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Conversion Attribution: What Is Missed by the Advertising Industry? he OPEC Model and Its Consequences for Media Mix Modeling

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ABSTRACT

Marketers are currently focused on proper budget allocation to maximize ROI from online advertising. They use conversion attribution models assessing the impact of specific media channels (display, search engine ads, social media, etc.). Marketers use the data gathered from paid, owned, and earned media and do not take into consideration customer activities in category media, which are covered by the OPEC (owned, paid, earned, category) media model that the author of this paper proposes. The aim of this article is to provide a comprehensive review of the scientific literature related to the topic of conversion attribution for the period of 2010–2019 and to present the theoretical implications of not including the data from category media in marketers' analyses of conversion attribution. The results of the review and the analysis provide information about the development of the subject, the popularity of particular conversion attribution models, the ideas of how to overcome obstacles that result from data being absent from analyses. Also, a direction for further research on online customer behavior is presented.

JEL classification: M31, M37

Keywords: online customer journey, budget allocation, multi-channel conversion attribution, paid owned earned category media

1. INTRODUCTION

The Internet has empowered consumers by giving them almost unlimited access to product information given by companies, other consumers, and independent reviewers (Kacprzak, 2017, p. 26). At the same time, the marketing industry has developed sophisticated tools to measure the impact of online advertising on the consumer journey and, finally, empowered marketers, who can now collect data about user online behavior in almost real time (Hanssens & Pauwels, 2016; Wedel & Kannan, 2016). Conversion attribution models allow marketers to assign the impact of particular advertising activities to marketing campaign goals (Shao & Li, 2011; Danaher & van Heerde, 2018). Currently, more money is spent on online advertising than on TV, radio, and press put together (Molla, 2018). 54% of marketers recognize conversion attribution as the most difficult obstacle to overcome in their work (eMarketer, 2018). Despite the increasing interest in the subject, there is a paucity of comprehensive literature reviews on the topic of conversion

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attribution models. An integration of research findings coming from this subject is, therefore, needed.

Marketers communicate with customers in owned media, paid media, and earned media (Harrison, 2013; Lovet & Staelin, 2016), and use data collected from those areas for media mix modeling (Srinivasan, et al. 2016). Those areas are a space for communication with customers. During the decision-making process, customers do not only rely on the content linked with a single advertiser but also on other product category content provided by independent publishers, users, and competitors (Lecinski, 2011; Lemon & Verhoef, 2016). Several pieces of research confirm the influence of competitors' activities on the brand sales analyzed (Sahni, 2016; Chae et al., 2017; Li et al., 2017). The author of this paper proposes to name this type of content and user activity *category media*, and finally to convert the model of paid, owned, and shared media into the OPEC (owned, paid, earned, category) media model. A comparison of this model with conversion attribution theory and practice brings new findings as well as provokes discussion on the results of some media sources being absent from conversion attribution analyses. A lack of this sort of data may lead to conversion attribution models yielding incorrect results and finally to inappropriate budget allocation. A theoretical analysis of this issue is, therefore, also necessary.

The aim of this paper is to provide an in-depth review of conversion attribution modeling literature and to analyze the potential implications of failure to include partial data in the OPEC model.

The structure of this paper is as follows: a systematic review of conversion attribution models, a proposition of an online content division called the OPEC (owned, paid, earned, category) media model, a presentation of the consequences that the proposed model can have on the results obtained from conversion attribution, and, lastly, conclusions and further research.

2. SYSTEMATIC REVIEW OF CONVERSION ATTRIBUTION LITERATURE

The systematic review was carried out according to the methodology proposed by Palmatier et al. (2018). The first step was to select the keywords crucial to the subject of conversion attribution: *conversion attribution, multi-channel attribution, marketing attribution*. The search process involved publications that fell within the timeframe of 2010–2019 as well as 10% of the most frequently cited marketing journals from the Scopus database. The search was conducted by searching for keywords, titles, and abstracts. Because only 17 articles were selected in the process, the next step involved searching for less popular journals indexed in: ProQuest, EBSCO, JSTOR, Web of Science, SAGE Journals, ScienceDirect, Springer, SSRN, Google Scholars and ResearchGate. During the research, several papers originating from international conferences were also found and included in the review. Thus, to be included in the review, a study that would present a theoretical approach to the conversion attribution of online media had to be pursued or a case study based on the conversion attribution of online media methodology and practice included. Articles that only mentioned the issue of conversion attribution without an in-depth, theoretical review were rejected. Out of the 90 articles found, 57 met the aforementioned criteria.

The number of papers treating of conversion attribution has been increasing during last 9 years. In the first half of the decade, this number reached 23, and in the second, it reached 34 (no papers published in 2020 were included so the real estimate will probably be higher). Also, the number of Google Search queries with the aforementioned keywords, from 2010 to 2019, rose 7.2 times worldwide. Conversion attribution will probably be an important scientific subject in the nearest future due to its influence on marketing spending profitability.

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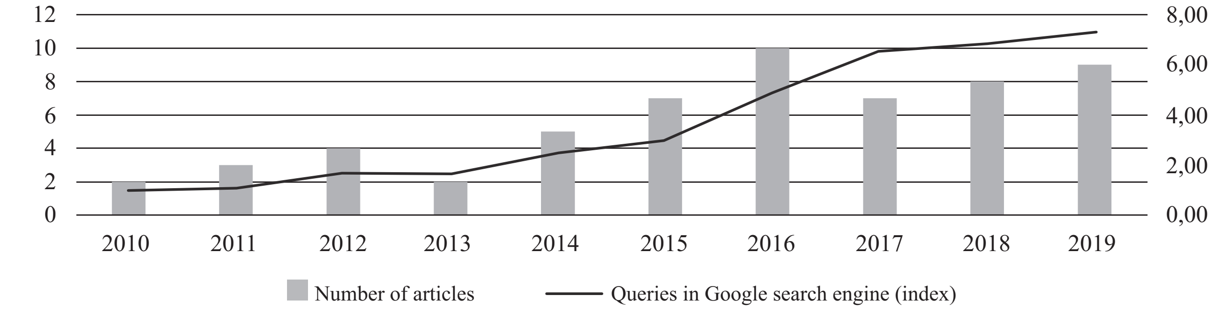
Figure 1
Scientific and practical interest in conversion attribution topic



Source: author's own elaboration, index: number of queries in current year to previous year, 2010 = 1.

These articles were selected and classified into one of three categories: theoretical review; data analysis/research, theoretical review, and data analysis/research; and theory in the case of one article. Also, some other areas of interest (type of media channel, attribution methods used) were explored.

Table 1 presents the development of conversion attribution methods in the current decade, types of analyzed data and media channels. The detailed review of literature including key findings is presented in Table 4 in the Appendix.

Table 1
Analysis of conversion attribution literature

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total
Conversion attribution methods used in case study papers											
Logistic regression		1	1			2	2	2	5	1	14
Shapley value					1	1		1	4	3	10
Markov chains			1		1		1		1	5	9
Probabilistic model		1			1		1	2	2		7
Machine learning			1			2	1		1	1	6
Hierarchical Bayesian model				1	2		1			1	5
Vector autoregression	1	1	1				2				5
Survival analysis						1	1	1	1		4
Neural networks									1	1	2
Other	1	2		1	1	2	3	1	2		13
Heuristic	1	1	1		3	1	4	2	4	3	20
Types of online media channels analyzed in case study papers											
Paid media	2	3	4	2	5	6	7	5	6	8	48
Owned media	2	1	1	1	4	3	4	3	4	6	29
Earned media	0	0	0	0	0	1	2	0	0	1	4
Types of data analyzed in all papers											
Online only data	1	2	4	2	5	6	6	4	8	7	45
Online and offline data	1	1	0	0	0	1	4	3	0	2	12
Total number of articles											
Total	2	3	4	2	5	7	10	7	8	9	57

One article may contain more than one method and more than one type of media channels. Heuristic models are used mostly as a reference point.

Source: author's own elaboration.

It shows a significant number of different approaches to conversion attribution—from logistic regression, through hierarchical Bayesian models and probabilistic models to deep neuron networks and game theory approach. In the last years, models based on Markov chains and the Shapley value have been gathering more and more interest – in the last two years researches used this methods in almost 1/3 of all publications. It is worth mentioning that also Google Data-Driven Attribution model available as an automated campaign strategy in Google Ads ecosystem is built on the assumption of the Shapley value (Google, 2020). Heuristic models, which have always been in use, are also popular, but used mostly as a benchmark to more sophisticated tools and to present a difference in results between proposed or analyzed models commonly used in marketers' approach.

The review shows that the scientific world has not yet adopted the broadly accepted conversion attribution methodology – logistic regression was a method used in 14 articles, probabilistic models in 7, Markov chains in 9, the Shapley value in 10 cases.

Table 2
Popular conversion attribution models

Category	Type	Model	General rules
Heuristic (arbitrarily given credit)	Single-touch	Last-click	The overall effect on the conversion is attributed to the last activity (source) 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.
		First-click	The overall effect on the conversion is attributed to the first activity on the path.
	Multi-touch	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; for example, 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.
		Customized 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)
Algorithmic (econometrically given credit)		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.
		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.

Source: author's own elaboration based on Jayawardane et al., 2015; Ji et al., 2015; Shultz & Dellnitz, 2018.

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Marketers seek and prefer solutions that allow the creation of daily reports which are based on day-to-day budget management (Shao & Li, 2011). Dalessandro et al. (2012) state that proper conversion attribution models must be:

- fair—all channels must be taken under consideration and show a proper impact on the final conversion,
- data-driven—a valuable conversion attribution model should be designed for advertising campaign goals and assess both consumer reaction to advertisements and data on conversions from the campaign,
- interpretable—it should be widely accepted by practitioners involved in the marketing industry; acceptance should arise on the basis of the gained metrics and an intuitive understanding of model rules.

Danaher and van Heerde (2018) distinguish five elements of a good attribution model:

- increases the marginal effect of a particular medium on purchase probability;
- equals to zero when the medium produces no effect;
- is proportional to the number of exposures to a medium;
- accommodates advertising carryover;
- reduces the results of the last-click model when there is no carryover or other interaction effects.

The aforementioned requirements explain the popularity of simplified and heuristic models—these types of models are easy to understand and easy to compute. Models based on the Shapley value and Markov chains in general also meet Dalessandro's requirements. This is why their popularity has been observed to increase. Logistic regression models are difficult to apprehend mostly due to the possible negative coefficients of some channels (Jayawardane et al., 2015). Methods that employ machine learning are also difficult to implement in day-to-day analyses.

The second half of the decade brought more studies that analyze the impact of online and offline marketing channels.

Because majority of studies were based on interaction with customers in terms of clicks, it is worth distinguishing papers focused on the influence of display ads on final conversion. Ren et al. (2018) state that analyses taking into account display impressions have higher accuracy. Display activities increase significantly the number of search clicks and conversions (Kiereyev et al., 2016) – also longer exposition to display ads, a higher probability of user engagement in search channel, especially when it is arranged on the early stage of online consumer journey (Ghose & Todri, 2016).

A huge body of research focuses on data from paid media and owned media while only 4 papers also focused on earned media. Also a minority of case studies involved offline data – only 6 papers analyzed additional data.

3. THE OPEC MODEL AS AN EXTENSION TO THE DIGITAL ADVERTISING ECOSYSTEM OF PAID MEDIA, OWNED MEDIA, AND EARNED MEDIA

Marketers use a widely known division of the online advertising ecosystem that separates it into three areas in which marketing content is published: owned media, which, among other things, include the company's website and social media profiles, paid media, which are simply paid advertising activities (banners, videos, etc.), and earned media, which are pieces of independent content directly related to a brand (reviews, opinions, etc.) and published by a third party (bloggers, influencers, journalists, users), which was extensively described by Harrison (2013), Lovet and Staelin (2016), Srinivasan et al. (2016). Several pieces of research (Xie et al., 2018; Golan et al., 2019) additionally distinguish shared media as part of earned media, which evolved strongly by virtue of the development of social media over the last decade. For the

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purpose of this paper, the paid, owned, earned media division was employed. This division is also supported by the Interactive Advertising Bureau (IAB, 2016, pp. 8–12).

This type of media division is built on two dimensions: 1) the ability to control advertising communication in owned and paid media, and 2) the commerciality of the message—the content in earned media, unlike that in paid and owned media, is not paid by advertisers (see Figure 2).

Classical decision-making models—for instance, EKB (Engel et al., 1968, 1978), Howard Sheth (1969), and Nicosia (1966)—assume that, during the decision-making process, consumers assess alternatives and search for the details of a product through the utilization of various sources. Also, more recent models that describe consumer behavior and the impact of advertising on the path to purchase—for instance, the Zero Moment of Truth theory (Lecinski, 2011), the AISAS model (Sugiyama, Andree, 2010), a process model of customer journey and experience proposed by Lemon and Verhoef (2016), and a typology of online decision-making behavior proposed by Karimi et al. (2015)—clearly show that users, during their path to purchase, research the competitors' content, independent product category reviews, etc., and, in general, do not only assess one product but the whole product category.

Sahni (2016) researched the impact of online advertisement on the advertiser's competitors and found that online advertisements increased the chance of a sale for non-advertising brands and produced a positive *spillover effect* in the selected industry in online media. Also, Chae et al. (2017) found multiple positive and negative spillover effects related to word-of-mouth marketing. Rutz and Bucklin (2011) found a positive spillover effect produced between media channels. There are other pieces of research (e.g. Nottorf & Funk, 2013; Lu & Yang, 2017) that present empirical results of the spillover effect in the online advertising industry.

Li et al. (2017) notice that the existing research on conversion attribution analyzes data that comes mostly from paid and owned media (this observation was also made in the author's literature review). They researched the impact of the competitors' websites on the results of conversion attribution and proved that the marketing activities of other companies have an impact on the entire customer journey. Also, Ailawadi and Farris (2017) and Choi et al. (2019) indicated the problem of only studying the marketer's own online touchpoints in scientific literature and market practice. They encourage researchers to explore the contribution of product category websites on the path to purchase more extensively and propose to use survey data if getting actual data is infeasible.

The information about the online customer journey coming from classical and modern decision-making models, the results of spillover research, and conversion attribution literature lead to the conclusion that the advertiser should take into consideration the area of online media not only related to their brand but also to the product category. The author proposes to name this type of media *category media*. Category media cover the competitors' own, paid, and earned media and independent publications related to the product category.

As a natural consequence to this conclusion, the author proposes to extend the existing paid, owned, earned media division (Srinivasan et al., 2016) to the OPEC (owned, paid, earned, category) media model. The type of content included in the four types of media is presented in Table 3.

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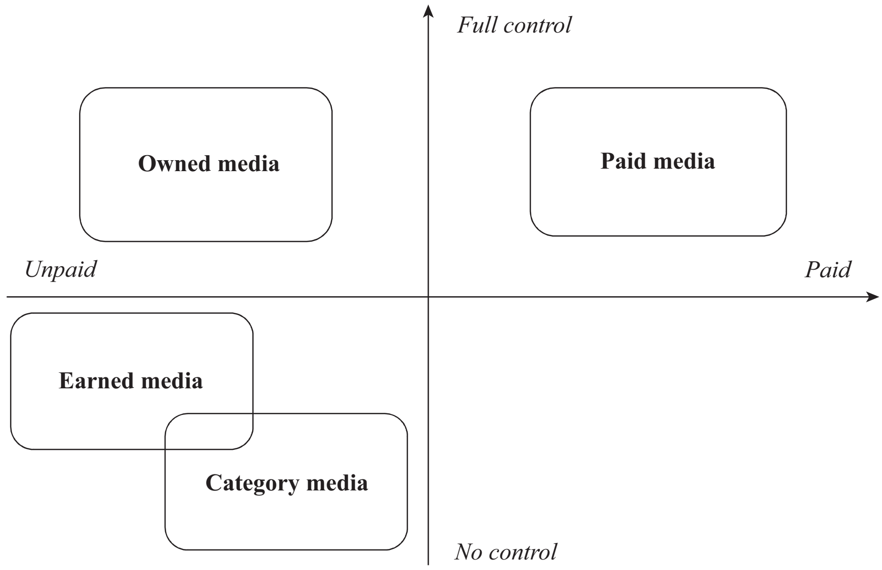
Figure 2
OPEC (owned, paid, earned, category) media model.



Source: author's own elaboration.

Table 3
Media tools in the different areas of an online customer journey as described by the OPEC model

Area of online promotion	Tools
Owned media	• Websites • Blogs • Social media channels • Mobile apps • E-mail and SMS marketing (internal databases) • Search Engine Optimization (SEO)
Paid media	• Search Engine Marketing – Pay Per Click (SEM – PPC) • Social media advertisements • Boosted posts • Display • Paid reporters and bloggers • E-mail marketing (external databases) • Affiliate marketing • Video
Earned media	• Social media (mentions, likes, shares, comments, retweets, etc.) • Online reviews • Word-of-mouth promotion • Business reporters and bloggers • Search Engine Optimization (SEO)
Category media	• Publications related to the topic/product category that do not mention the advertiser's brand and competing brands • The competitors' paid media, owned media, and earned media

Source: author's own elaboration on the basis of Srinivasan et al., 2016; Garman, 2019.

It is worth remembering that, in general, marketers are not able to control communication in the competitor's paid, owned, and earned media. It is also impossible to control and manage the content published by professional or amateur authors that relates to the product category, which may challenge the idea of consumers purchasing products from a selected category. However, marketers are able to analyze the content published in category media and use this data for better budget allocation. To illustrate, a manufacturer of automatic vacuum cleaners may invest money

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to build the SEO position of an independent article that compares ordinary vacuum cleaners vs. automatic vacuum cleaners.

4. CONSEQUENCES OF THE OPEC MODEL ON THE RESULTS OF THE CONVERSION ATTRIBUTION MODEL AND ASSESSMENT OF THE ONLINE CUSTOMER JOURNEY

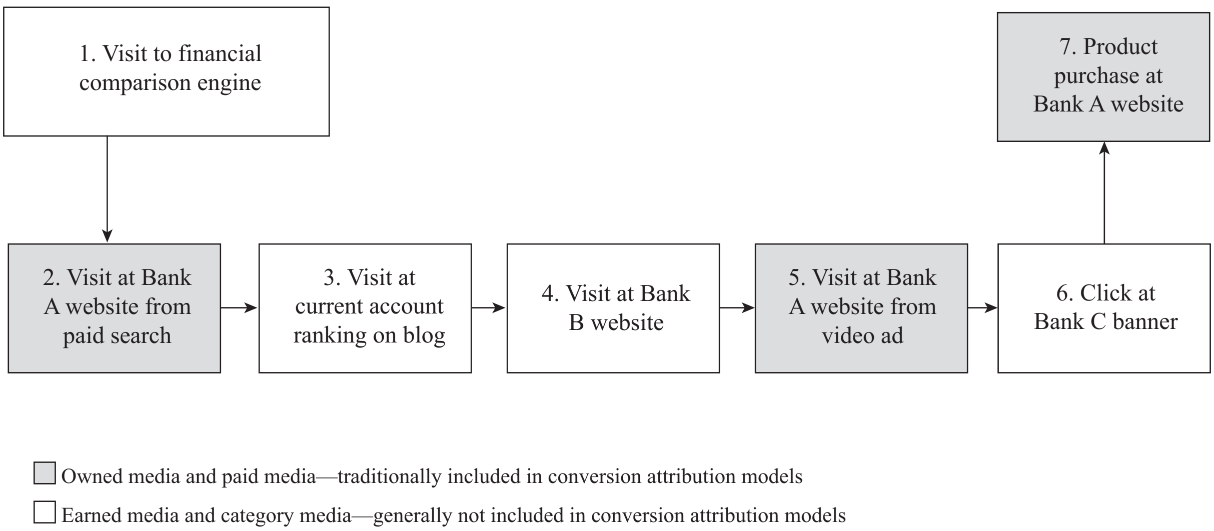
Current conversion attribution models (Markov chains, the Shapley value, logistic regression, etc.) take the complexity of consumers' real decision paths into consideration and are based on analyses of all touchpoints on the path. However, 24.5% of marketers still use the last-click model, 43.2% of them rely on another single-touch model called first-click, which assigns all conversions to the touchpoint that opens the decision path, and less than half of them decide do use multi-touch models (eMarketer, 2018).

The literature review of the aforementioned paper clearly shows that few studies research the impact of earned media on conversion in multi-channel analyses. Not a single paper focused on category media.

According to the research conducted by Lecinski (2011), customers use, depending on the industry, 5.8 to 18.2 information sources (at least one being the advertiser's website). Hence, it may very well be possible that paid media and owned media constitute only a minority of online customer activities.

Bearing this in mind, two questions related to the problem of measuring the real impact of advertising on the customer's decision path arise: 1) what is the share of consumer activities in earned media and category media? 2) what is the difference between conversion attribution models based on data from paid and owned media activities and data from all activities in all media categories? The theoretical analysis of a customer journey presented in Figure 3 clearly describes the problem and shows potential differences.

Figure 3
An illustration of an online customer journey



Source: author's own elaboration.

Figure 3 illustrates a decision path and demonstrates a research idea of how the study differs from other analyses by taking into account the areas of earned and category media not included in the studies analyzed in that paper.

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Figure 3 shows an example of a full consumer decision path, which is comprised of seven interactions with an advertising message regarding a product search—a bank account for micro-companies. The consumer begins their product search by analyzing a ranking of business bank accounts to note that Bank A is a recommended choice (Interaction no. 1). Then, after some time, they search for the phrase "bank accounts for companies in Bank A" and click on a redirecting advertisement (Interaction no. 2). In later steps, they visit a financial blog (Interaction no. 3) and the website of another bank (Interaction no. 4), click on a video advertisement of Bank A (Interaction no. 5), and go to the website of yet another bank (Interaction no. 6). Ultimately, they decide to open an account at Bank A by browsing the website of the institution directly (Interaction no. 7). An analysis of this decision path from the perspective of a marketer employed by Bank A who only has the ability to measure activity from paid and owned media would consist of only three touchpoints: clicking on a Bank A advertisement two times (first interaction in paid search, second interaction after viewing video ad), directly accessing the website of Bank A, and completing the application for a bank account.

Using the conversion attribution methods mentioned above, marketers can use their own methods to allocate the advertising budget. Regardless of which of the conversion attribution methods seems superior, it is easy to notice that skipping four steps out of the seven in a customer decision path carries the risk of error. For instance, in a heuristic multi-touch linear model each owned and paid media activity achieves the credit of 1/3 but, if category and earned media are taken into account as well, the credit plummets to 1/7, and this generates a difference of almost 50% in results.

Applying a conversion attribution model to the same data set causes differences in results and interpretations (Kakalejcik et al., 2019; Zaremba, 2019; Singal et al., 2019), hence the questions of what differences can result from incorporating data from earned and category media into the attribution process, which media are underestimated, and which of them are overestimated.

Going back to the analyzed example, such an approach would require the marketer to find a way to increase visibility on bank account comparison websites and blogs by, for example, investing in search engine positioning or sponsored/display presence. Naturally, then, these media would move from category media to paid media but such an investment could have a significant impact on the effectiveness of the entire advertising campaign. Furthermore, advertisers face the problem of cross-device analysis, which only multiplies the difficulties already present (Brookman et al., 2017).

5. CONCLUSION AND FURTHER RESEARCH

This paper contributes a comprehensive presentation of conversion-attribution–related studies to the existing literature. The research presents the development of the studies in terms of the methods and data sets used as well as the consequent findings. The prepared material may prove helpful for scientists and practitioners looking for a theoretical background on the selected conversion attribution models. The proposed OPEC media model aims to build new perspectives for conversion attribution research and shows a potential direction for further studies.

The literature review shows that there is no broadly accepted conversion attribution model and there are numerous pieces of research that introduce entirely novel lines of approach. There are many discussions among researchers referring to choosing the best approach. An increasing amount of research in the last two years on models based on Markov chains and the Shapley value is because of their fairness and easy interpretability. The Shapley value method appears to be difficult in computation as Singal et al. (2019) and Zhao et al. (2018) proposed simplified Shapley value methods for the attribution problem. Simplified multi-touch algorithmic models may deter marketers from employing heuristic models. According to eMarketer (2019, 2019a),

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more and more companies apply multi-touch attribution models but still less than 40% of CMOs rate themselves as good or excellent at the topic. This figures shows that simplified algorithmic methods of conversion attribution are needed.

Theoretical and conceptual papers related to the conversion attribution topic focus mostly on usage of this methods to predict and manage customer experience, loyalty, customer lifetime value. Researchers state that it may be difficult due to the long media-planning cycles and limitations of available technology in terms of gathering data of users behavior out of advertiser's media touchpoints. But necessity of that kind of studies seems obvious.

Most research studies rely on clickstreams, and this may lead to incorrect results and suboptimal media budget allocation—ad impression always has a significant impact on the final purchase. The influence is not direct – display ads encourage users to use other channels finally driving to conversion, especially in an early stage of the path to purchase.

Researchers analyze data form paid and owned media and, in general, miss information from the other parts of a customer path to purchase. This approach is currently loudly criticized due to the evidence based on conversion attribution methods of the strong impact of, for instance, the competitors' websites on the final purchase decision.

Because of this, the author of this paper proposes a new classification of media activities, where not only paid, owned, and earned media are included but also user activities related to product category content. This type of content is called *category media* and is part of the OPEC (owned, paid, earned, category) media model.

The OPEC media model combined with conversion attribution methods and literature review raises numerous questions that can, in turn, stimulate further research.

- How many user activities are there in earned and category media?
- How does data from earned media and category media affect conversion attribution models based on paid media and owned media?
- Which paid and owned media are overestimated and which are underestimated?
- Do the competitors' display impressions create a significant demand for brand analysis?
- What are the differences in a customer journey seen through the OPEC model in different industries?
- What are the differences in a customer journey seen through the OPEC model for high-engaging and low-engaging product categories?
- What is the contribution of earned and category media viewed on mobile devices to the final conversion?
- Is there any simplified method to involve the effects of earned and category media without having a complete view on the entire customer journey? (as proposed by Dalessandro et al. (2012) for display advertising without experiments and extended data sets)
- What is the impact of touchpoints coming from particular OPEC model areas on customer experience, loyalty, customer lifetime value?
- Does the quality of the content faced by customers in earned media and category media significantly influence final purchase?

Due to technological limitations, a precise measurement of user activities in earned and category media may be difficult, but an adequate combination of conversion attribution methods with other methods (e.g. surveys) may provide helpful and yield results that will lead to a better understanding of media mix modeling.

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APPENDIX

Table 4
A collation of papers and the related conversion attribution topics

T – theoretical/conceptual paper, CS – case study paper, P – paid media, O – owned media, E – earned media, ON – online channels/environment, OFF – offline channels/environment (e.g. sales data in stationary points of sales)

Study	Type	Media	Channels	Methods	Findings / Implications
Sikdar & Hooker (2019)	T, CS	P, O	ON, OFF	• Markov chains	• Development of a multivariate hidden semi-Markov model framework. • The proposed model helps to determine the expected length of channel activity and inactivity of customers and to identify the risk of customer attrition.
Kaatz et al. (2019)	CS	P, O	ON	• Markov chains	• Mobile users mostly rely on direct traffic. • Social paid touchpoints have great impact on purchase decisions.
Singal et al. (2019)	T	–	ON	• Markov chains • Shapley value • Heuristic	• Proposition of a new simplified metric (counterfactual adjusted Shapley value) for the attribution problem. • Provided an underlying axiomatic framework motivated by game theory and causality for the proposed model.
Zaremba (2019)	CS	P, O	ON	• Heuristic	• Varied results of conversion attribution between heuristic and simplified models. • Every heuristic and simplified model should be used for other reasons and problems/questions.
Kadyrov & Ignatov (2019)	T, CS	P, O	ON	• Gradient boosting over decision trees (machine learning) • Logistic regression • Markov chains • Shapley value	• Development of gradient boosting over the decision trees approach and algorithm. • The new solution gave the best results among all models analyzed in terms of ROC and AUC (Receiver Operating Characteristic and Area Under Curve).
Du et al. (2019)	T, CS	P, O	ON	• Recurrent neural network + Shapley value	• Presentation of a practical system for multi-touch attribution.
Kakalejcik et al. (2019)	CS	P, O, E	ON	• Markov chains • Heuristic	• High-value customers use some marketing channels differently than low-value customers. • High-value customers take more steps in the interaction with the website before purchasing than low-value customers.
Winter & Alpar (2019)	T, CS	P	ON	• Hierarchical Bayesian model	• Proposition of a model that analyzes user considerations: whether and where to click, whether to convert, what and how much to buy. • Each effect may be regressed and quantified in the search context.
Choi et al. (2019)	T	P	ON, OFF	–	• A lack of a perspective on the entire customer journey is a research gap.

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Study	Type	Media	Channels	Methods	Findings / Implications
Berman (2018)	T	–	ON	• Shapley value • Heuristic	• More accurate measurement of the uncertain state of the campaign always benefits advertiser. • The last-click model may lower the advertiser's profits compared to not using attribution at all. • A model based on the Shapley value should increase the profitability of a campaign.
Ren et al. (2018)	T, CS	P, O	ON	• Recurrent neural network • Survival analysis • Logistic regression • Probabilistic model	• Analysis not only of the impact of clicks but also of impressions. • Analysis that takes into account impression information significantly improves accuracy. • Proposition of a dual-attention, recurrent neural network.
Li et al. (2018)	T, CS	P	ON	• Deep neural network • Logistic regression • Markov chains • Heuristic	• Introduction of a deep neural network model for conversion attribution.
Zhao et al. (2018)	T, CS	P, O	ON	• Shapley value	• Proposition of a simplified Shapley value model.
Danaher & van Heerde (2018)	T, CS	P, O	ON	• Dorfman-Steinman theorem • Probit model • Heuristic	• Presentation of a new approach: marginal increment in the purchase outcome variable in the presence versus absence of a medium, relative to the increments in all media. • Proposition of 5 requirements for a proper attribution model. • Allocation decisions should be proportional to elasticities rather than proportional to attribution weights – common attribution models drive to wrong conclusions and lower purchase conversion rates
Zhao et al. (2018)	T, CS	P	ON	• Linear regression • Logistic regression	• Proposition of two revenue-based attribution models. • Differences between applied multi-channel models are not significant except for small channels.
Nisar & Yeung (2018)	T, CS	P, O	ON	• Shapley value • Logistic regression • Heuristic	• The last-click model overstates display. • Social media are underestimated and may have strong behavioral impact not visible in used conversion attribution methods.
Mahboobi et al. (2018)	T CS	P	ON	• Shapley value • Logistic regression • Probabilistic model	• Attribution methods blur the differences between contribution and efficiency. • The use of the Shapley value gives better results when compared to other models.
Kannan & Li (2017)	T	–	ON, OFF	–	• The crucial research gaps in the subject of conversion attribution are the impact of offline media and attribution across different devices.
Ailawadi & Farris (2017)	T	–	ON, OFF	–	• The current attribution models only study behavior across the marketer's own online touchpoints. • There is a strong need to expand analyses to include all of the customers' activities during their journey to purchase, including the competitor's website.

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Study	Type	Media	Channels	Methods	Findings / Implications
Abhishek et al. (2017)	T, CS	P, O	ON	• Game Theory • Shapley value • Heuristic	• Popular multi-touch models might not lead to the most effective choices for both advertisers and publishers. • In industries where the cost of creating awareness is similar to the cost of displaying ads to drive conversion, the advertisers should use channels showing ads in awareness and consideration stages of the funnel. • If advertiser knows that brand awareness is higher than conversion probability in the consideration stage, they should spend more on brand building.
Li et al. (2017)	T, CS	P, O	ON, OFF	• Logistic regression	• The competitors' advertisements influence product information search, alternative evolution stages, and purchase.
Diemert et al. (2017)	T, CS	P	ON	• Probabilistic model • Heuristic	• Proposition of a novel, effective bidding policy leveraging attribution modeling.
Ji & Wang (2017)	T, CS	P, O	ON	• Survival analysis • Additive hazard • Probabilistic model • Logistic regression	• Proposition of an additional multi-touch attribution model based on two objectives: – The effects of advertising exposure are fading with time. – The effects of advertising exposure on the search path are additive.
Zantedeschi et al. (2017)	T, CS	P	ON	• Hierarchical Bayesian model	• Proposition of a new model that allows accounting for differences in conversion propensity and response. • Targeting the most responsive customers increases the predicted ROI by 70% versus traditional recency, frequency, and monetary value–based targeting.
Wedel & Kannan (2016)	T	–	ON	–	• Solving the attribution problem is an intermediate step toward predicting its effects on the whole customer journey and complete media mix. • A lack of better understanding of the impact of marketing mix elements and simultaneously accommodating planning cycles is a research gap.
de Haan et al. (2016)	T, CS	P, O, E	ON, OFF	• Vector autoregression • Heuristic	• Last-click attribution underestimates content-integrated marketing activities generating 10–12% less revenue. • The last-click method overestimates the power of e-mail and branded paid search while underestimating comparisons and portals.
Anderl et al. (2016)	T, CS	P, O	ON	• Markov chains • Logistic regression • Heuristic	• Markov chains attribution models outperform heuristic models and simple logit models • Company-initiated channels are underestimated by simplified lines of approach. Direct and paid search are overestimated. • The new approach to attribution based on Markov chains allows the calculation of the probability of conversion to a single customer, and this might be beneficial for real-time bidding decisions.

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Study	Type	Media	Channels	Methods	Findings / Implications
Kanaan et al. (2016)	T	–	ON, OFF	–	• The use of conversion attribution methods for the purpose of analyzing the influence of particular touchpoints on customer experience, loyalty, retention, and customer lifetime value constitutes a chief research gap. • Media-planning cycles are long (spanning months or quarters) and not in line with attribution solutions (short perspective, data taken from a short, frozen period, etc.).
Kireyev et al. (2016)	T, CS	P	ON	• Multivariate time series	• Display advertisements increase search conversion significantly. • Display advertisements increase the number of search clicks and increase search advertising costs.
Grewa et al. (2016)	T	–	ON, OFF	–	• Attribution problems originating from mobile marketing are similar to the problems of digital advertising in general. • The inclusion of the user's location in attribution analysis may be an interesting research gap.
Li et al. (2016)	T, CS	P	ON	• Simultaneous equations model • Heuristic	• A group of keywords performs better under last-click or first-click; therefore, it is crucial to identify the groups that open or close the conversion path.
Ji et al. (2016)	T, CS	P	ON	• Survival analysis • Additive hazard • Probabilistic model • Logistic regression • Heuristic	• Proposition of a new approach: probabilistic multi-touch attribution model. • The new model presents high accuracy in attribution and conversion prediction.
Srinivasan et al. (2016)	T, CS	P, O, E	ON, OFF	• Vector autoregression	• One of the few pieces of research that include earned media in the data set. • Online activities are strongly affected by offline activities. • Consumer disengagement measured through Facebook unlikes has a substantial negative effect on sales. • Online metrics may assess the efficiency of TV campaigns (e.g. paid search).
Ghose & Todri (2016)	T, CS	P, O	ON	• Difference-in-differences matching	• The research involved information about ad impressions. • Display advertising engages users in both active and passive search. • The longer the duration of display exposure, the higher the probability of search engagement. • Display advertising has a higher impact on the final purchase when arranged in an early stage of the path.
Klapdor et al. (2015)	T, CS	P, E	ON	• Logistic regression	• The number of different channels in a path to purchase is a new predictor of purchase probability. Purchase probability increases with the number of channels used. • A transition from information (affiliate, blogs, etc.) to navigation (paid search, SEO, etc.) channels increases conversion probability.

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Study	Type	Media	Channels	Methods	Findings / Implications
Dalessandro et al. (2015)	T, CS	P, O	ON	• Proxy model (machine learning)	• Presentation of a novel methodology for insufficient sets of data. • Site visits are a good predictor of purchase while clicks are not. • Using CTR to build or optimize targeting models is suboptimal.
Yadagiri et al. (2015)	T, CS	P, O	ON	• Logistic regression + Shapley value • Logistic regression • Random forest (machine learning)	• Implementation of a non-parametric approach to conversion attribution modeling to counter high levels of synergy between marketing channels in a parametric approach.
Woof & Anderson (2015)	T, CS	P, O	ON	• Sequential analysis • Heuristic	• Proposition of a time-weighted attribution model.
Barajas et al. (2015)	T, CS	P	ON	• Bayesian estimation	• CPA (cost per action) campaigns incentivize the selection of converting users. • The results of optimization should be used to target high-potential customers.
Jayawardane et al. (2015)	T	–	ON, OFF	–	• Proposition of a categorization of conversion attribution models. • The review of methods used for conversion attribution
Zhang et al. (2015)	T, CS	P	ON	• Survival analysis	• Proposition of a new approach to conversion attribution and conversion probability.
Li & Kannan (2014)	T, CS	P, O	ON	• Hierarchical Bayesian model • Heuristic	• Proposition of a conceptual framework that includes carryover and spillover effects across online channels. • The framework constitutes a functional tool with the capacity to identify incremental contributions of a channel.
Liu et al. (2014)	T, CS	P, O	ON	• Monte Carlo simulation	• Presentation of a time response and revenue to spend response model.
Geyik et al. (2014)	T, CS	P, O	ON	• Probabilistic model • Heuristic	• Implementation of a new model with multi-channel attribution that optimizes ROI.
Xu et al. (2014)	T, CS	P	ON	• Hierarchical Bayesian model	• Presentation of the new attribution model. • Display advertising has a small direct effect on purchase but stimulates visits to other advertisements.
Anderl et al. (2014)	T, CS	P, O	ON	• Markov chains • Shapley value • Heuristic	• Development of practical framework for conversion attribution using Markov chains • SEO, display, newsletter, retargeting are overestimated by all heuristic approach.
Karande et al. (2013)	T, CS	P, O	ON	• Game theory	• Introduction of the concept of fair allocation (analogous to the Nash equilibrium).

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Study	Type	Media	Channels	Methods	Findings / Implications
Nottorf (2013)	T, CS	P	ON	• Hierarchical Bayesian model	• Proposition of a new approach to conversion attribution that uses Bayesian methods. • Paid search advertising seems to be overestimated and retargeting underestimated.
Chaffey & Patron (2012)	T	–	ON	–	• Introduction of the RACE (Reach, Act, Convert, Engage) model framework that optimizes the performance of online marketing.
Abhishek et al. (2012)	T, CS	P, O	ON	• Markov chains • Logistic regression • Heuristic	• Display advertising brings a lot of value to the results of a campaign. • Proposition of an attribution methodology based on the marginal effect on consumer conversion probability.
Rosales et al. (2012)	T, CS	P	ON	• Machine learning	• Creating a foundation for post-click conversion predictions based on contextual information (CTR, CVR, click-to-conversion delay, etc.)
Dalessandro et al. (2012)	T, CS	P	ON	• Causal effect estimation methods	• Examination of the causal effect of display advertising on post-impression conversions. • Presentation of the new approach for assessing the display effect without the need for controlled experiments (even A/B tests).
Shao & Li (2011)	T, CS	P	ON	• Logistic regression • Probabilistic model • Heuristic	• Proposition of two statistical multi-touch attribution models.
Wiesel et al. (2011)	T, CS	P	ON, OFF	• Vector autoregression	• The profit impact of customer-initiated contacts is higher than company-initiated.
Rutz & Bucklin (2011)	T, CS	P, O	ON	• Nerlove–Arrow model • Bayesian dynamic linear model	• Generic search activities positively affect future branded search activities. • Spillover is asymmetric—branded search has no impact on generic search.
Lee (2010)	T, CS	P, O	ON	• Assist correlation • Heuristic	• Conversion attribution modeling may be financially beneficial.
Srinivasan et al. (2010)	T, CS	P, O	ON, OFF	• Vector autoregression	• Mindset metrics (awareness, consideration, liking) show their value as a diagnostic measure. • Mindset metrics may explain sales performance beyond the part explained by marketing mix actions.

Source: author’s own elaboration.

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