A decision-making characteristics framework for marketing attribution in practice: Improving empirical procedures.

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Abstract

In today's multi-channel environment, It is becoming increasingly difficult to implement advanced multi-touch attribution (MTA) models to facilitate advertising decision-making. This is due to the rising number of advertising platforms, such as TikTok, Metaverse and Google — each with its own unique attribution principles — and the decline in user-level disaggregated data. Over time, the development of marketing models has matured in parallel with the greater availability of consumer data and understanding of consumer behaviour. To overcome media optimisation challenges at the tactical and channel levels, e-commerce brands have replaced traditional media-mix methods with attribution methods that provide immediate insights into return on advertising spend. However, existing MTA models lack simplicity, robustness, ease of interpretation, and accuracy, all of which are critical attributes of decision-supporting models. To address this, this paper proposes a holistic conceptual framework that captures the various interplaying characteristics of attribution models in practice. The concept is based on the evolution of modelling and insights into the development of decision-making paradigms. The proposed architecture highlights the interactions between various tools, media categorisation and metrics, and how they influence media spend optimisation at the channel and tactical levels.

The paper also describes some of the most recent advances in media measurement practices. By adopting the proposed framework, future advertisers can identify the best way to overcome the challenges of analysing marketing performance.

Keywords

marketing attribution, incrementality, measurement, digital attribution, decision support framework

DECISION-MAKING MODEL

Marketing attribution is heavily dependent on the availability of user-level consumer data. The availability of data is directly proportional to the performance of model development and essential for advancing marketing knowledge and enhancing the decision-making process. There has been limited focus on capturing the critical components which can be unveiled using the stages in the model building process with focus on implementation previously proposed by Leeflang and Wittink.[1] The following steps help to deconstruct the complexity and critical components of existing marketing attribution models:

1. opportunity identification
2. model purpose
3. model scope
4. data availability
5. model-building criteria to include model structure — robustness, ease of use, implementation strategy
6. model specification
7. parameterisation
8. validation
9. cost-benefit considerations
10. use
11. updating

Identifying the actual reason for sales or conversion in consumer's purchase journey (ie causation) remains a major challenge for advertisers. Indeed, within the online environment, the issue is becoming increasing complex due to the growing number of channels and tactics and the lack of adequate user-level behaviour data. According to causal decision theory, decision-makers cannot make optimal decisions without first understanding the causal structure that relates actions, potential states of the world and outcomes.[2] The three key structural elements in media measurement are the availability of user-level data, consumer behaviour models and attributions models. Lack of clarity regarding any of these elements can lead to poor decision making. To address this issue, this paper seeks to reduce the risk associated with attribution models and environmental dependencies to enable marketing managers to take data-driven decisions and understand the limitations of those decisions.

Isolating these stages of the model development process is helpful for understanding the complex attribution models in practice. Stage 2 (model purpose) and stage 3 (scope) are perhaps best left to the platforms (eg Google, TikTok or Metaverse) to describe and explain to marketers. Compared with basic heuristic attribution models such as last-touch attribution (LTA), which are derived automatically from incomplete customer journey data points, stage 5 metrics such as 'ease of use' and 'implementation strategy' are highly complex. Use of LTA continues to be widespread within the marketing industry, however, as it is easily available from the respective platform provider.[3] As discussed by Hulsadu and

Teteberg, parameterisation issues can be observed in many marketing attribution models.[4] Stage 8 (validation) is achieved via field experiments like incrementality randomised control trial experiments (also called lift tests), while the final step — updating[5] — is vital for those using basic heuristic models because post-experiment calibrations to refine the weights assigned to channels by heuristic models (LTA) will improve model accuracy.

Third-party advertising measurement agencies, such as Measured.com, draw on a corpus of vendor reports to develop incrementality control experiments (lift studies).[6] This has been a huge success in the direct-to-customer (DTC) sector where retailers depend heavily on paid media for sales/conversion. Measured.com meets the decision-support model requirements, such as ease of use, interpretability and robustness, and helps marketers in the decision-making process. These third-party measurement agencies utilise their customers' source-of-truth conversion/sales data from customer relationship management systems and offline as an additional validation step to aggregate the results of their randomised incrementality experiments.They attempt to find deviation of percentage from LTA reported by different vendors by running repeated randomised incrementality experiments to identify incremental return on ad spending results for marketers.

The basic heuristic commonly used LTA model is a deterministic model that assigns full credit to the last touch point before the conversion. Decision-makers use this model when planning and scheduling continuous online advertisement promotions such as scaling, bidding etc as the data are immediately available on analytics platforms. LTA was used to solve immediate media optimisation decision challenges, ie channels that are delivering results for each campaign and reinvest to those channels etc as a prescriptive model.

The purpose of prescriptive models is to determine a recommended course of action for performance improvement or an optimum course of action. Danaher and van Heerde highlight several caveats in using attribution for multimedia budget allocation.[7] They show that the general attribution model presents a descriptive summary whereas a profit-maximising model is prescriptive in nature providing required weight for each medium to maximise profit. Through empirical simulations, they show that the budget allocation weights of the models differ widely. So, should the attribution model still be referred to as a prescriptive measurement tool for budget allocation or as simply a descriptive approach that identifies the relative contribution of each channel to the purchase?

RECOGNISING AND MANAGING CONSUMER BEHAVIOUR AS THE DECISION-MAKING PROBLEM

Consumer behaviour refers to the process that customers go through when making a purchase, and it includes a variety of aspects that influence their decision. Purchase decisions for many products and services are the result of a lengthy, complex process that may include a broad search for information, brand comparison and evaluation. Apart from final conversions or sales, earned media channels and paid media channels both play a pivotal role in moving customers from the preliminary stage of the purchase funnel towards the final stage of the funnel, indirectly contributing to sales. Marketers' ability to influence purchasing behaviour is largely determined by their understanding of consumer behaviour. Using attribution approaches to incorporate aspects that indicate consumer context can provide insights into the media mix and buying funnel for the customer journey. The customer journey becomes predictable when developing technologies can detect the characteristics of a consumer's internal and external context.[8] Contextual factors are crucial as marketing without them may have less influence on customer conversion. Personalised targeted advertisements are effective when customer data and customer context-recognition technology align with the automated and real-time adaptation of each touch point to the needs and preferences of customers.[9] Marketers must also understand the exact needs that customers are attempting to meet and how they translate these needs into purchasing attributes. They must also understand how consumers obtain knowledge about the various options available via web search and use that information to choose among rival brands.[10]

Critical literature review on consumer decision-making discusses traditional consumer decision-making models and variations in consumer decision-making.[11] The customer stage/funnel in the customer journey gave rise to AIDA (attention, interest, desire and action) and this five-stage decision process serves as a base for modern concepts.[12] Following the explosion of digital channels, customers are well informed about their needs and their options, and do not necessarily follow the traditional funnel stages. The four phases in McKinsey's dynamic models are:[13] initial consideration; active evaluation — the process of researching potential purchases; closure — when consumers buy brands; and post purchase. By identifying the customer's exact position in the buying process and the moment-of-truth stage (the stage customer decides the brand to purchase) marketers can learn to influence their customers. Li *et al*.[14] merged data from first-party cookies with third-party cookies to build a more comprehensive click-stream evaluation of the customer journey. They found customer-initiated channels (paid search, referral and direct) to be more effective in reducing consumer search cost in the early consumer decision-making stages, while firm-initiated channels (e-mail and display) contribute more at later stages. Thus, adopting a funnel that recognises what stage the consumer is at in their consumer decision journey and aligning specific marketing activity that can trigger consumer desired action at each stage of the customer funnel is a significant challenge for marketers.

INFLUENCING CONSUMER BEHAVIOUR THROUGH MARKETING ATTRIBUTION

Customers use a range of media channels on their path to purchase. The literature distinguishes paid, owned, earned media (POE model), which is a function of integrated marketing that helps marketers to allocate spend in advertising and promotion (paid media), social (earned media) and original and predominantly digital branded content (owned media).[15] Zaremba[16] proposed a fourth area of product information sources called 'category' media, which includes the customer's activities with brand competitor content. These four media areas include media channels (eg display, organic search, etc) which represent touch points from the customer perspective.[17] The marketer's main goal is to influence online consumer behaviour and manage the various media points effectively to generate revenue. To achieve that aim they use marketing attribution methods.

An attribution model is defined as a rule or set of rules that determine how credit for sales or conversion is assigned to touch points along conversion paths.

The sequence of interactions in the conversion paths is important in the generation of multi-channel funnel reports.[18] In basic rules such as the first-touch model, 100 per cent credit is given to the touch point that initiates the customer conversion path. In cases when a customer revisits a website after a long break, then those customer journeys will begin afresh due to this lookback window limitation.[19] The marketing attribution method requires careful understanding of every touch-point value[20] because each touch point in the customer journey can have a positive, negative or neutral effect on the customer's decision to move along the purchase funnel.[21] Businesses employ multiple channels to achieve their business goals, called firm-initiated channels. Customers can visit the company website from all these various sources at different stages of the customer life cycle, such as the initial consideration stage, visit stage and even in the purchase stage. Customers can go from one part of the journey to another and back again, or skip parts altogether, creating many different intermediate variable possibilities. The visit experience can influence subsequent visits and purchases to the website through the same channel (carryover) or different channel cumulative effect (spillover).[22] Long-term intermediary effect is when a customer views the branded content on the company website (owned media) and may not make an immediate purchase, but it may improve brand attitude, therefore, has long-term effect. Those paths that are not leading to conversion within the last 30 days (adjustable 90 days lookback or attribution window) are removed from the data storage by leading platforms. With so many potential paths and account for multiple effects (intermediate of customer effect) which demands an integrated customer behaviour method.[23] Especially when different attribution models bring varied results.[24]

LITERATURE REVIEW

A systematic review was carried out according to the methodology proposed by Peacock and Greenhalgh.[25] The first step was to identify the keywords crucial for the subject of conversion attribution, marketing attribution, multichannel attribution, digital attribution, data-driven attribution, multi-touch attribution from the titles, abstracts and keywords of business reports and articles published between 2010 to 2022 and indexed on major databases such as Proquest, Web of Science, Scopus or made available through sources such as Google Scholar. After filtering out those papers with no relevance to the present study, a total of 89 papers were identified for review. The authors adopted a snowballing search strategy due to the developing nature of marketing attribution and its terminology. This strategy was adopted after the initial keyword search to ensure all relevant studies were captured. We also conducted a backward snowballing search to find any articles that the initial keyword search had missed, with emphasis given to the data type (POE media). Table 1 shows the number of papers from various publications reported between 2010 and 2022. Based on systematic literature review on the topic of MTA models[26] covering papers from 2010 to 2022 and updates made by authors for the period from 2019 to 2022, the data scope used for MTA models was analysed (Table 2). Visits to the website are key data types included in the models. Visits are generated by direct traffic or through 'clicks' from different ad types and referrals. Some researchers also included impressions (ad views). Only a small number of papers analysed cross-device problems treating mobile and

Table 1: Number of papers each year — Marketing attribution (synonym) different databases (unique).

Database	*2010-2010*	*2011-2015*	*2016-2020*	*2021-2022*	*Total*
Web of Science	0	1	9	0	10
ProQuest	0	3	8	4	15
Scopus	1	9	18	12	40
Other	1	16	15	0	32
Total unique	2	29	45	13	89

Table 2: Range of data included in the case study model.

Data range	*No. papers*	*Share of papers (%)*
Impressions	7	15.2
Visits (clicks or direct traffic)	46	100.0
Cross device	1	2.2
Online and offline transactions	3	6.5
Content quality	5	10.9
Competitors	2	4.3

desktop paths as separate user paths. A few articles incorporated offline transactions to the model.

CHARACTERISTICS INFLUENCING MARKETING ATTRIBUTION ACCURACY

Based on the systematic literature review, a number of characteristics were identified. These are discussed below.

Media categorisation

Several e-commerce brands spend a significant amount of money on paid web ads and their primary focus is on determining whether paid channels have generated results, with earned media channels being mostly neglected. According to the Chief Marketing Officer of PR Newswire, 81 per cent of senior marketers believe earned media has a greater positive impact than paid media.[27] Several offline, public relations efforts, reviews, news mentions, content shares, word of mouth (WOM) could significantly impact the conversion are non-trackable media. Additionally, paid media in the attribution calculations also does not cover spillover effects from earned media and brand value effects (user intent and brand equity). Some of the earned media contributions is directed towards the upper sales funnel (ie branding activities) and there are no attribution methods to identify how branding has impacted sales hence it is exposed in the proposed framework in figure 1. The constant digital media convergence (earned, owned and paid media) demands an understanding of the relationship of various POE channels.[28]

Paid media: Advertising channels and strategies

The prominent advertisement online channels are display ads, search ads and video advertisements.

Generally, there are two broad objectives that advertisers set out to achieve: (a) immediate direct response and (b) long -term brand equity. Display advertisements are well researched and there is a lack of advertising effect understanding in executing the campaign to reach specific objectives and the optimisation of media spend.[29]

Kireyev *et al*.[30] examine evidence on consumer search behaviour changes with display ads. Their model suggests that both paid search and display advertisements exhibit dynamics that improve their effectiveness and return on investment over time. Several researchers have highlighted sales or conversions influenced from touch points across POE media. Display advertisements and search marketing directly or indirectly influence customer ad click-through or conversions through increasing awareness, impressions and salience of products.[31] In addition to such broad long-term and short-term strategies, tactical strategy decisions are built[32] for various tactics based on the channel's unique characteristics such as retargeting, prospecting, etc.

Retargeting and prospecting tactics

Display advertisements can be further classified into 'retargeting' and prospecting which is shown in Figure 1 as Paid Ads channels and tactics:. Retargeting is a form of online advertising tactic that allows marketers to target consumers who have recently visited the website.[33] Prospecting on the other hand refers to a scenario for displaying advertisements to users with no previous exposure to the partner's advertisements. Ghose and Todri[34] were among the first researchers to focus on the efficacy of retargeted advertisements in driving customer conversion using individual-level data. They highlight that even though digital advertisements offer better measurability and accountability than traditional advertising media, there are still substantial hurdles to overcome when disentangling the many effects (spillover) and calculating the true efficacy of advertising. They conducted a randomised control experiment to highlight the impact of display advertisements (prospecting, retargeting, affiliate targeting) on online consumer search of brands.

Cross-device and multi-apps

The rapid adoption of smartphones and tablets, especially the number of devices per user has increased massively, causing direct implications for measuring the value of marketing investment as marketing attribution requires the ability to attribute some desired behaviour to the marketing activity that occurred in the past. Lee[35] was the earliest research to explain that each channel has its own data tracking in its own system, leading to multi-sources of data that are disconnected. The problem of cross-device in assessing online marketing performance has been broadly discussed.[36] The average consumer owns multiple internet-connected devices, and even on a single device such as a smartphone, the user can access the internet through a variety of applications, including multiple browsers and social media apps. Referring to the Facebook internet browser available in Facebook mobile app was responsible for a significant share of traffic.[37] The marketing content can be delivered not only through websites but also by podcasts available on apps like Spotify, iTunes, Tidal, video apps like YouTube and social media apps like Instagram, Facebook, Twitter and TikTok which cannot be easily tracked by external analytical tools.[38] The result for cross-device and multi-app is the same which means a high possibility of treating one person as multiple users due to the limitation of analytics technology.

Attribution models and vendor platforms analytics

According to eMarketer,[39] an important challenge that lies ahead for a digital marketer is to determine how marketers can advance their attribution efforts because nearly seven in ten respondents/performance marketers use basic heuristics marketing attribution methods such as first and last touch attribution models.[40] There are various types of approaches and models for applying marketing attribution in the industry, as per the literature review table. Marketers diversify their ad placement using different marketing channels in order to reach a wider audience, hence they would need to integrate different vendor reports which run as per their own vendor platform measurement standards, eg Google Analytics, Facebook/Meta analytics and LinkedIn. This makes it harder for marketers to understand each platform's results to optimise ad spending based on attribution results. At present, how measurement ad agencies have been able to support DTC customers to integrate multiple ad vendors platform results and track whether agencies are under or over-reporting their LTA results.

Content, context and location

The literature review conducted for this paper identified no articles related to marketing attribution which consider the content quality as a factor for model accuracy as shown in the Figure 1: Marketing attribution characteristics framework.This is likely because content quality is very difficult to measure, especially in the case of display, paid search and organic activities. We are aware that including content quality in the attribution modelling is a difficult task, but taking into consideration brand sentiment or average score from opinion websites may bring additional value to assessing model accuracy.

Technology has enhanced the mapping, modelling and aligning processes to

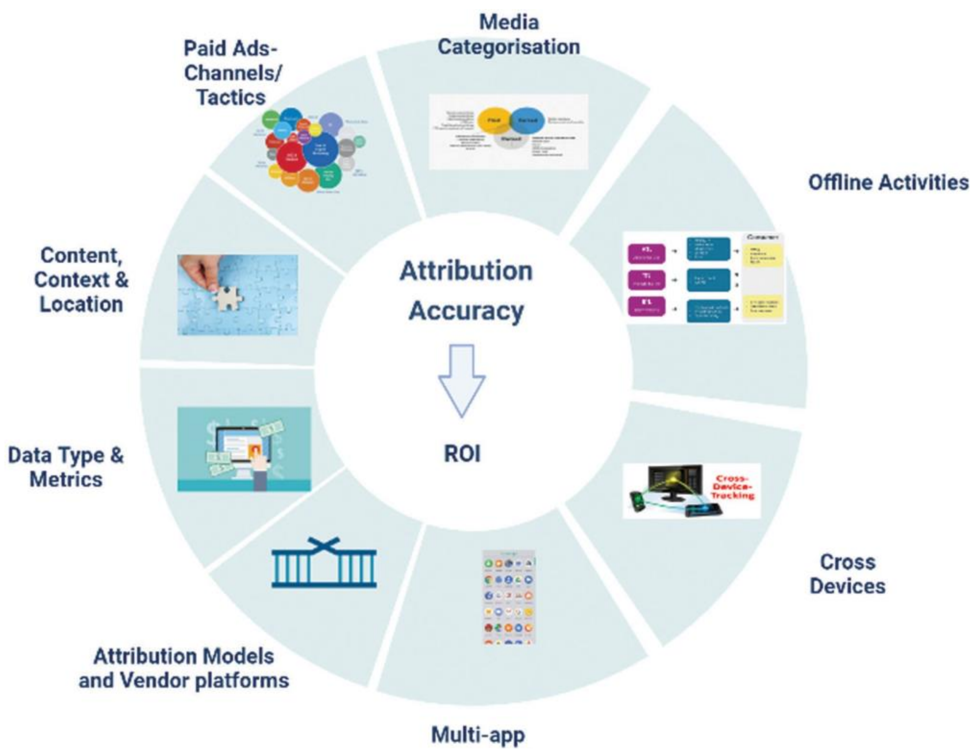

Figure 1 Marketing attribution characteristics framework

implement and is far more accurate due to the widespread availability of Big Data on purchasing behaviours and commercially available software and systems such as Google Analytics. Big Data facilitates the use of marketing analytics to assess the buying process, but tracking technology and metrics to focus on accurate customer behaviour data. According to Buhalis, 'Consumer decision-making research will evolve with the context-recognition technology that can recognise the difference in the effects of the touch-point in a particular context and realise who initiated the communication (customer or firm) as consumer behaviour is motivated by customer's immediate existing needs'.[41] The focus lies now to engage customers at the personal level and many marketers have initiated communication to increase customer engagement levels.[42]

Offline activities

Kannan and Li[43] in the attribution analytics body of knowledge the impact of offline activities on the attribution results is the key challenge for scientists. Papers related to marketing multi-channel attribution topics very rarely touch on the idea of including offline activities into the model. Every customer shopping online is exposed to offline activities of other brands and the opinions of other people. Brand awareness cannot be simply skipped. The abundant research proving the positive impact of brand awareness on sales[44] encourages scientists and practitioners to include at least brand awareness level into the attribution models; for example, different attribution models can be built for users knowing the brand well and poorly. Sciarrino *et al*.[45] also included brand awareness in their customer journey modelling framework.

Data type and metrics

Enumerable indicators, such as the number of website visits,exposures,impressions and clicks on banners and e-mail newsletters and conversion rates, are commonly used in attribution approaches. Impressions, for example, are tracked and reported by all ad networks, despite the metric indicating no more than the number of times an ad has been displayed, as opposed to how much time consumers have spent reading it. The poor use of metrics leads to bias and inaccurate measures of the impact of advertising on consumer behaviour.[46] The Media Rating Council and IAB recommend a standard threshold of 2 seconds for a video ad impression, but the industry has yet to comply.[47] Choi *et al*.[48] raise a significant question: are advertisers using the right metrics (impressions, visits and purchases) to drive profitability? Additionally, as discussed previously, the limited look-back window provided by major analytics platforms plays a major role in accuracy of attribution measurement.These metrics are collected from a variety of sources, including the company's website, search engines, affiliated websites, social media sites and multiple devices. The effectiveness of the attribution model depends on its capability to integrate the above metrics into the model calculus from all the customer journey touch points, which will ensure higher accuracy in the allocation of value to each of them.[49]

CONCLUSION, LIMITATIONS AND FURTHER RESEARCH

Leeflang[50] introduced the concept of stages in model building, which emphasises the importance of fulfilling model scope, data availability and model-building criteria to ensure model accuracy. When it comes to marketing attribution analysis, there are various dimensions that influence the results, including the attribution models, user context and advertising message/content/creatives. Despite a lack of consensus on the ideal combination of data and media type for achieving the highest accuracy in MTA, it is important for researchers and practitioners to recognise the complexity of this phenomenon. To this end, the proposed framework outlines the various characteristics that impact the accuracy of MTA results. The authors argue that any paper related to MTA should be justified in light of this framework.

The framework presented, which was derived from a review of papers focused on model building, offers several opportunities for further research. Specifically, it is important to consider the impact of various characteristics, such as context, data and media type, when evaluating the most influential factors in marketing attribution. However, there is a dearth of articles addressing this issue and the attribution problem remains a challenge without a consistent solution. A comparison of the long and short-term impact of using MTA would be highly valuable.

The authors analysed the range of data used in the white papers included in the literature review. As shown in Table 3, the results indicate that the majority of papers only cover minor aspects of the proposed framework, highlighting the need for future research or case studies to consider additional dimensions of the framework.

The marketing industry spends billions of dollars on advertising, and discovering recurring solutions can bring significant cost savings. MTA models are used as ad purchase prediction models for real-time bidding solutions, where algorithms participate in auctions and determine whether or not to purchase display impressions.[51] With high accuracy, a proper MTA model can be readily adapted as a purchase prediction model for the entire spectrum of marketing activities.

Table 3: Usage of proposed framework dimensions among case study papers.

No. dimensions used	*No. papers*	*Share of papers (%)*
1	31	67.4
2	12	26.1
3	3	6.5
≥4	0	0.0

It is worth noting that even if a perfect attribution model is found for a particular industry or company, results may vary across industries due to different decision-making processes and variations in the saturation of rationality and emotions during customer journeys, as proposed in the Foote-Cone-Belding (FCB) matrix.[52] Moreover, transactions occur both online and offline in almost all industries. As a result, it is necessary to analyse and compare attribution results separately for companies that operate exclusively online and those that rely on a research online, purchase offline model.

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