respondents' familiarity with Attribution and Incrementality methodologies and their professional engagement in the online advertising industry. Over 50% of respondents had over 10 years of work experience in the marketing field and were exploring the Randomized Control Trials Tests (Incrementality) to validate the results obtained from either LTA (Last Touch Attribution) or MMM (Media Mix Modeling). The surveyors belong to both brands and measurement agencies including top Incrementality measurement agencies and D2C brands marketers such as Measured, Ruler Analytics, Nielsen, Search Discovery, Lifesight, Adfactors PR, Visual IQ Technology Services, Canvas worldwide, Tinuiti, Incrmntal, The questions were carefully designed to learn the decision-making criteria with specific to MMM models (Robyn, Lightweight and In-house) and usage of RCT incrementality models.

4.3. Data Analysis

Responses obtained from the survey were subjected to thorough analysis to extract meaningful insights and trends. Mostly quantitative data analysis techniques were utilized to identify common themes and patterns among respondents' feedback. Numerical Ratings and Statistical Techniques - the analysis is primarily descriptive, the data in the table consists of numerical ratings on a scale from 1 to 5 for various decision-making criteria where 5 being the highest. These ratings are quantitative in nature, representing the respondents' assessments of the models. The analysis involves calculating percentages and summarizing the distribution of ratings for each criterion. The interpretation of the findings focuses on percentages, averages, and patterns within the numerical ratings. It aims to provide a quantitative understanding of how respondents perceive different aspects of the models.

4.4. Limitations of survey methodology

While diligent efforts were undertaken to encompass diverse perspectives in this study, it is crucial to acknowledge inherent limitations associated with survey-based research. The findings may be susceptible to the influence of sample size and selection bias, potentially compromising their generalisability. Common limitations include response bias, where respondents may provide biased or socially desirable answers, leading to distorted data accuracy. Sampling bias may arise, impacting the representativeness of the population if certain demographics are over-represented or underrepresented. Furthermore, questionnaires, though efficient, have limitations such as offering structured response options, potentially missing qualitative nuances and limiting the exploration of complex issues. Ambiguity and misinterpretation in question wording can lead to inconsistent responses. Respondents may also exhibit social desirability bias by aligning their answers with accepted norms. Lack of context, inability to probe for deeper insights, and limited flexibility in adapting to emerging insights or changing circumstances are additional constraints. Non-response bias and the potential overemphasis on quantitative data pose challenges to the study's generalisability. Moreover, the dependence on self-reported information introduces the risk of memory lapses, inaccuracies, or intentional misrepresentation. Lastly, the qualitative nature of the study restricts the generalisability of findings beyond the sampled population.

4.5. Ethical Considerations

All participants provided informed consent before participating in the survey, and their confidentiality and anonymity were strictly maintained throughout the research process

5. Results and Discussion

The main MMM models used by the marketers are Lightweight by Google, Robyn by Meta and in-house models. We designed this survey to highlight the decision-making challenges faced by Marketers in implementation of these models as there were increasingly higher dependency to use MMM in practice post GDPR to measure the online advertisement. The rating 5 states it is high or good and 1 is low or poor rating

Lightweight MMM is a lightweight Bayesian Marketing Mix Modeling (MMM) library that allows users to easily train MMM's and obtain channel attribution information. Lightweight is supposed to help advertisers easily build Bayesian MMM models by providing the functionality to appropriately scale data, evaluate models, optimise budget allocations and plot common graphs used in the field.

Table 3 Decision-making Criteria Ratings with Percentages for MMM Lightweight model used by marketers

Criteria	1	2	3	4	5
Ease to use	14.29%	14.29%	0%	28.57%	42.86%
Ease to control	0%	0%	42.86%	28.57%	28.57%
Relevance	0%	0%	28.57%	57.14%	14.29%
Accuracy	0%	0%	28.57%	57.14%	14.29%
Validation	0%	14.29%	57.14%	14.29%	14.29%
Robustness	0%	14.29%	14.29%	28.57%	42.86%
Actionability	0%	14.29%	28.57%	14.29%	42.86%
Transparency	0%	28.57%	0%	42.86%	28.57%
Predictiveness	0%	28.57%	0%	28.57%	42.86%
Ethical and legal compliance	0%	0%	14.29%	14.29%	71.43%

Table 4 Decision-making Criteria Ratings with Percentages for MMM Robyn model used by marketers

Criteria	1	2	3	4	5
Ease to use	0%	20%	40%	13.33%	26.67%
Ease to control	6.67%	6.67%	46.67%	26.67%	13.33%
Relevance	0%	0%	13.33%	40%	46.67%
Accuracy	0%	0%	26.67%	26.67%	46.67%
Validation	0%	0%	26.67%	33.33%	40%
Robustness	0%	0%	26.67%	26.67%	46.67%
Actionability	0%	0%	20%	20%	60%
Transparency	0%	6.67%	20%	53.33%	20%
Predictiveness	0%	0%	26.67%	33.33%	40%
Ethical and legal compliance	0%	0%	20%	20%	60%

Table 5 Decision-making Criteria Ratings with Percentages for MMM In-house models used by marketers

Criteria	1	2	3	4	5
Ease to use	0%	26.67%	33.33%	0%	40%
Ease to control	6.67%	20%	26.67%	13.33%	33.33%
Relevance	0%	0%	6.67%	40%	53.33%
Accuracy	0%	0%	33.33%	40%	26.67%
Validation	0%	6.67%	20%	33.33%	40%
Robustness	0%	0%	0%	40%	60%
Actionability	0%	0%	0%	20%	80%
Transparency	0%	0%	13.33%	20%	66.67%
Predictiveness	0%	6.67%	26.67%	13.33%	53.33%
Ethical and legal compliance	6.67%	0%	0%	46.67%	46.67%

In Tables 3 4 and 5, respondents rated decision- making criteria for three different models used by marketers: Lightweight, Robyn, and In-house models. The analysis of the table reveals that respondents rated the decision-making criteria on a scale from 1 to 5, with 5 being the highest.

For the Lightweight model, respondents expressed a positive view, with ”Ease to use” and ”Actionability” receiving the highest percentages of 42.86% and 42.86%, respectively. ”Validation” and ”Robustness” also garnered favorable responses, while ”Relevance” received a relatively lower percentage of 14.29%.

The Robyn model ratings showcase a positive sentiment, with ”Ease to control,” ”Robustness,” and ”Predictiveness” obtaining high percentages of 46.67%, 46.67%, and 40%, respectively. However, ”Ease to use” and ”Relevance” had lower percentages, suggesting potential areas for improvement.

In the In-house model, marketers displayed positive sentiments towards ”Actionability,” ”Transparency,” and ”Predictiveness,” with the highest percentages of 80%, 66.67%, and 53.33%, respectively. However, ”Ease to use” and ”Relevance” had relatively lower percentages, indicating potential focus areas.

Overall, these tables provide insights into marketers' perceptions of decision-making criteria for different marketing models, highlighting areas of strength and potential improvement. Some of the pitfalls with MMM post GDPR are, Open source MMM tools (Robyn or Lightweight) data feeds are limited to the respective platform's data. Collecting data from other media platforms, including offline media, is necessary to build a comprehensive MMM model,” Additionally, when marketers need ongoing analysis or insights at a tactical level, MMM is unable to deliver. Due to a lack of granularity, platforms supported MMM such as Meta's Robyn and Google's Lightweight MMM does not provide high level accurate insights into campaign-level performance and decision-making Bharadwaj, 2022; Lim, 2023

5.1. Comparative analysis for 3 main MMM Models

The comparative analysis of the average ratings for each criterion across the ”In-house”, ”Lightweight”, and ”Robyn” workbooks yields the following insights: Ease to Use: The ”Lightweight” model has the highest average rating (3.71), suggesting it is perceived as the easiest to use among the three. The ”Robyn” and ”In-house” models have similar ratings, with 3.47 and 3.53, respectively. Ease to Control: Here, the ”Lightweight” model again scores slightly higher (3.86) than the other two, indicating it may offer better control to marketers. The ”Robyn” model has the lowest average rating (3.33) in this category. Relevance: The ”In-house” model scores the highest (4.47), indicating it aligns well with specific needs. The ”Robyn” model also scores high (4.33), while the ”Lightweight” model has a lower average (3.86). Accuracy: The ”Robyn” model scores the highest in accuracy (4.20), closely followed by the ”In-house” model (3.93). The ”Lightweight” model has an average rating of 3.86. Validation: The ”In-house” model is perceived as the best in supporting validation (4.07), with the ”Robyn” model closely behind (4.13). The ”Lightweight” model has the lowest average rating (3.29) in this criterion. Robustness, Actionability, Transparency, Predictiveness, and Ethical and Legal Compliance: In these areas, the ratings vary, but generally,

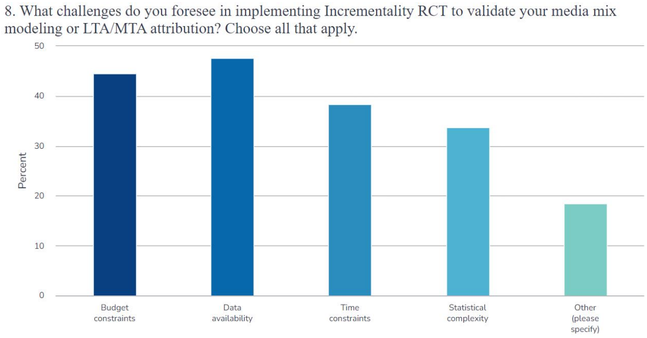

Figure 3 key challenges faced by marketers when implementing Incrementality Randomized Controlled Trials (RCT)

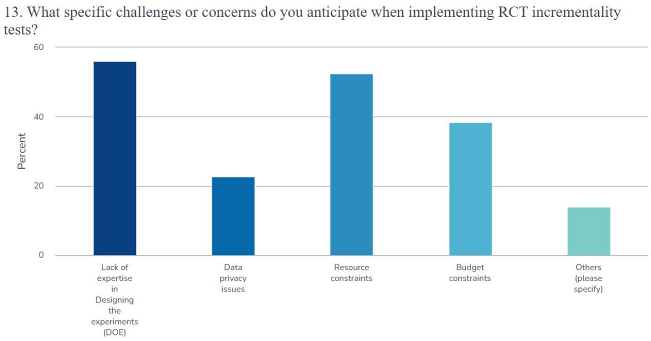

Figure 4 key challenges faced by marketers when implementing Incrementality Randomized Controlled Trials (RCT)

the ”In-house” and ”Robyn” models tend to score higher, indicating they are perceived as more robust, actionable, transparent, predictive, and compliant compared to the ”Lightweight” model. Notably, the ”In-house” model scores exceptionally high in actionability (4.80) and robustness (4.60). Overall Trends: The ”In-house” model appears to be highly regarded for its robustness, actionability, and relevance, scoring the highest in these categories. The ”Lightweight” model, while scoring slightly lower in some areas, is perceived as the easiest to use and control. The ”Robyn” model offers a good balance across all criteria, scoring particularly well in accuracy and relevance. These insights suggest that the choice between these models may depend on the specific priorities of the users or the context in which the model is to be used. For instance, if ease of use and control are paramount, the ”Lightweight” model might be preferred. However, for applications where accuracy, relevance, and compliance are critical, the ”In-house” or ”Robyn” models may be more suitable.

5.2. Recommendation for Incrementality RCT Framework: Survey Reveals Strong Scores in Decision-Making Criteria

The predominant obstacles cited were a lack of expertise in experiment design (56%), resource constraints (52.6%), budget limitations (38.6%), and concerns related to data privacy (22%). A subsequent inquiry regarding data availability indicated that respondents were notably concerned about GDPR-related issues (47.7%). Additional challenges included statistical complexity (33.8%), time constraints (38.5%), and budget limitations (44.6%). Future research by researchers as well as industry experts could focus on these areas in building commericially viable and effective decision-making model.

Table 6 Decision-making Criteria Ratings with Percentages for RCT Incrementality model used by marketers

Criteria	1	2	3	4	5
Accuracy of the model	2 (3.8%)	1 (1.9%)	6 (11.5%)	19 (36.5%)	24 (46.2%)
Robustness	0 (0.0%)	2 (3.8%)	13 (25.0%)	27 (51.9%)	10 (19.2%)
Ease of use, interpretation and implement	1 (1.9%)	2 (3.8%)	18 (34.6%)	20 (38.5%)	11 (21.2%)
Cost effectiveness	1 (1.9%)	8 (15.4%)	20 (38.5%)	12 (23.1%)	11 (21.2%)
Predictiveness	1 (1.9%)	5 (9.6%)	10 (19.2%)	23 (44.2%)	13 (25.0%)
Relevance	0 (0.0%)	4 (7.7%)	7 (13.5%)	18 (34.6%)	23 (44.2%)
Ethical and legal compliance	4 (7.7%)	6 (11.5%)	15 (28.8%)	13 (25.0%)	14 (26.9%)

In assessing the effectiveness of marketing models, respondents highlighted key decision-making criteria. Notably, accuracy emerged as crucial, with 46.2% assigning it the highest rating of 5. Robustness, the model’s ability to navigate market fluctuations, was also emphasized, garnering ratings of 4 and 5 from 71.1% of respondents. The ease of interpretation and implementation followed suit, with 60.6% recognizing its significance by rating it 4 and 5. Cost effectiveness, while relevant, did not stand out prominently, with responses distributed across various ratings, showing a slight preference towards 3 and 4. Predictiveness, indicating the model's ability to foresee outcomes, was considered important by 69.2% of respondents, who assigned ratings of 4 and 5. Relevance, aligning the model with specific goals and objectives, received the highest emphasis, with 78.8% rating it as 4 and 5. The analysis underscores a strong emphasis on accuracy, robustness, predictiveness, and relevance. Ethical and legal compliance, though important, was slightly less highlighted, and cost effectiveness, while acknowledged, did not emerge as a top priority.

The insights extracted from the survey suggest that marketers prioritize Incrementality models due to their prowess in accuracy, robustness, predictiveness, and relevance. The incorporation of Randomized Control Trials (RCT) in Incrementality testing contributes to the validity, usability, and applicability of insights, bolstering trustworthiness and practicality. Future research is deemed necessary for refining Incrementality-based approaches. When considering Marketing Mix Modeling (MMM) in conjunction with Incrementality testing, customer feedback surveys, advertising testing, and data enrichment, a comprehensive, data-driven measurement approach emerges. Additionally, in the absence of user-level data, advertisers may explore alternative attribution methods, such as relying on first-party data and contextual targeting. The evolving landscape, marked by the diminishing significance of cookies and iOS changes, positions the combined MMM and Incrementality approach as a potential gold standard for marketers, warranting ongoing research and exploration in the field.

It can also be argued that RCT and MMM collectively can meet the other decision making criteria. RCT incrementality contribute to the validity, usability, and applicability of the insights derived from the testing. Advertisers rely on incrementality results to make effective ad spending optimisation decisions, and adherence to these criteria enhances the trustworthy and practicality of the findings Kohavi *et al.*, 2020.

The current state of the art is a limbo state to test Ad effectiveness. Practitioners and researchers have accepted incrementality as a gold standard for marketing Ad measurement as they do depend heavily on user-level dis-aggregated data unlike Attribution methods Runge *et al.*, 2023Barajas *et al.*, 2016. However controlled experiments require robust experimentation methodologies, control groups, and a deep understanding of data analysis.Moreover the platform runs the tests in the background without sharing the design or methodology details with marketers incase of Ghost Ads for example. Therefore there is further research required from both practitioners and researchers towards Incrementality based approach. MMM can be coupled with other techniques including incrementality testing, Customer feedback survey, advertising testing, data partnership, and enrichment of first-party data for a more data-driven measurement approach. Kohavi *et al.*, 2020 recommend that online controlled experiments to be conducted to inform organizational decisions at all levels from strategy to tactics. Incrementality experiments is now that decision-making tool for both tactical and strategic decision making. Bharadwaj, 2022 incrementality experimental results help avoid correlation/causality issues by using incrementality outputs to train the MMM model. Incrementality provides fresh data on which to make rapid tactical decisions, complementing MMM's long-term strategic and planning strengths.Moving forward, the combination of MMM and incrementality will likely be the gold standard in a post-iOS, post-cookie world.

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