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The path to purchase and attribution modeling: Introduction to special section

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ABSTRACT

Firms make significant marketing investments in online, mobile and offline media and channels such as search engines, social media, e-mail, display advertising, print, TV, etc., to draw in customers to their websites, mobile apps, and stores to effect conversions and spur sales. As customers go through a series of touch points across media, channels and devices on their paths to purchase, attributing the appropriate credit for each touch point has emerged as an important problem. By focusing on estimating the incremental value of a touch point and spillover effects across channels, attribution models can provide insights for allocating marketing investments across channels and targeting customers across channels and devices. In this paper, we provide a survey of the state-of-the-art in attribution modeling and analytics. As part of the survey, we also introduce the articles in this special section and position them in our classification framework. Finally, we propose a research agenda to guide future work in the area.

1. Introduction

In recent years, firms have been making significant marketing investments in online, mobile and offline media and channels – search engines, display advertisement, social media, e-mail, print ads, radio, TV ads, to name a few – to attract customers to their website, mobile apps or sites, and/or stores to effect conversions and related outcomes to spur sales. As customers go through a series of touch points across media, channels and devices on their paths to purchase understanding the effectiveness of each touch point and their complementary roles in leading to overall conversions is becoming very important. This is especially so as retail environment is rapidly morphing into an omni-channel world as new channels, media and devices compete for marketing investments (Verhoef et al., 2015). Traditionally firms have used aggregate measures of conversions associated with each channel last touched before conversion as a rough metric of its effectiveness, more so because of the lack of data on the more involved roles channels and media play in consumers' purchase funnel. With the availability of path data of customers detailing their interactions with different touch points in their purchase funnel, there is a heightened academic and practitioner interest in attribution modeling. In attribution modeling online and offline channels in a customer's purchase funnel are attributed the appropriate credit for the conversion related outcomes, taking into account the carry over effects within and spillover effects across channels. Emphasizing the importance, the recent Marketing Science Institute (MSI) research priorities summary (2016–2018) highlights attribution as #1 priority.

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Attribution modeling and analytics can help answer many questions that are relevant for marketing managers. Some examples include: which ads are driving conversions? Which keywords are driving acquisitions? Which channels should the firm use to target customers? What is the incremental value of an online channel? What is the incremental impact of mobile channel? Are there differences between devices? How do social interactions (within social media) affect the purchase funnel? Answers to these questions have important implications for measuring marketing ROI and for determining optimal online and offline marketing investments. In order to spur new thinking and research in this area, we initiated this special section with the support of past editors Eitan Muller and Jacob Goldenberg in 2013. We received 21 submissions for this special section and the five articles appearing in this section represent the varied approaches taken by researchers to address the above questions.

Our objective in this paper is to provide a broad survey of the state-of-the-art and a framework for classifying the different research approaches and granularity of data used. We also discuss in this context how the papers in this special section contribute to the area. We then highlight the specific research issues that future research needs to examine. In the next section, we define the problem, propose a classification framework and discuss extant research and the articles in the special section.

1.1. The state-of-the-art

From marketing practitioners' viewpoint, attribution modeling is defined as the science of using advanced analytics to allocate appropriate credit for a desired customer action to each marketing touch point across all online and off-line channels (Moffett et al., 2014). From an academic viewpoint, the objectives of attribution modeling can be accomplished using a variety of modeling approaches and data. The classification framework in Table 1 is a good starting point to survey the extant work relevant to attribution modeling and path to purchase. While the attribution problem is an age-old problem, solving the problem requires appropriate data at the right granular level. Early work focusing on measuring synergies across media and channels has used investment and aggregate data (e.g., Naik & Raman, 2003), and user level and aggregate data has been used to determine cross-channel impacts and customers' channel migration (e.g., Ansari & Mela, 2003; Ansari, Mela, & Neslin, 2008) focusing on offline and online channels. Key objectives of these studies are to understand how to target customers and allocate marketing investments across channels taking into account the estimated impacts.

While understanding the impact of carryover within and spillovers across channels have been always important in multi-channel contexts, the renewed interest in attribution as a problem started with the availability of individuals' path to purchase data with clear identification of the touch points prior to any conversion event. Given the path data, many firms have started using heuristic attribution rules such as last-touch attribution, or first-touch attribution, or equal attribution across all touches assuming all touches play equal role in conversion or fractional attribution, and so on. Such rules are generally based on firms' intuition on how each channel plays a role in the purchase funnel of customers.

Early academic work viewed the problem as a prediction problem – that is, given a string of past touch points making up the purchase funnel, how best to predict the outcome of interest. Towards this objective, Shao and Li (2011) propose a bagged logistic regression model to identify the best fitting model in terms of predictive fit and then use simple probabilistic models (second- or higher-order models) to attribute credit for the outcome for past touch-points. Dalessandro, Stitelman, Perlich, and Provost (2012) propose a data-driven casual approach that uses observational data to estimate the impact of a touchpoint by empirically comparing the outcome with that touch point with the counterfactual of the outcome without the touch point, all else being the same. Using the different conditioning touch points, they use the concept of Shapley value (Shapley, 1953) to estimate the attribution of a specific touch point. Both the approaches are fast and easy to implement. However, while they focus on solving the attribution problem, they do not go beyond to estimating spillovers or providing specific approaches for media mix optimization using the attribution estimates. The attribution solutions that are provided by some firms in the marketing analytics market (Google's Adometry, Visual IQ, etc.) use variants of the above approaches. The key reasons that these approaches are commonly used include ease of implementation and interpretability.

Table 1
A framework for classification.

Granularity and type of data	• Investment in each channel • Aggregate visits/touches for each channel • Individual customer level path to purchase
Central focus of research	• Overall impact on outcome • Carryover within and feedback over time • Spillover across channels • Attribution of conversions to channels
Types of channels/media	• Offline channels/media • Online channels (including mobile, social) • Cross-device
Outcome of interest	• Conversions/purchase • Customer equity • Brand/brand equity
Tactical objective	• Attribution • Segmentation • Targeting • Media mix and optimal investment allocation

Using individual level path to purchase data in the context of online channels, Li and Kannan (2014) propose a conceptual framework and a three-level, nested measurement model of customers' consideration of online channels, their visits through these channels and subsequent purchase at the website, which accounts for carryover and spillover effects both the visit and purchase stages. Attribution of credit for the different channels based on the model estimates is accomplished through Shapley values, which they find are significantly different as compared to estimates of the widely-used "last-click" attribution model. They also validate the ability of the model in estimating the incremental effect of a channel on conversions through a field study by turning off paid search for a week. While Li and Kannan (2014) show how customers can be targeted using the model estimates, the implications for media mix allocation are limited by self-selection and endogeneity concerns.

Using individual level data, Xu, Duan, and Whinston (2014) propose a multivariate point process where each customer touch in a specific channel is viewed as an outcome of a univariate (marginal) point Poisson process. Thus, each channel touches and purchase events are viewed as separate point processes, while the conditional intensity function of each point process is a function of occurrences of events on other point processes. This creates a system of mutually exciting point processes, and estimating the model using Bayesian methods, the authors estimate the carryover effects within and spillovers across channels. They then estimate attribution weights using simulations. Abhishek, Fader, and Hosanagar (2012) explicitly address the issue of customer purchase funnel by modeling customers' states in their decision processes using a Hidden Markov Model (HMM), which enables them to address the impact of various channels at different stages of the decision process. For example, they find that display ads have a significant effect in the early stages of the purchase funnel moving customers from disengaged to engaged state, while search ads have a significant effect across all stages.

All the above models assume that campaigns involve channels whose actions are not motivated by individual channel (player's) utility but actions are coordinated at the overall level by the firm. But this need not be the case. For example, Berman (2015) examines the attribution problem in a game setting where multiple publishers vie for credit for conversions that result at a firm's (client's) website where attribution becomes complex and noisy as more publishers take part in a campaign. He considers the issues of baseline exploitation – where publishers target those who a higher propensity for conversion – and free-riding among publishers – where there is incentive for a publisher to be the last-touched contact before conversion. He finds that the attribution based on Shapley values provides well behaved pure strategy equilibria that lead to better efficiency and profits as compared to last-touch attribution.

1.1.1. Papers in special section

All the above papers we have discussed in the previous sub-section have focused on individual customer level path to purchase data in the online context. All of them highlight the perils of ignoring the touch points making up the purchase funnel and the interactions among them and defining the impact of the channels solely based on some specific heuristics such as last-click attribution or first-click attribution. Many of the papers also focus on the nature of carryover and spillover effects across these online channels – specifically display, search, e-mails, etc. Continuing in the same genre, Anderl, Becker, von Wangenheim and Schumann (2016) model the sequential nature of customers' path to purchase as first-order and higher-order Markov walks. While their model results highlight the shortcoming of last-click attribution strategy, the interesting feature of their paper is the application of their model to four large datasets from diverse industries and contexts each encompassing at least seven distinct online channels. This feature of the paper affords development of empirical generalizations and industry-specific results with regard to carryover within and spillovers across channels. In addition, the model combines rigor of academic work with practical necessity that real life implementation demands. More such studies are needed to establish general patterns which can be very insightful from both academic and practitioner viewpoints.

While establishing the carryover and spillover effects, it is also important to understand the dynamics in such effects. For example, display may have an instantaneous effect on search channel, but the effect may wear out slowly. It can even have a long-run impact. Kireyev, Pauwels and Gupta (2016) focus on such dynamics in attribution. They focus specifically on the relationship between display ads and search clicks and attempt to quantify the effect sizes and the patterns in the dynamic relationship, using aggregate level data on display impressions and search clicks over time. Their use of a vector error correction (VEC) model to the aggregate time series data of all endogenous variables allows them to examine whether there exists a long-term equilibrium among display ads, search clicks and revenue. One notable contribution of the paper is that the model estimates inform the budget allocation process with regard to the optimal mix. In this regard, the aggregate data does not have any downsides as compared to the individual data. Another advantage of their model is that they can develop dynamic versions of metrics such as CPA (cost per acquisition), which are also useful in building time-based budget allocation plans.

When it comes to combining data from offline and online channels and examining the spillovers across these channels, use of aggregate data could be a good option in many cases. In most cases, data on offline channels will be at the marketing expenditure form, while online channels can have data in expenses as well as visits and conversions. De Haan, Wiesel and Pauwels (2016) examine the long-term effectiveness and spillovers across nine forms of advertising—seven online and two offline—using a structural vector autoregressive (SVAR) model and restricted impulse responses. They examine these media in the context of pure online retailer focusing on the outcome variables of website traffic, conversion, and revenue. Their focus in the study is on understanding which form of advertising is the most effective in terms of revenue elasticity, when does the effect of different forms of advertising occurs (wear-in and wear-out effects) and where in the purchase funnel the effect occurs (at the visit stage or at the conversion stage). Their study also provides useful information for optimal budget allocation based on the model.

An important contribution that establishes the positive spillover linkage between offline advertising and online search behavior is the paper by Joo, Wilbur and Zhu (2016). The paper examines offline TV advertising at an hourly interval and search behavior of

180,000 randomly chosen users at AOL's website, thus examining the association using data on individual user level search behavior. The authors propose a three level conditional choice model, incorporating search behavior, keyword choice and click-through behavior and relate the choices at each level to hourly changes in brands' television advertising expenditures. They focus on identifying the deviations from baseline trends in search behaviors as a function of ad stock. The key finding from the research is that television advertising increases the number of searchers using branded keywords (as against generic keywords), which could help to reduce their exposure to competitive information (as compared to the case if they had used generic keywords) and thereby drive increase in conversion rate. The paper also estimates elasticities for conversions through spillover effects.

The last paper in the special section by Saboo, Kumar and Ramani (2016) focuses exclusively on the relationship among online earned media and their impact on sales. The authors measure the types of engagement with human brand (artist) over time in context of the music industry and relate them to digital track sales of all music past and present by the artist in each time period of analysis. The authors focus on three dimensions of earned media: sampling artists' music on social media, following music artists on social media, and commenting on the artists' social media websites. The paper proposes that, in line with brand attachment theory, these touch points in social media influence consumers' purchase behavior (music sales). Examining the spillover across the three dimensions and their relationship with sales, the authors find that the influence of sampling music on sales decreases at a decreasing rate while influence of following artists on social media increases at a decreasing rate, and the influence of social media word of mouth increases at an increasing rate.

In summary, the papers in the section together with the extant papers cover much ground in the area of attribution modeling. Many of the extant work has provided clear answers to what firms lose by using naïve heuristic metrics such as last-touch attribution or first-touch attribution and by ignoring the interactions among touchpoints in the purchase funnel. Some of the papers also focus on the nature of carryover and spillover across online channels/touch points including search, social media, display, e-mail, etc. others focus on spillovers across offline to online channels (e,g, Joo et al.,2016). At least one paper in our special section (De Haan et al., 2016) focuses on the impact of various types of advertising media in different stages of the purchase funnel. While the progress is good in answering many of the questions that the call for papers for our special section raised, much remains to be done. We explore this in the next section.

1.2. Going forward

Our proposed research agenda for the future is at two levels – one, at a tactical and methodological level and the other at a more strategic level. We will first focus on the tactical and methodological issues before moving on to the strategic issues.

1.2.1. Ad viewability, cookie deletion, ad blocking and un-tracked media

Currently, one of the negative aspects of measurement for attribution studies is the lack of complete and/or accurate data. Issues such as display ads and marketing interventions not being viewed by the customers targeted because they are below the roll in a webpage can lead to the question "is a registered touchpoint really a touchpoint for the customer?" Similarly, cookie deletions by users and media that are not tracked can lead to the question "are there touchpoints for the customer that are not actually registered as touchpoints?" Also, there is an increasing trend among consumers to use ad-blocking (e.g. a core feature of the new Firefox Browser which is extremely popular in Europe), which blocks display ad impressions. Such errors can adversely impact the outcome of attribution studies. This is a big problem in mobile devices, where mobile ad blockers have become particularly widespread in emerging markets as they help conserve data by not downloading the ads on the mobile phones and help websites load faster (Scottmay, 2016).

The important question therefore is: how to deal with this methodologically or otherwise to only account for ads that have truly been seen? One way the ad viewability issue can be eliminated is through better technology, while the issues of un-tracked media can be controlled by using appropriate econometric methodologies under specific assumptions. A good example of research in this direction is the paper by Ghose and Todri (2016) who use a technological solution to register the actual viewability of display impressions as well as measure the duration of exposure to display ads. Taking advantage of the quasi-experiment due to viewable and non-viewable aspects of their setting, they employ a difference-in-differences, matching methods and instrumental variables to control for both unobservable and observable confounds. They find that display ads increase customers' propensity to search and their propensity to make a purchase. In addition, they find that longer the duration of display ad exposure, the more likely the consumers are to visit the website rather than search at search engines. If ad blocking can be tracked at the individual customer level, it can be explicitly modeled and accounted for in attribution studies. The other way and a totally different philosophy to tackle the issue of ad viewability is explore ways in which display ad exposures are purposefully limited (to reduce the negative externality of the ads) in such a way to reduce the backlash of ad blocking. This could also lead to display being more effective in the results of attribution studies.

The above discussion also highlights the importance of incorporating the *characteristics* of the touchpoints (duration of display ad exposure, duration of search session, meta-data of website where display ad was shown, etc., e-mail features and so on) in attribution research, (see, for example, Zantedeschi, Feit, and Bradlow (2016). Hierarchical Bayesian methods may particularly lend themselves well to such studies. This is an important area of future research.

1.2.2. Elements of purchase funnel: segmenting and targeting

Some of the touch points in a customer purchase funnel are customer-initiated touch points while others are firm-initiated, which are under a firm's control. The distribution of such touch points in the different stages of the purchase funnel can provide insights into the baseline propensities for purchase for each customer. Estimating the baseline propensities and accounting them in the attribution models is important for obtaining unbiased attribution estimates. While field experiments can be one way to estimate baseline propensities and propensity score matching can be ways to attenuate such biases, more sophisticated methods that use observational data are necessary to tackle this problem. Similarly, more studies are needed to determine the effect of different channels and touch points in different stages of the purchase funnel across different products and service categories. These could extend the studies of Anderl et al. (2016) to account for stages of the purchase funnel.

An example of a study along the above lines is by Song, Sahoo, Srinivasan, and Dellarocas (2016) who propose a generalized multivariate autoregressive (GMAR) model to relate purchase volume to consumer activity sequences, or paths, starting from an initial marketing stimulus leading to the purchase response. This model is then embedded in a clustering framework that endogenously identifies segments of consumers who exhibit similar paths to purchase. Thus, they segments customers based on their path to purchase, and perform policy simulations to show they can use the path information to dynamically optimize marketing campaigns for each segment. Extending the focus of similar studies, future research could focus on customizing targeting strategies for each customer. This would involve using personalization strategies using dynamic optimization techniques to target promotions to specific customers (see for example, Zhang & Wedel, 2009).

1.2.3. Cross-device path to purchase

As usage of multiple devices such as smartphones, tablets, laptops and desk tops increase for pre-purchase and purchase consummation stages, customers' path to purchase includes not only multiple channels and touchpoints but also multiple devices. Attributing credit to the usage of multiple devices in the different stages of the purchase funnel is important for understanding how devices play a role in the purchase funnel.

While syndicate market research firms already collect clickstream data of customer touchpoints within each device, cross-device path to purchase data is necessary to get an accurate picture of the device attributions. Third party firms use techniques such as probabilistic matching to create such path to purchase data. In probabilistic matching stings of paths from different devices are matched using probabilistic methods to connect devices IDs to specific customers based on the information in each string. Currently, these tend to be 60–70% accurate. In deterministic matching (which firms such as Google and Facebook use) device IDs are determined on the basis of users having apps such as Gmail, Facebook on their different devices. The matching is very accurate as long as these apps are used on all the devices that each customer uses. Retailers can use deterministic matching to create such paths if users have to log into their accounts from whichever device they use.

De Haan, Kannan, Verhoef, and Wiesel (2015) examine how consumers' shopping behavior differs across devices and how device switching affects their path to purchase and, ultimately, conversion. Based on clickstream data from a large European online retailer, they find that switching from a more mobile device (e.g., smartphone) to a less mobile device (e.g., PC) on average almost doubles the conversion probability compared with continuing with the same device. The strength of this switching effect on the conversion probability depends on customer-, session-, product-, and time-specific variables. Their study shows why it is important to understand the roles different devices play at different stages of the purchase funnel of a customer. For example, if one were to just consider conversions that occur on smartphones, it would grossly underestimate the role of smartphones on the ultimate purchases and lead to lower investments for touch points on the mobile device. As consumers' use of devices such as smart watches and virtual reality increase understanding the role of such devices in the path to purchase is essential for designing effective marketing strategies.

Another important area that needs examination is the interaction between channels and devices. For example, the effect of a given channel such as e-mail or a display ad can have different impact when accessed using a smartphone versus a desk top. Understanding the main effect of the channels and devices and their interactions can help design campaign effectively.

1.2.4. Integrating online and offline path to purchase

While we have seen examples of models using offline and online data, they have been in the context of aggregate offline data or data on expenditure on offline media and conversions occurring online. While the attribution models and results could be more precise with offline individual level path to purchase data, they are by and large very hard to obtain except in the case of catalogs and in-store observations. The more pressing of an issue is attributing the *offline* conversions. There have been a few studies that have linked up online customer touchpoint data with offline conversions. Kumar, Bhaskaran, Mirchandani, and Shah (2013) link social media engagement with offline store sales in a retail context. Kumar, Bezawada, Rishika, Janakiraman, and Kannan (2016) link customers' engagement with a wine retailer's Facebook page with offline sales. They examine the linkage in the presence of TV advertising and e-mail campaigns and find that e-mails enhance the impact of social media much more than TV advertising. However, in both these studies, data collection was specially designed to enable such examination. Google has been conducting studies on measuring the impact of search and display on offline in-store conversions using Acxiom's technology to link up ad exposure and search activity with purchase in any channel including offline (Barr, 2015). This is an emerging area of research which could see more activity with increasing availability of appropriate data.

1.2.5. Methodological issues

One of the challenges with attribution studies is that customer-initiated touchpoints and firm-initiated touchpoints are not exogenous. There is self-selection of customers involved in customer-initiated touchpoints and specific targeting of customers for firm-initiated actions. If this endogeneity is not accounted for then firm-initiated touchpoints such as display and e-mails can be made to look effective or ineffective depending on the specific targeting of customers. If customers with inherently high propensities to purchase are targeted then the conversion credit attributed to these marketing actions will be high and vice-versa. Thus, any demand side model that does not account for customer self-selection and firm targeting will lead to biased results. The interpretation of attribution estimates will have to done with care – may be conditional on the targeting by the firm. A model that includes supply side targeting could be an option or field experiments to eliminate such endogeneity could be another option (see Zamora, 2015). However, a problem with field experimentation approach is that it has to be repeated in different settings and over time to tease out the inherent propensities and the incremental value of marketing actions in those specific settings. This can be costly in terms of time and budget. An approach that includes supply side targeting with the observational data generated as part of the marketing campaigns could provide more viable alternatives.

One of the advantages of including the supply side actions in attribution studies is that the solutions can inform how budget should be allocated across competing targeting options. In a good illustration of such an approach, Li, Kannan, Vishvanathan, and Pani (2016) examine how attribution strategies impact the investment in search keywords in the context of their roles in the purchase funnel. Considering both supply side as well as demand side, they model the relationship among the advertiser's bidding decision for keywords, the search engine's ranking decision for these keywords, and the consumer's click-through rate and conversion rate on each keyword, and analyze the impact of the attribution strategy on the overall return-on-investment of paid search advertising. They show that returns for keyword investments vary significantly under the different attribution strategies, and based on a quasi-experiment show how bidding for keywords under a budget constraint can be optimized. There are two important implications of this work. One is to show that attribution strategies can be incorporated within programmatic buying of keywords. This is essential as many marketing campaigns are now automated and incorporation of optimal attribution strategies within such a setting can lead to effective and efficient campaigns. Second, and more importantly, the study highlights the role different marketing interventions (keywords in the study, but can be generalized to display ad exposure, TV, e-mails, etc.) play at different points within customers' purchase funnel and how a wrong attribution strategy can lead to a wrong mix of investments in the marketing instruments resulting in starving some high impact instruments at different stages of the purchase funnel. This results in ignoring significant portion of the target segments and thus a lower ROI. Incorporating supply side in attribution studies in other setting is an important avenue for future research.

1.2.6. Big data and real-time analytics

Much of the academic work has focused on data sets of sizes that are easily handled in academic setting, but the actual implementation of attribution solutions in practice involves big data and need for real-time analytics, especially if the by-product of attribution solution is used for segmenting and targeting customers dynamically in online settings. It is no surprise that the analytics solutions available in the market tend to be simple but fast and capable of handling large volumes and velocity of data. However, they fall short of modeling customers' behaviors appropriately and also in the ways to handle variety in data. Specifically, while a touch such as a website visit or display is attributed an estimated weight, this weight is impacted by the content in the website, the design of the website, the creative of the display ad, the extent of exposure and so on. Thus, the estimated weight has to be decomposed into these design elements to provide actionable insights for specific marketing campaigns and website elements in a parsimonious yet sophisticated manner. Output of such models can help in personalized targeting of customers. Developments in personalization technologies (see for example, Chung, Rust, & Wedel, 2009) and closed-loop marketing technologies (Wedel & Kannan, 2016) combined with appropriate attribution strategies can allow attribution results be used in real-time for targeting purposes. As more and more marketing interventions get automated, developments in this area are needed to ensure that such marketing campaigns result in maximal ROI.

1.2.7. Attribution and marketing mix

Attribution estimates are never an end in themselves. They should form an input to the media/marketing mix optimization problem. Without appropriate attribution the input to the optimization is flawed and thus leads to sub-optimal results. However, there are many challenged to accomplishing this. Online attribution is based on individual level path data while media mix optimization is performed using aggregate data. Also, the planning cycles for the optimization problem are of much longer durations – weeks, months and quarters, while attribution solutions are at a much shorter duration – days and weeks. Thus, integrating the two is not straightforward. As a result, attribution solutions in practice are generally used within specific channels such as display ads, e-mails and search to optimize within each silo. Thus, firms are not taking full advantage of the insights that attribution studies provide. Much research is needed in this direction to enable insights derived from attribution studies to be appropriately incorporated in media/marketing mix optimization. This could involve hierarchical planning models, real time optimization and targeting.

1.2.8. Attribution, customer equity and brand equity

In our discussions thus far we have focused only on outcome variables that are short-term in nature (visits, conversions, etc.). However, the more impactful benefit of individual level path to purchase data is in understanding how the touch points along the purchase funnel impact other outcome variables which are longer-term such as customer satisfaction, customer loyalty, customer life time value, customer equity and brand equity. This area of research is very important from the viewpoint of value creation for the firm and value creation for customers (see also Kumar & Reinartz, 2016; Lemon & Verhoef, 2016) and leads to many interesting research questions. For example, what differential roles do channels play in acquisition versus retention and expansion of customers? How do different touchpoints impact customer experience and customer loyalty? How are customer profitability and customer equity shaped by customers' path to purchase as a function of the specific types of touchpoints (see Reinartz, Thomas, & Kumar, 2005)? The research area of implications of attribution modeling for customer relationship management (CRM) strategies is ripe for examination. Another closer related issue is to determine how the various sales and marketing activities interact along the purchase funnel and across acquisition, retention and expansion of customer base.

In addition to the above outcomes, many firms are also interested in understanding the impact on longer term brand metrics. In fact, the return on investment in marketing instruments is measured by sales as well as brand impacts. To date no research has used brand impacts as dependent measures in attribution models. This need is urgent as firms use multiple dimensions to evaluate the success of marketing campaigns, and not capturing such important dimensions in attribution studies can clearly bias ROI estimates.

1.2.9. Challenges in implementing attribution

Attribution is all about providing the right credit for the sales and brand impacts. Within a firm, many of the marketing interventions are managed by different groups – e-mail marketing may be managed by a group, display ads by another, search by another, loyalty programs by another and so on. All these units/silos vie to take credit as it has important implications for the slice of the budget they handle. This creates a multi-player game setting where actions of each could be increase the credit for its action. While similar settings have been researched (e.g., Berman, 2015), there is a need for mechanism designs that can impact units' actions to reveal the true attributions under general conditions. In practice, silos within firms make it difficult to implement attribution solutions unless the budget is controlled at a top level. More research is needed in organizational design of marketing groups to render implementations of attribution solutions effective.

In conclusion, we hope that this introduction along with the papers in the special section serve as an impetus for further research in this important topic of path to purchase and attribution modeling. As co-editors we were very fortunate to have a set of very knowledgeable and responsive reviewers whose critical and constructive suggestions helped significantly in shaping the special section papers. We extend our sincere thanks to them.

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