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THE ATTRIBUTION PROBLEM: AN ANALYSIS FOR A FOCAL COMPANY

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ABSTRACT

In today's digital world, companies use a multitude of online marketing channels to communicate with potential consumers. The online customer journey is also more complex than it has ever been. Consequently, firms face an attribution problem: how to allocate the credit of a conversion to the consumers' touchpoints with the brand? Focusing on a focal company, by studying user's characteristics, analyzing the online customer journey and exploring the results given by different attribution models, it was discovered that the customer journey for this firm was both short in terms of length and time. As the main output, the present work appoints an attribution model as the one best reflecting the customer journey and the focal firm's advertising goals - the Position Based model. The implications of a switch in attribution model are many fold and means to improve budget allocation were suggested.

Keywords: attribution model, customer journey, online marketing channels, online advertising

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1. INTRODUCTION

Nowadays, several online marketing channels are used to communicate with potential customers (Anderl, Becker, Schumann & Wangenheim, 2016). Before achieving a certain goal, such as a purchase, consumers go through a series of interactions with the firm: the customer journey (Edelman & Singer, 2015; Lemon & Verhoef, 2016). Given the array of online channels a firm can use and the complexity of this journey (Lemon & Verhoef, 2016), attributing the appropriate credits of a conversion presents a crucial challenge (Shao & Li, 2011; Abhishek, Fader & Hosanagar, 2015; Anderl et al., 2016) - a challenge whose name is "attribution". Marketing attribution determines the influence of distinct channels on the customer journey, so that value can be allocated to the touchpoints that impacted the purchase (or other preferred outcome) (Econsultancy, 2012). Still, research on attribution modeling is limited. This paper uses secondary data from an ecommerce company, which currently faces an attribution problem. By presenting a methodology based on firm decision making, the attribution model offering the best fit for the focal firm will be identified. Firstly, a section on the attribution problem and the existent models is presented. Next, the theoretical background on consumer decision journey and attribution modeling is given. The methodology is described, the results are presented and the main research question is addressed. Finally, implications for the firm are discussed and avenues for further research are highlighted.

2. THE ATTRIBUTION PROBLEM

Attribution modeling aims to determine how the credit of a conversion is allocated to the consumers' touchpoints with the brand throughout their customer journey. Hereinafter "conversion" will refer to a purchase transaction. Indeed, the path towards an online purchase (customer journey) might include multiple exposures to advertisements (Ghose & Todri-Adamopoulos, 2016) and a variety of online channels used to visit the company's website at different occasions (Li & Kannan, 2014). With the prevailing use of the internet and the proliferation of online channels, research on attribution modeling in a multichannel perspective is a novel in academic work (Berman, 2015).

When a user converts successfully on a website, the credit of the conversion can be attributed to a single channel or more, depending on the attribution model used by the firm (Criteo, 2013). To highlight, a distinct attribution model simply allocates conversions differently between channels, for the same total number of conversions. Attribution models can be divided into simplistic models - which incorporate a single touchpoint and attribute all the credit of a conversion to it - and fractional - which incorporate multiple touchpoints (Forrester Consulting, 2012; Interactive Advertising Bureau, 2016). Fractional models are more advanced approaches and can be separated into two further categories: rule-based and algorithmic. Rule-based attribution assigns the credit of a conversion based on a set of rules, whereas algorithmic models are more complex, assigning conversions based on a mathematical approach. For a visual approach of the attribution model's classification, see Annex I. Fundamentally, whether simplistic, rule-based or algorithmic, each firm must determine which attribution model offers the best fit for the business, as no universal solution can be applied (Jayawardane, Halgamuge & Kayande, 2015). Amongst attribution solution providers, Google (with *Attribution 360*) and AOL Convertro (with *Unified Marketing Activation Platform*) have the highest market presence (Moffett & Nail, 2016).

Table I shows the attribution models provided by Google in *Attribution 360* (Google Analytics premium version), with the respective description (Google, 2017a; Google, 2017b). Table I attribution model's terminology is the one adopted in this work. Google defines an interaction as the central activity associated with the advertising format (for example, a click for a display ad and a view for a video ad). The Data-Driven model (Table I) is an algorithmic model, requiring the setting of specific goals by the company and data collection over time for the model to emerge and improve, hence it will not be considered in this paper.

Table I - Summary of attribution models according to Google's *Attribution 360*

Single-touch	Multi-touch
Last Interaction: all the credit of a conversion is given to the last channel the customer interacted with before conversion	Linear: the credit of a conversion is equally split between all the channels the customer interacted with before conversion
Last Non-Direct Click: all the credit of a conversion is given to the last channel the customer clicked before conversion, ignoring traffic that comes directly to the website (e. g. URL type in)	Time Decay: the credit of a conversion is exponentially awarded to the channels the customer interacted with, with the last touchpoints before conversion (most recent) receiving more credit than the older ones
Last AdWords Click: all the credit of a conversion is given to the last paid text ad the customer clicked before conversion	Position Based: the credit of a conversion is distributed between the channels, with first and last touchpoints receiving more credit
First Interaction: all the credit of a conversion is given to the first channel the customer interacted with	Data-Driven: the credit of a conversion is determined through a data-modeling algorithm based on advertising goals

3. Literature Review

3.1 Consumer Decision Journey

As consumers interact with firms through numerous touchpoints across channels and time, it becomes crucial for companies to fully understand the journey their customers go through when purchasing a product or service (Lemon & Verhoef, 2016). The "Hierarchy of Effects Model", by Lavidge and Steiner (1961), and the "Theory of Buying Behavior", by Howard and Sheth (1969), are the academic foundation for the "buying funnel". Commonly used in literature, the buying funnel is a process encompassing the various stages consumers go through when making a purchase (Ramos & Cota, 2008; Lee & Seda, 2009). It is often referred to as the "funnel metaphor" (Court, Elzinga, Mulder & Vetvik, 2009), in the sense that consumers begin with a set of initial brands and reduce them as they progress. A prevalent approach of the buying funnel is the Awareness, Research, Decision and Purchase stages (Jansen & Schuster, 2011), although various classifications can be adopted. More recently, research has adapted the notion of buying funnel to integrate changes in buying behavior arising from the emergence of digital channels and well-informed consumers. Court et al. (2009) suggest a circular approach composed of four phases (Consideration, Evaluation, Closure and Postpurchase). Consumers add or remove brands over time, contrary to the traditional marketing funnel, in which consumers consequently subtract brands. Edelman and Singer (2015) build on this work, shortening the initial phases of Consideration and Evaluation. They emphasize the concept of a "loyalty loop", griping consumers and setting the start of a new journey in the Closure phase. Building on the work of Howard and Sheth (1969), Neslin et al. (2006) propose a model combining consumer's decision process with the firm's decision process. The consumer's process encompasses four stages, starting with need recognition, moving to search, purchase and ending with after-sales. Thereon, with the consumer's decision process data, the firm can proceed with channel evaluation and strategy.

3.2 Online Advertising

Numerous online marketing channels can be used to reach potential customers and a user can return to a website via the same channel he/she first used to reach it - carryover effect - or via a different one - spillover effect (Anderl et al., 2016). This section focuses on two important online channels, display advertising and search advertising.

Firstly, Xu, Duan and Whinston (2014) conclude that display advertising encourages future clicks on different advertising types, even though their direct relation with a conversion is rendered low. By attributing conversions based on a Hidden Markov Model, Abhishek, Fader and Hosanagar (2015) advocate that different ad formats influence consumers in distinct ways. More specifically, display ads prove to be more significant during early stages of the buying funnel. Kireyev, Pauwels and Gupta (2015) focus on the interaction between display advertising and search advertising. The authors find spillover effects between these advertising formats, which usually occur only after a couple of weeks. Ghose and Todri-Adamopoulos (2016) add that an increased duration of exposure to the ad also increases the propensity of the consumer to search afterwards. Once again, spillover effects take place and the authors support credit division between online channels. Li, Kannan, Vishvanathan and Pani (2016) examine the importance of a suitable attribution model, being possible to increase total returns when different models are used to measure keyword contribution.

3.3 Multichannel Marketing

Studies have proposed data-driven frameworks to approach the attribution problem. Shao and Li (2011) suggest two data-driven models, a bagged logistic regression and a probabilistic model, the first of its kind to be available in the industry. Employing a Bayesian network, with secondary data, Li and Kannan (2014) study carryover and spillover effects between six online channels, both at visit and purchase stages. Comparing the proposed approach to simplistic attribution models, they discover significant differences in conversions, with e-mails, display ads and referrals being substantially underestimated when Last Click metric is adopted. Furthermore, at visit and purchase stages, there is evidence of meaningful carryover effects in most channels. For one retailer, De Hann, Wiesel and Pauwels (2015) apply a structural vector autoregression model to compare the effects of nine categories of advertising (online and offline) across different product groups. The study points out content-integrated advertising (advertising already included in the content of the website) as the most effective one in driving conversions, diverging from Last Click model's underestimation. Anderl et al. (2016) expand prior research by presenting a first- and higher-order Markov chain based on four data sets from different industries. They recognize carryover and spillover effects between and across online channels. Plus, differences between the proposed approach and simplistic attribution frameworks (Last Click and First Click) are observable, leading to conclusions that simplistic models tend to undervalue the inputs of certain channels. Studying effects between online and offline sales, Dinner, Heerde and Neslin (2014) develop a multi-equation model considering online and traditional advertising. These authors conclude that online advertising influences offline purchases, identifying cross-channel effect elasticities.

3.4 Research Question

Mathematical approaches (fractional algorithmic models) have been proposed to examine and provide a solution for the attribution problem (for instance, Li and Kannan (2014) and Anderl et al. (2016)). However, despite being data-driven and therefore a more customized result (Jayawardane, Halgamuge & Kayande, 2015), algorithmic models have been used more extensively amongst scholars and still constitute a novelty in academic work (Kannan, Reinartz & Verhoef, 2016). Within practical usage, algorithmic models are seen as complex endeavors and difficult to explain (Forrester Consulting, 2012). Thus, simplistic and fractional rule-based models tend to be used in a commercial context. More specifically, Last Interaction model is widely adopted (Li & Kannan, 2014; Berman, 2015; AdRoll, 2016), being intuitively easy to explain and considered as the "standard model" (Forrester Consulting, 2012). Nevertheless, this model has been pointed out by academics as being greatly inaccurate, as it completely disregards touchpoints that are made earlier in the purchase funnel (Li & Kannan, 2014; De Hann, Wiesel & Pauwels, 2015; Anderl et al., 2016; Abhishek, Fader & Hosanagar, 2015). The current paper aims to bridge the gap between simplistic and rule-based models, offered in commercial context, and data-driven approaches, offered in academic context. It analyses the attribution problem for the partner company, aiming to provide an answer to the following research question:

Which attribution model, among simplistic and rule-based models, offers the best method to evaluate channel contribution and the best fit for the focal company?

While answering the above research question, the present work will also shed light into the customer journey of the focal company. Furthermore, it will explore rule-based models which have not previously been compared in academia - Time Decay and Position Based models -, contributing with new input to the academic world. Considering the research question at hand, the following methodology was proposed.

4. METHODOLOGY

4.1 Data

The present research is based on secondary data provided by an online retailer, who chose to remain anonymous. Hereinafter referred to as Company A. Company A is part of the Fashion Industry, operating exclusively online (without physical stores). Therefore, cross-channel effects between online and offline sales are absent. The data provided corresponds to a period of 20 months, from January 2016 until August 2017 (inclusive). The time-frame chosen allows for sufficient and recent observations, while minimizing the effects of business environment variations (for example, a drastic change in investment strategy). The data corresponds to a single country in which the company operates, Germany, to account for cultural dimensions and country specific advertising figures. Table II showcases the online marketing channels used by the firm, both organic and paid mediums (in parentheses).

Table II – Online marketing channels and description

Channel	Description
Affiliate (Paid)	A commission based channel, in which the company rewards the affiliate for showing their product and referring the user to the company's website.
DTI (Organic)	Direct Type In (DTI) occurs when visitors type in the URL of the website in the navigation bar of their browser or use a shortcut to access it, such as a favorite/bookmark.
Display (Paid)	Diverse ad formats that are shown on websites when consumers are online, but not actively searching for the product (as opposed to search advertising).
E-mail Non Paid (Organic)	E-mail chains automatically triggered when a user registers in the website, using the company's own customer database (for instance, a newsletter sent to the consumers who registered in the website).
E-mail Paid (Paid)	E-mail sent via third parties, by rewarding a partner to send the company's email to their own customer lists (as opposed to E-mail Non Paid).
Facebook (Paid)	Targeted ads that are shown to Facebook users based on their activity and other metrics. According to Company A's channel split, Facebook advertising only comprises paid advertising (as opposed to Social Media).
Price Comparison (Paid)	Vertical search engine that aggregates products based on type and allows visitors to compare them regarding price and characteristics. Price comparison websites redirect users to the company's website.

Referrer (Organic)	All the traffic that arrives to the company's website being forwarded by external websites, without remuneration.
Retargeting (Paid)	Targets visitors that already know the brand, searched, but failed to complete a purchase, via Display Advertising, Facebook and SEM.
SEM (Paid)	Search Engine Marketing (SEM) aims to increase the visibility of the website via paid advertising. Sponsored search (keyword bidding) may be product related or brand related.
SEO (Organic)	Search Engine Optimization (SEO) aims to increase the visibility of the website by redesigning the structure of the website to increase its ranking by the search algorithm.
Social Media (Organic)	Posts and shares on the company's social media networks (Facebook, Instagram, etc.). According to Company A's channel split, it includes Facebook posts that are exclusively organic (as opposed to Facebook advertising).
Other (Organic)	All the advertising formats that do not fit into one of the above categories.

Company A uses Google as an analytical provider, with the *Attribution 360* product version. Secondary data provided by the firm is three-fold. Firstly, a dataset comprising all the online customer journeys ending with a conversion for the 20-month period. The author defines an online customer journey according to Anderl et al. (2016), as a journey incorporating all touchpoints across all online marketing channels that generate a visit to the firm's website, preceding a possible purchase. As so, the dataset includes information regarding the source of the touchpoint (channel) and tracks customer journeys in a thirty-day lookback window to conversion. Overall, it includes information regarding almost 1 million online customer journeys ending with a conversion, ranging from one interaction up to more than one hundred in the longer journeys. Secondly, demographic and behavioral data reports from the company's users regarding age, location, device type and interests - as a first dimension - and gender - as second dimension (Annex II to V). The corresponding reports have been organized according to transactions, in decreasing order. These reports can be easily exported from Google Analytics, by consulting the Audience Tab. Lastly, channel performance data reports for the different attribution models provided by Google (Table I, except for Data-Driven). The reports, per attribution model, have information regarding number of conversions and conversion values per channel. These reports can be easily exported from Google Analytics, by consulting the Conversions Tab.

4.2 Data Analysis

The current work presents a methodology incorporating firm data to best appoint the simplistic/rule-based attribution model for the focal firm. The proposed approach adopts the framework suggested by Neslin et al. (2006) of consumer and firm's decision processes. The author adapts the framework by adding an additional initial step.

Firstly, research has shown that individual-level disparities among consumers impact channel selection (Puccinelli, Goodstein, Grewal, Price, Raghubir & Stewart, 2009; Ansari, Mela & Neslin, 2008; Inman, Shankar & Ferraro, 2004). The first step involves understanding Company A's consumers through the demographic and behavioral data provided by the company. To better illustrate Company A's target customers, buyer personas were created. By providing real-life examples of possible consumers, they are used to improve understanding of the target market and decision making (Kotler & Keller, 2012).

Introducing purchasing insights in the profile of the buying personas gives a better understanding of how consumers shop and improve guidance for managerial decision (Revella, 2015). The second step involves analyzing the customer journeys. Descriptive statistics were computed to better understand the distribution of conversions, such as the number of channel interactions needed to convert. Transition probabilities were calculated taking into consideration one previous interaction (definition developed in Section 5.2).

Thirdly, channel evaluation aims to determine the contribution of each marketing channel to the business (Neslin et al., 2006). This contribution is measured by the number of conversions attributable to the channel, depending on the attribution model used by the firm.

Note that distinct attribution models simply allocate conversions differently between channels. Thus, to proceed with channel evaluation, it is firstly necessary to determine which attribution model the firm should use. Consequently, the channel evaluation phase is split into three stages: (1) comparison of the contribution to conversions of each channel across attribution models (Google's attribution solutions, described in Table I) - Section 5.3; (2) selection of the attribution model with the best fit for the focal company - Section 6.1; (3) analysis of key performance indicators (KPIs) according to the model selected - Section 6.2.

Lastly, channel strategy includes channel resource allocation and coordination. Along with channel evaluation KPIs, Section 6.2 will discuss the implications for the firm arising from the results obtained, suggesting approaches to improve budget allocation and the channels in which the firm should focus more.

5. RESULTS

5.1 User Characteristics

Learning about a firm's customers and building personas is a powerful tool towards getting actionable insights of attribution (AdRoll, 2016). Demographic and behavioral data (Annex II to V) was used to identify the top characteristics among Company A consumers regarding age group, location, device type when browsing/shopping and affinity categories (interests). By combining each one of the four characteristics with gender (as a second dimension in the same report), it becomes possible to identify not only the top age group, but also the top age group per gender (same for location, device type and interests). For instance, the top age group for female consumers is 25-34 years (Annex II), corresponding to 17.98% of sessions and 16.99% of transactions, whereas the top locations are Berlin and Munich (Annex III). Considering device type, female consumers prefer mobile (Annex IV), corresponding to 45.15% of sessions and 37.98% of transactions, whereas males prefer desktop, showing the highest percentage of transactions for this device type (15.60%).

Regarding affinity categories, females who shop at Company A have an interest in “Lifestyles & Hobbies” and “Home & Garden/Home Decor”, whereas males also have an interest in “Lifestyles & Hobbies”, “Media and Entertainment” and “News & Politics” (Annex V). The same logic was applied for the remaining characteristics and used to craft buyer personas.

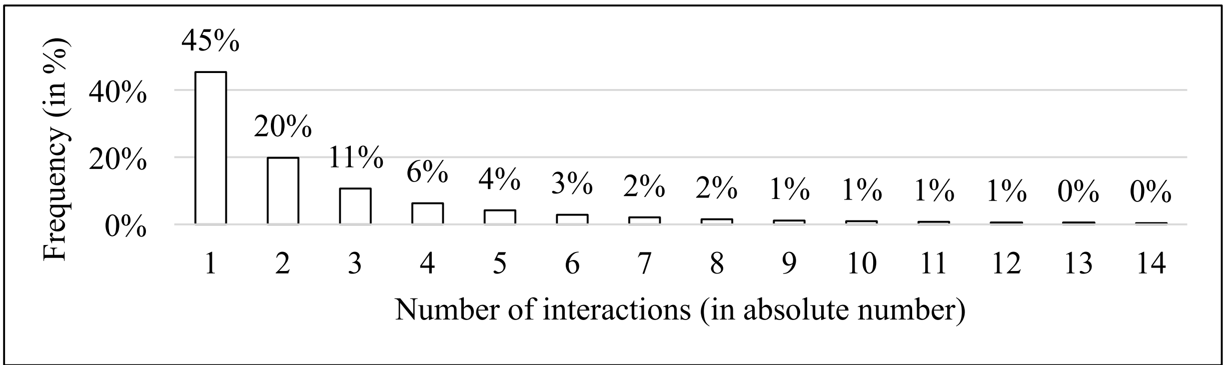
The first buyer persona is Maria, female and 32 years old. She was born in Germany and currently lives in a big city in the Bavaria region. Leading a busy life, Maria is an enthusiast of online shopping – she likes its convenience and flexibility. She enjoys browsing on her mobile phone and spends a couple of hours a day checking her social networks. Sometimes she clicks on Facebook ads that are shown on her feed if she really likes the product, searches on the company’s website and eventually makes a purchase. Maria really likes the commodity of using her phone for online shopping. She also dedicates her time to cooking delicious meals and searching house decoration ideas, her biggest hobby. The second buyer persona is Jakob, male and just turned 28. He is a German citizen and currently lives in a shared flat in Berlin. He is a big media and entertainment fan, watches a lot of movies online and occasionally goes to music concerts. Jakob likes to be informed by reading the news, something he does every day. For him, buying clothes is not a main priority and he prefers to save money for his various hobbies instead. If Jacob needs a piece of clothing, he just goes on his laptop, searches on Google and clicks on some of the first results. Occasionally, he also searches using his mobile, as he often uses it to read the news, but he prefers using his desktop when it comes to the actual purchase.

5.2 Consumer Decision Journey

A customer journey involves distinct phases (Court et al., 2009) and consumers differ from one another. To better illustrate Company A’s customer journey dataset, a journey with three interactions would be represented as Facebook > Facebook > Direct Type In > Conversion. In this example, Direct Type In (DTI) preceded the purchase.

Firstly, consumer distance to conversion was studied (the number of interactions before a conversion was achieved). As it can be seen in Figure I, 45% of consumers converted with a single interaction. As the distance to conversion increases, conversions per number of interactions decrease at a steep rate, with Figure 1 exhibiting a long right tail. As so, 86% of conversions occurred with 5 or less interactions. Such percentage might be explained by differences in customer journeys between existing and new customers. Intuitively, it is natural that existing customers already know the brand and require less interactions, therefore jumping the Consideration and Evaluation stages of the customer journey, as proposed by Edelman and Singer (2015). Still, most consumers (55%) required more than one interaction before a purchase occurred, supporting the idea that consumer-company interaction goes beyond a mere search and conversion outline (Archak, Mirrokni & Muthukrishnan, 2010).

Figure I - Distance to conversion



Given this property, further analyses were conducted within the first 5 interactions. Prior studies indicate that website visit source and channel order can be used to predict purchase probability (Klapdor, Anderl, Schumann & Wangenheim, 2015). Transition probabilities were calculated taking into consideration one previous interaction. Following the groundwork of Anderl et al. (2016), a transition probability can be shown as: $P(I_t = x_t \mid I_{t-1} = x_{t-1})$, in which I = interaction, x = {Facebook, DTI, SEO, Price Comparison, SEM, Referral, Email Non Paid, Affiliate, Display, Email Paid, Social Media, Retargeting, Other, Conversion} and t = time. For instance, a transition probability answers the question *what is the probability of the channel SEM being the second interaction, knowing that the channel Facebook was the first interaction?* The output of a transition probability between an interaction at time t-1 and time t is, therefore, a 13 x 14 matrix (see Table III). "Conversion" does not apply in the row axis, as this is the final step in the consumer's journey. Four transition probabilities were computed in absolute values and then put into percentage form (Annex VI to XII): from 1st Interaction to 2nd Interaction (Matrix 1, shown in Table III), 2nd to 3rd (Matrix 2, annex VIII), 3rd to 4th (Matrix 3, annex X) and 4th to 5th (Matrix 4, annex XII).

Table III – Matrix 1 (transition probability from 1st Interaction to 2nd Interaction, in %)

	2nd Interaction														
1st Interaction	Facebook	DTI	SEO	Price Comparison	SEM	Referral	Email n/ Paid	Affiliate	Display	Email Paid	Social Media	Retargeting	Other	Conversion	***TOTAL***
Facebook	18.82%	15.15%	0.79%	0.43%	1.00%	4.75%	0.88%	0.51%	0.02%	0.02%	0.93%	1.40%	0.16%	55.12%	***100.00%***
DTI	3.22%	36.41%	2.37%	1.17%	3.67%	1.70%	8.37%	0.71%	0.20%	0.09%	0.25%	1.28%	0.08%	40.48%	***100.00%***
SEO	1.34%	32.79%	1.28%	2.15%	4.88%	2.05%	2.08%	0.92%	0.16%	0.03%	0.11%	1.39%	0.04%	50.78%	***100.00%***
Price Comparison	1.17%	13.61%	3.19%	31.22%	4.96%	1.48%	1.07%	0.93%	0.08%	0.03%	0.05%	1.32%	0.05%	40.84%	***100.00%***
SEM	1.19%	20.08%	6.51%	2.49%	19.13%	1.66%	1.92%	0.78%	0.16%	0.06%	0.08%	1.86%	0.10%	43.96%	***100.00%***
Referral	16.60%	17.10%	1.25%	0.69%	1.62%	2.52%	1.66%	0.67%	0.12%	0.02%	2.17%	1.41%	0.10%	54.06%	***100.00%***
Email n/ Paid	1.91%	21.02%	2.03%	0.58%	1.93%	0.87%	40.52%	0.62%	0.28%	0.27%	0.09%	2.52%	0.23%	27.13%	***100.00%***
Affiliate	9.11%	22.22%	2.19%	1.67%	2.74%	1.86%	1.51%	11.72%	0.11%	0.09%	0.31%	1.75%	0.12%	44.59%	***100.00%***
Display	0.98%	22.33%	3.38%	1.22%	2.89%	2.35%	3.00%	0.64%	19.83%	0.04%	0.01%	9.49%	0.01%	33.85%	***100.00%***
Email Paid	1.80%	26.93%	1.20%	0.73%	2.52%	1.50%	7.73%	0.80%	0.06%	5.90%	0.03%	4.03%	1.62%	45.15%	***100.00%***
Social Media	16.68%	11.56%	0.91%	0.49%	1.12%	9.32%	0.72%	0.77%	0.03%	0.01%	18.25%	1.52%	0.02%	38.59%	***100.00%***
Retargeting	10.55%	21.84%	4.05%	1.46%	3.52%	1.86%	9.88%	0.77%	1.83%	0.15%	0.35%	24.17%	0.37%	19.19%	***100.00%***
Other	5.39%	20.22%	1.02%	0.66%	3.15%	1.73%	5.59%	0.91%	0.51%	0.36%	0.05%	4.88%	28.00%	27.54%	***100.00%***

The conversion probability, shown in column 14, exhibits a decreasing trend for most channels as we move from Matrix 1 to 4, which is consistent with the previous analysis of the distance to conversion (Figure I). For instance, the transition from Facebook to Conversion, is 55.12% in Matrix 1 (Table III), 44.58% in Matrix 2 (Annex VIII), 38.86% in Matrix 3 (Annex X) and, finally, 33.42% in Matrix 4 (Annex XII). The exception is Retargeting (lowest value is in Matrix 1, 19.19%), which is logical as this channel targets users who have already visited the website beforehand (with specific products for those users). Other interesting trends can be noticed as we progress from Matrix 1 to Matrix 4.

Firstly, it is possible to identify successions of equal channels between interactions. When highlighting the top 2 transactions per row in each matrix (without the column Conversion), it becomes easier for the reader to observe a diagonal starting at the top left corner (cells with grey background). For instance, in Matrix 1, when Price Comparison is the preceding channel, 31.22% of second interactions are also Price Comparison (Table III). This property can be verified in all matrixes. In Matrix 2, if one does not consider the column “Conversion”, the highest value per row, in most channels, is the transition from one channel to the very same channel in the following interaction. SEO, Email Paid, Retargeting and Referral are the exceptions (highest transition is to DTI in the case of SEO, Email Paid and Retargeting, with 30.18%, 22.84% and 21.20% respectively). SEO and Referral also exhibit the highest transitions to DTI in Matrix 3 and 4, whereas Email Paid exhibits the highest transition to Email n/ Paid in these matrixes (26.03% and 23.92%). Indeed, Li and Kannan (2014) and Anderl et al. (2016) suggest preceding visits to a website can have an impact in subsequent visits and that same channel usage might induce a lower visit cost for the user.

Secondly, as already pointed out, high transition probabilities in the direction of DTI can be identified in all matrixes (Table III, column DTI). In other words, consumers are likely to come back via DTI in a subsequent visit, after getting in touch with the brand through another channel. The reverse effect is not visible, as DTI always exhibits the highest transition values to DTI (36.41%, 41.83%, 46.14% and 49.80% for Matrix 1, 2, 3 and 4, respectively).

5.3 Attribution Model Comparison

Different online channels can be involved in different steps of the consumer journey (Klapdor et al., 2015). For instance, display advertising is more significant during initial stages of the journey (Abhishek, Fader & Hosanagar, 2015; Xu, Duan & Whinston (2014)). As different attribution models allocate conversions differently between channels, they reveal insights of the customer journey (AdRoll, 2016). To evaluate the channels’ performance, it is firstly necessary to determine the attribution model with which this evaluation will take place. The current section compares conversion percentages across each attribution model. For an easier comparison, percentages were used, simply by dividing the number of conversions per channel by the total number of conversions, per attribution model (Table IV).

Table IV - Conversions per channel and model (in %)

Model / Channel	Conversion %						
	Last Interaction	Last Non-Direct Click	Last AdWords Click	First Interaction	Linear	Time Decay	Position Based
Facebook	23.10%	27.97%	22.67%	29.01%	25.43%	25.08%	25.82%
DTI	30.82%	11.18%	24.91%	17.53%	26.12%	26.75%	24.86%
SEO	7.23%	10.92%	5.94%	9.38%	7.82%	7.76%	8.14%
Price Comparison	7.12%	8.60%	9.89%	9.65%	8.17%	8.08%	8.32%
SEM	10.40%	13.15%	16.57%	12.92%	11.13%	11.07%	11.49%
Referral	5.50%	6.55%	4.76%	4.38%	4.84%	4.83%	4.91%
Email n/ Paid	8.52%	11.85%	7.44%	8.65%	8.59%	8.62%	8.58%
Affiliate	2.88%	3.75%	2.60%	3.92%	3.19%	3.12%	3.33%
Display	0.90%	1.24%	1.04%	1.72%	1.19%	1.15%	1.27%
Email Paid	0.44%	0.61%	0.43%	0.80%	0.57%	0.55%	0.60%
Social Media	0.99%	1.16%	0.96%	1.05%	1.05%	1.05%	1.03%
Retargeting	1.90%	2.76%	2.63%	0.80%	1.69%	1.75%	1.46%
Other	0.19%	0.26%	0.16%	0.20%	0.21%	0.20%	0.20%
TOTAL	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***

Company A currently attributes conversions based on Last Interaction. By examining Table IV, single-touch models (Last Interaction, Last Non-Direct Click, Last AdWords Click and First Interaction) attribute very distinct conversions between each other, an expected outcome as these models take a single touchpoint into consideration. Firstly, Last Interaction model attributes the highest percentage of conversions to DTI (30.82%), followed by Facebook (23.10%) and SEM (10.40%). Interestingly, SEM, Price Comparison and Display showcase the lowest values across all models when Last Interaction is used (10.40%, 7.12% and 0.90% respectively), which indicates these channels tend to be used in earlier interaction stages with the firm. This model disregards touchpoints that are made earlier in the purchase funnel - DTI receives a big amount of credit, most likely at the expense of other channels.

The opposite can be argued about First Interaction model, which disregards later touchpoints. In this model, Facebook receives the biggest amount of contribution to conversions (29.01%), followed by DTI (17.53%) and SEM (12.92%). By giving credit to the first interaction, this model places emphasis on the first channel consumers interact with, being suitable to measure brand awareness for instance (Google, 2017a). Next, Last Non-Direct Click attributes credit to the last channel used that is not DTI. It ignores DTI from journeys that have different preceding channels, being the contribution of DTI spread to other channels (only 11.18% when compared to the other models). However, as seen in Section 5.2, DTI is highly used in subsequent interactions. The Last AdWords Click also ignores channels, as it attributes the credit of the conversion to the last paid text ad of the journey (SEM's contribution is 16.57% under this model). Therefore, this model is useful when the firm's goal is to track the AdWords campaign closer to the moment of conversion (Google, 2017a).

Taking into consideration multiple touches along the customer journey, multi-touch models (Linear, Time Decay and Position Based) credit more than a single channel when attributing conversions. The credit of the conversion is spread throughout the customer journey, building on the fact that each touchpoint the consumer is exposed to can have an impact on their conversion, either a direct or indirect one (Lemon & Verhoef, 2016). From Table IV, Linear and Time Decay models show similar allocations: Facebook with 25.43% and 25.08%, DTI with 26.12% and 26.75%, SEM with 11.13% and 11.07% respectively, and so forth. With Time Decay, an interaction at the moment of conversion receives double the credit of one occurring 7 days before, as the half-life was set to be 7 days (Google, 2017a). The fact that these two models show fairly similar results indicates that the time decaying effects are rather small. These effects might not have time to appear when the consumer journey is short in terms of temporal length (Jayawardane, Halgamuge & Kayande, 2015). In fact, Lavidge and Steiner (1961) propose the lower the commitment of the consumer with the product, the more likely consumers are to move faster to the purchase. In the Position Based model, the channels' contribution lies between the Last and First Interaction models (e.g. Facebook with 23.10% in Last Interaction < 25.82% in Position Based < 29.01% in First Interaction). Indeed, in this model, bigger weight is allocated to the first and last touchpoints.

6. DISCUSSION

6.1 Research Question - Attribution Model Outcome

An attribution model provides key insights into understanding the customer journey and the interplay of online channels (AdRoll, 2016). Therefore, the customer journey needs to be reflected in the attribution model used by the company, so that it better reflects the true credit of conversions. For Company A, more than half of consumers, like Maria and Jakob, needed at least 2 interactions to convert (55%). Nonetheless, journeys are short, as 86% of consumers converted with 5 or less interactions (see Section 5.2). Facebook is the channel responsible for attracting more consumers (higher contribution to conversions in First Interaction model) and DTI is the channel used the most before the moment of conversion (higher contribution to conversion in Last Interaction model) (see Section 5.3). Moreover, when starting their customer journey in one channel, customers move to DTI in their subsequently interaction very often (see Section 5.2). These facts align both with the product from Company A, fashion goods, and buyer personas, who are young (25 to 34 years of age), social media/technology savvy and informed. Maria and Jakob's consumer journey is short, as Company A's products can be considered as a low-involvement category for them.

Last Interaction model, used by Company A, disregards individual differences in consumer journeys, as it only gives credit to the last touchpoint with the brand (Leeflang, Verhoef, Dahlström & Freundt, 2013). The channel leading to the conversion is not necessarily the one that most impacted the customer journey. All in all, none of the single-touch models consider that previous visits influence subsequent visits and that carryover and spillover effects between channels were identified (Li & Kannan, 2014; Anderl et al., 2016). In fact, previous website visits of a user do not only influence their future visits, but the channels used for those visits, as well as the channel they end up converting with (Anderl et al., 2016). So, an attribution model incorporating multiple touchpoints (Linear, Time Decay or Position Based) would offer a better fit for Company A.

Secondly, for a proper channel performance evaluation, it is fundamental that the goals of the company and of the attribution model are in line (Shao & Li, 2011). Company A's main advertising goal is to generate online conversions. Therefore, the attribution model should also reflect this goal. Amongst multi-touch models, the Linear considers that all the interactions have the same contribution to conversion, which deviates from the firm's advertising aim. In other words, all interactions would be equally responsible for the conversion. The Time Decay model considers the factor time when allocating conversions, with the last touchpoints before conversion receiving more credit than the first ones. Considering that the customer journey for Company A is not only short in number of interactions, but also short in time (see Section 5.3), the Time Decay model is not a good fit for the focal company. In fact, due to the reduced effects of time decaying, the allocation of conversions for the Time Decay model is similar to the Linear model.

Lastly, the Position Based model attributes a bigger percentage of the credit of a conversion to the first and last touchpoints of the consumer (40% to the first interaction and 40% to the last, in default values). The remaining credit of the conversion (20%, in default values) is spread equally between the remaining interactions - the lower the number of middle touchpoints, the more credit they will receive. This model is both aligned with the business's goals - gives considerably high importance to the last interaction, leading to a conversion -, while considering previous touchpoints - credits all interactions, but not with the same importance -, and with the fact that the consumer journey involves a small number of interactions. Given the short time frame and path length of the customer journeys, the first step is close to the last touchpoint (purchase).

All in all, given the user characteristics represented by Maria and Jakob, the analysis of the customer journeys for Company A, the insights revealed by the comparison of attribution models and the firm's advertising aim, the most logical method to evaluate the channels performance is the Position Based model.

6.2 Implications for the Firm

The present section will address the last steps of the proposed methodology, channel evaluation continuation and channel strategy. Knowing that Company A will maintain the same advertising goals for the future, generate online conversions, a transition to the Position Based model proves to be the logical choice given the results presented above. From Table IV, the Last Interaction model (currently used by the firm) overestimates the contribution of DTI, Referral and Retargeting. On the other hand, the Position Based model reveals that the contribution of Facebook (25.82%) and SEM (11.49%), among other channels, is higher than Last Interaction's attribution (23.10% and 10.40%, respectively). A shift in attribution model requires a revisit of the channel's strategy. Consequently, it helps moving towards a more efficient use of the online marketing channels and subsequently improve results.

As the main research question has been answered and a model has been proposed, it is possible to evaluate channels under the Position Based model. Several key performance indicators (KPIs) can be used for channel evaluation, however, their alignment with the firm's business goals is fundamental (Google, 2014). As Company A focuses on generating online leads, the Cost per Acquisition (CPA) and Return on Advertising Spend (ROAS) metrics are the ones adopted in this paper (Google, 2014). CPA reveals how costly a conversion is for a channel and can be calculated as *Channel Spend/Conversions* (Lee & Seda, 2009). ROAS reveals the revenues obtained per unit of investment per channel, calculated as *Conversion Value/Channel Spend* (Lee & Seda, 2009). Table V reports the KPI results for the Last Interaction and Position Based models.

Table V – Channel Spend (%), Conversion (%), CPA (€) and ROAS (€)

Metric / Channel	Channel Spend	Last Interaction Conversion	Last Interaction CPA	Last Interaction ROAS	Position Based Conversion	Position Based CPA	Position Based ROAS
Facebook	63.27%	23.10%	21.74	1.81	25.82%	19.46	2.06
DTI	0.00%	30.82%	0.00	NA	24.86%	0.00	NA
SEO	0.04%	7.23%	0.04	1426.39	8.14%	0.04	1635.60
Price Comparison	12.92%	7.12%	14.42	3.91	8.32%	12.34	4.68
SEM	7.25%	10.40%	5.53	10.70	11.49%	5.01	11.95
Referral	0.00%	5.50%	0.00	NA	4.91%	0.00	NA
Email n/ Paid	0.40%	8.52%	0.37	128.92	8.58%	0.37	131.92
Affiliate	6.63%	2.88%	18.28	3.15	3.33%	15.83	3.61
Display	3.70%	0.90%	32.65	1.58	1.27%	23.12	2.31
Email Paid	2.98%	0.44%	53.33	0.95	0.60%	39.19	1.33
Social Media	0.00%	0.99%	0.00	NA	1.03%	0.00	NA
Retargeting	2.81%	1.90%	11.74	3.98	1.46%	15.21	3.15
Other	0.00%	0.19%	0.00	NA	0.20%	0.00	NA
TOTAL	***100%***	***100%***			***100%***		

As organic channels, DTI, Referral, Social Media and Other (negligible) do not require investment and therefore, CPA is null and ROAS is not-applicable (NA). For SEO and E-mail Non Paid, also organic channels, the spending refers to the value paid for the software to operate these channels. Hence, the analysis will focus on the paid channels, which require budget allocation: Facebook, Price Comparison, SEM, Affiliate, Display, Email Paid and Retargeting. The CPA of all paid channels, except Retargeting, is lower for the Position Based model (Table V). As a distinct attribution model merely allocates conversions differently between channels (for the same total number of conversions), an increase/decrease in CPA between models was expected, as channel spend is divided by number of conversions. The channel spend for the considered period is the same, regardless of the attribution model used. Consequently, when the number of conversions increases for Facebook, Price Comparison, SEM, Affiliate, Display and Email Paid in the Position Based model, the CPA decreases. With more conversions being allocated to these channels, the price for acquiring a customer decreases. The same reverse logic applies to Retargeting.

The first recommendation for the firm arises from the Email Paid KPIs. Despite the decrease in CPA from Last Interaction to Position Based model (€53.33 to €39.19 respectively), this CPA is still the highest by a great margin (second highest CPA is Display with €23.12). Furthermore, ROAS is also the lowest amongst all channels - per each euro invested, the business gets a return of €1.33. Compared to other paid channels, which return between €2.31 (Display) and €11.95 (SEM) per euro invested, the Email Paid CPA is very high for a very low return. Moreover, the channel gets credit for less than 1% of conversions (0.60%) and its budget represents approximately 3% of the total budget. Considering these results, the investment in this channel should be reconsidered, or even dropped completely. Consequently, budget could be reallocated to another channel showcasing better KPIs.

Secondly, Display exhibits a high CPA (€23.12) and low ROAS (€2.31). Facebook also has a low value of return (€2.06) and the third highest CPA (€19.46), despite contributing to the highest conversion percentage, 25.82%. More, Facebook takes the highest percentage of budget share by far, as 63% of the total investment went to this channel. Note that the present computations are an average of the total period and, naturally, CPA varies across time. Nonetheless, considering the KPIs of well-performing channels (SEM and Price Comparison for instance), investment in these channels should be reviewed and possibly trimmed down.

Lastly, SEM receives credit for 11.49% of conversions, whereas its spending represents 7.25% of the total investment. Amongst the paid channels, it has the lowest CPA (€5.01) and highest ROAS (€11.95). Taking this into perspective, budget allocation for SEM has space to increase. Considering the nature of this channel, keyword bidding can account for more keywords and/or a higher bid per keyword, if budget is increased. Reallocating budget spend from Email Paid to SEM is an option Company A should consider. Nonetheless, budget allocation should be done carefully and while measuring results constantly, as channel elasticity and exogenous factors, like seasonality, can play an important role.

6.3 Limitations and Further Research

The present work has limitations. The major limitation arises from the data itself, which comes from a secondary source, Company A. Thus, the current work assumes all the data tracking has been correctly implemented for the considered analysis period and that data was correctly exported from Google Analytics. Secondly, only customer journeys ending with a conversion were studied. The research question is linked to the model that best allocates conversions among the touchpoints, however, incorporating journeys not ending with a conversion in future research can pinpoint additional insights. For instance, further research can analyze differences between journeys ending and not ending with conversion. Thirdly, although representing the bulk of consumer paths, transition probabilities were calculated up to the 5th interaction. Future research can incorporate further transition probabilities to increase the robustness of the analysis of the customer journey. Another limitation arises from the fact that KPIs were calculated for an aggregate period. For instance, by calculating KPIs per week or month in future research, one can better account for seasonality or promotions, which have an impact in the Fashion Industry. Lastly, it would also be interesting to conduct similar analysis in other countries in which the company operates, in order to analyze the role of consumer individualities and culture, among others, in the customer journey.

7. CONCLUSION

Although focusing on the focal company, the present research creates a methodology that can be used by other companies when facing the attribution problem. By studying user's characteristics, analyzing the customer journey and exploring the results given by each attribution model, it was possible to pinpoint crucial aspects regarding the interplay of online channels. Therefore, an attribution model - the Position Based - was appointed as the one best reflecting the customer journey and firm advertising goals. Lastly, the implications of a switch in attribution model are many fold and budget allocation can be improved.

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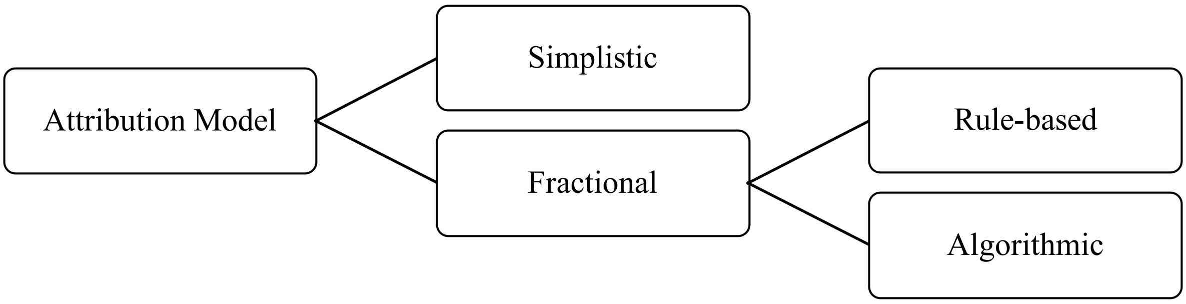
ANNEXES

Annex I: Attribution model's classification (Forrester Consulting, 2012; Interactive Advertising Bureau, 2016)



Annex II: Audience Report – Age, Google Analytics 360 (Company A, 2017)

Demographics: Age

All Users
100.00% Sessions

Jan 1, 2016 - Aug 31, 2017

Age	Gender	Acquisition			Behavior			Conversions eCommerce		
		Sessions	% New Sessions	New Users	Bounce Rate	Pages / Session	Avg. Session Duration	Transactions	Revenue	Ecommerce Conversion Rate
		27,186,307 % of Total: 64.28% (42,293,547)						635,130 % of Total: 64.37% (986,736)		
1. 25-34	female	4,889,124 (17.98%)						107,901 (16.99%)		
2. 35-44	female	4,168,619 (15.33%)						98,337 (15.48%)		
3. 18-24	female	3,946,619 (14.52%)						86,130 (13.56%)		
4. 45-54	female	3,316,816 (12.20%)						82,774 (13.03%)		
5. 25-34	male	2,151,397 (7.91%)						50,919 (8.02%)		
6. 55-64	female	2,042,782 (7.51%)						47,452 (7.47%)		
7. 18-24	male	1,829,270 (6.73%)						43,055 (6.78%)		
8. 35-44	male	1,672,269 (6.15%)						39,239 (6.18%)		
9. 45-54	male	1,261,289 (4.64%)						32,931 (5.18%)		
10. 55-64	male	715,415 (2.63%)						18,303 (2.88%)		
11. 65+	female	702,980 (2.59%)						15,978 (2.52%)		
12. 65+	male	489,727 (1.80%)						12,111 (1.91%)		

Note: only Sessions and Transactions data disclosed in order to protect the anonymity of Company A; 12 out of 12 rows showed.

Annex III: Audience Report – Location, Google Analytics 360 (Company A, 2017)

Location

All Users
100.00% Sessions

Jan 1, 2016 - Aug 31, 2017

City	Gender	Acquisition			Behavior			Conversions eCommerce		
		Sessions	% New Sessions	New Users	Bounce Rate	Pages / Session	Avg. Session Duration	Transactions	Revenue	Ecommerce Conversion Rate
		27,211,310 % of Total: 64.34% (42,293,547)						618,573 % of Total: 62.69% (986,736)		
1. Berlin	female	1,614,316 (5.93%)						37,471 (6.06%)		
2. Munich	female	917,160 (3.37%)						20,160 (3.26%)		
3. Hamburg	female	850,545 (3.13%)						18,955 (3.06%)		
4. Berlin	male	707,783 (2.60%)						16,873 (2.73%)		
5. Cologne	female	741,419 (2.72%)						14,572 (2.36%)		
6. Munich	male	418,534 (1.54%)						10,189 (1.65%)		
7. (not set)	female	464,003 (1.71%)						9,970 (1.61%)		
8. Frankfurt	female	520,319 (1.91%)						9,642 (1.56%)		
9. Cologne	male	361,561 (1.33%)						9,423 (1.52%)		
10. Stuttgart	female	383,474 (1.41%)						9,313 (1.51%)		
11. Hamburg	male	377,886 (1.39%)						8,765 (1.42%)		
12. Leipzig	female	279,059 (1.03%)						7,889 (1.28%)		

Note: only Sessions and Transactions data disclosed in order to protect the anonymity of Company A; 12 out of 1808 rows showed.

Annex IV: Audience Report – Device Category, Google Analytics 360 (Company A, 2017)

Overview

All Users
100.00% Sessions

Jan 1, 2016 - Aug 31, 2017

Device Category	Gender	Acquisition			Behavior			Conversions eCommerce		
		Sessions	% New Sessions	New Users	Bounce Rate	Pages / Session	Avg. Session Duration	Transactions	Revenue	Ecommerce Conversion Rate
		28,898,156 % of Total: 68.33% (42,293,547)						649,606 % of Total: 65.83% (986,736)		
1. mobile	female	13,048,522 (45.15%)						246,738 (37.98%)		
2. desktop	female	4,893,565 (16.93%)						150,322 (23.14%)		
3. desktop	male	3,280,565 (11.35%)						101,347 (15.60%)		
4. mobile	male	4,718,154 (16.33%)						83,159 (12.80%)		
5. tablet	female	2,170,462 (7.51%)						50,838 (7.83%)		
6. tablet	male	786,888 (2.72%)						17,202 (2.65%)		

Note: only Sessions and Transactions data disclosed in order to protect the anonymity of Company A; 6 out of 6 rows showed.

Annex V: Audience Report – Interests, Google Analytics 360 (Company A, 2017)

Interests: Affinity Categories (reach)

All Users
69.43% Sessions

Jan 1, 2016 - Aug 31, 2017

Affinity Category (reach)	Gender	Acquisition			Behavior			Conversions eCommerce		
		Sessions	% New Sessions	New Users	Bounce Rate	Pages / Session	Avg. Session Duration	Transactions	Revenue	Ecommerce Conversion Rate
		29,365,031 % of Total: 69.43% (42,293,547)						682,343 % of Total: 69.15% (986,736)		
1. Lifestyles & Hobbies/Shutterbugs	female	11,001,056 (2.56%)						252,675 (2.62%)		
2. Home & Garden/Home Decor Enthusiasts	female	11,408,919 (2.66%)						248,420 (2.58%)		
3. Media & Entertainment/TV Lovers	female	10,152,918 (2.37%)						234,975 (2.44%)		
4. Food & Dining/Cooking Enthusiasts/Aspiring Chefs	female	10,508,555 (2.45%)						224,130 (2.33%)		
5. News & Politics/News Junkies/Entertainment & Celebrity News Junkies	female	9,842,990 (2.29%)						211,331 (2.19%)		
6. Shoppers/Shopaholics	female	9,726,293 (2.27%)						210,588 (2.19%)		
7. Technology/Social Media Enthusiasts	female	8,991,817 (2.09%)						204,149 (2.12%)		
8. News & Politics/News Junkies	female	8,686,388 (2.02%)						198,416 (2.06%)		
9. Media & Entertainment/Movie Lovers	female	9,050,007 (2.11%)						197,405 (2.05%)		
10. Lifestyles & Hobbies/Family-Focused	female	8,251,705 (1.92%)						179,431 (1.86%)		
11. Beauty & Wellness/Beauty Mavens	female	8,411,672 (1.96%)						173,474 (1.80%)		
12. Travel/Travel Buffs	female	7,848,062 (1.83%)						170,802 (1.77%)		
13. Media & Entertainment/TV Lovers/Game, Reality & Talk Show Fans	female	7,108,421 (1.66%)						158,910 (1.65%)		
14. Food & Dining/Cooking Enthusiasts/30 Minute Chefs	female	6,811,960 (1.59%)						152,201 (1.58%)		
15. Media & Entertainment/Music Lovers	female	6,808,370 (1.59%)						147,898 (1.54%)		
16. Technology/Technophiles	female	6,498,500 (1.51%)						144,812 (1.50%)		
17. Technology/Mobile Enthusiasts	female	6,321,020 (1.47%)						143,060 (1.49%)		
18. Lifestyles & Hobbies/Pet Lovers	female	6,227,694 (1.45%)						141,317 (1.47%)		
19. Lifestyles & Hobbies/Fashionistas	female	6,239,189 (1.45%)						134,648 (1.40%)		
20. Food & Dining/Cooking Enthusiasts	female	5,807,885 (1.35%)						131,383 (1.36%)		
21. Media & Entertainment/Music Lovers/Pop Music Fans	female	5,662,251 (1.32%)						124,855 (1.30%)		
22. Sports & Fitness/Sports Fans	female	5,640,295 (1.31%)						123,749 (1.28%)		
23. Sports & Fitness/Health & Fitness Buffs	female	5,834,415 (1.36%)						122,057 (1.27%)		
24. Sports & Fitness/Sports Fans/Soccer Fans	female	5,394,891 (1.26%)						121,642 (1.26%)		
25. Shoppers/Bargain Hunters	female	5,069,443 (1.18%)						117,231 (1.22%)		
26. Vehicles & Transportation/Auto Enthusiasts	female	4,787,936 (1.12%)						107,227 (1.11%)		
27. Lifestyles & Hobbies/Shutterbugs	male	4,419,114 (1.03%)						106,952 (1.11%)		
28. Lifestyles & Hobbies/Outdoor Enthusiasts	female	4,727,936 (1.10%)						106,225 (1.10%)		
29. Media & Entertainment/TV Lovers	male	4,412,299 (1.03%)						105,217 (1.09%)		
30. Lifestyles & Hobbies/Green Living Enthusiasts	female	4,824,104 (1.12%)						103,971 (1.08%)		
31. Lifestyles & Hobbies/Pet Lovers/Dog Lovers	female	4,508,071 (1.05%)						103,400 (1.07%)		
32. Food & Dining/Foodies	female	4,695,979 (1.09%)						98,843 (1.03%)		
33. News & Politics/News Junkies	male	4,160,518 (0.97%)						98,702 (1.02%)		
34. Media & Entertainment/Movie Lovers	male	4,243,280 (0.99%)						97,655 (1.01%)		
35. Media & Entertainment/TV Lovers/TV Drama Fans	female	4,497,296 (1.05%)						97,401 (1.01%)		

Note: only Sessions and Transactions data disclosed in order to protect the anonymity of Company A; 35 out of 218 rows showed.

Annex VI: Transition Probability from 1st Interaction to 2nd Interaction, in absolute values

	2nd Interaction														
1st Interaction	Facebook	DTI	SEO	Price Comparison	SEM	Referral	Email n/ Paid	Affiliate	Display	Email Paid	Social Media	Retargeting	Other	Conversion	***TOTAL***
Facebook	53879	43377	2256	1227	2867	13610	2531	1463	57	56	2654	4000	470	157785	***286232***
DTI	5578	62988	4101	2017	6346	2938	14486	1221	351	151	436	2207	133	70024	***172977***
SEO	1238	30344	1185	1994	4515	1894	1921	855	145	30	100	1283	39	46994	***92537***
Price Comparison	1111	12958	3039	29718	4718	1410	1018	883	80	31	52	1252	49	38884	***95203***
SEM	1517	25603	8305	3172	24394	2121	2443	991	207	80	107	2373	131	56052	***127496***
Referral	7171	7386	541	296	701	1087	717	290	51	10	939	611	44	23356	***43200***
Email n/ Paid	1632	17939	1732	499	1647	743	34582	532	238	228	75	2147	199	23153	***85346***
Affiliate	3519	8586	848	646	1060	720	585	4529	43	34	118	678	45	17233	***38644***
Display	167	3794	574	207	491	399	509	109	3370	6	2	1612	1	5753	***16994***
Email Paid	142	2125	95	58	199	118	610	63	5	466	2	318	128	3563	***7892***
Social Media	1722	1194	94	51	116	962	74	80	3	1	1885	157	2	3985	***10326***
Retargeting	836	1730	321	116	279	147	783	61	145	12	28	1915	29	1520	***7922***
Other	106	398	20	13	62	34	110	18	10	7	1	96	551	542	***1968***
TOTAL	***78618***	***218422***	***23111***	***40014***	***47395***	***26183***	***60369***	***11095***	***4705***	***1112***	***6399***	***18649***	***1821***	***448844***	***986737***

Annex VII: Transition Probability from 2nd Interaction to 3rd Interaction, in absolute values

		3rd Interaction														
		Facebook	DTI	SEO	Price Comparison	SEM	Referral	Email n/ Paid	Affiliate	Display	Email Paid	Social Media	Retargeting	Other	Conversion	***TOTAL***
2nd Interaction	Facebook	18345	14365	821	347	922	3624	1334	632	43	26	1139	1788	184	35048	***78618***
	DTI	8776	91376	3893	2187	7031	3824	15432	1212	570	168	727	3804	205	79217	***218422***
	SEO	586	6974	574	768	2393	495	963	270	77	12	32	519	26	9422	***23111***
	Price Comparison	644	4651	1371	13402	2179	620	580	455	65	20	37	509	45	15436	***40014***
	SEM	785	7413	3245	1493	12206	1534	1283	472	83	44	48	940	59	17790	***47395***
	Referral	3938	3369	530	148	553	1815	686	364	115	42	584	352	33	13654	***26183***
	Email n/ Paid	1216	14525	1321	295	1288	500	26123	330	151	182	50	1635	128	12625	***60369***
	Affiliate	927	1579	268	265	383	365	304	2667	22	11	46	168	10	4080	***11095***
	Display	48	964	161	40	131	101	221	18	1344	0	2	468	0	1207	***4705***
	Email Paid	39	254	20	8	29	22	201	7	2	87	0	64	29	350	***1112***
	Social Media	1180	593	47	19	55	741	59	41	2	1	1583	91	1	1986	***6399***
	Retargeting	1762	3954	677	274	690	339	1506	180	261	40	75	3805	56	5030	***18649***
	Other	188	361	36	20	49	30	180	11	4	20	3	78	348	493	***1821***
	TOTAL	***38434***	***150378***	***12964***	***19266***	***27909***	***14010***	***48872***	***6659***	***2739***	***653***	***4326***	***14221***	***1124***	***196338***	***537893***

Annex VIII: Transition Probability from 2nd Interaction to 3rd Interaction, in percentage form

	3rd Interaction														
2nd Interaction	Facebook	DTI	SEO	Price Comparison	SEM	Referral	Email n/ Paid	Affiliate	Display	Email Paid	Social Media	Retargeting	Other	Conversion	***TOTAL***
Facebook	23.33%	18.27%	1.04%	0.44%	1.17%	4.61%	1.70%	0.80%	0.05%	0.03%	1.45%	2.27%	0.23%	44.58%	***100.00%***
DTI	4.02%	41.83%	1.78%	1.00%	3.22%	1.75%	7.07%	0.55%	0.26%	0.08%	0.33%	1.74%	0.09%	36.27%	***100.00%***
SEO	2.54%	30.18%	2.48%	3.32%	10.35%	2.14%	4.17%	1.17%	0.33%	0.05%	0.14%	2.25%	0.11%	40.77%	***100.00%***
Price Comparison	1.61%	11.62%	3.43%	33.49%	5.45%	1.55%	1.45%	1.14%	0.16%	0.05%	0.09%	1.27%	0.11%	38.58%	***100.00%***
SEM	1.66%	15.64%	6.85%	3.15%	25.75%	3.24%	2.71%	1.00%	0.18%	0.09%	0.10%	1.98%	0.12%	37.54%	***100.00%***
Referral	15.04%	12.87%	2.02%	0.57%	2.11%	6.93%	2.62%	1.39%	0.44%	0.16%	2.23%	1.34%	0.13%	52.15%	***100.00%***
Email n/ Paid	2.01%	24.06%	2.19%	0.49%	2.13%	0.83%	43.27%	0.55%	0.25%	0.30%	0.08%	2.71%	0.21%	20.91%	***100.00%***
Affiliate	8.36%	14.23%	2.42%	2.39%	3.45%	3.29%	2.74%	24.04%	0.20%	0.10%	0.41%	1.51%	0.09%	36.77%	***100.00%***
Display	1.02%	20.49%	3.42%	0.85%	2.78%	2.15%	4.70%	0.38%	28.57%	0.00%	0.04%	9.95%	0.00%	25.65%	***100.00%***
Email Paid	3.51%	22.84%	1.80%	0.72%	2.61%	1.98%	18.08%	0.63%	0.18%	7.82%	0.00%	5.76%	2.61%	31.47%	***100.00%***
Social Media	18.44%	9.27%	0.73%	0.30%	0.86%	11.58%	0.92%	0.64%	0.03%	0.02%	24.74%	1.42%	0.02%	31.04%	***100.00%***
Retargeting	9.45%	21.20%	3.63%	1.47%	3.70%	1.82%	8.08%	0.97%	1.40%	0.21%	0.40%	20.40%	0.30%	26.97%	***100.00%***
Other	10.32%	19.82%	1.98%	1.10%	2.69%	1.65%	9.88%	0.60%	0.22%	1.10%	0.16%	4.28%	19.11%	27.07%	***100.00%***

Note: top 2 values per row (without the column Conversion) in grey background.

Annex IX: Transition Probability from 3rd Interaction to 4th Interaction, in absolute values

3rd Interaction \ 4th Interaction	Facebook	DTI	SEO	Price Comparison	SEM	Referral	Email n/ Paid	Affiliate	Display	Email Paid	Social Media	Retargeting	Other	Conversion	***TOTAL***
Facebook	9348	7791	463	272	486	1912	939	341	15	6	704	1129	94	14934	***38434***
DTI	5962	69380	2455	1517	5004	2369	12739	854	415	111	495	3007	160	45910	***150378***
SEO	336	4094	354	434	1289	315	737	170	50	4	16	312	13	4841	***12965***
Price Comparison	265	2192	731	6936	1175	278	333	199	17	5	16	282	10	6827	***19266***
SEM	450	4586	2075	868	7917	857	1019	272	42	21	27	530	31	9214	***27909***
Referral	1679	1829	387	122	320	1420	519	317	58	26	404	236	16	6677	***14010***
Email n/ Paid	1076	12093	1130	259	1062	421	21902	277	141	112	38	1419	114	8828	***48872***
Affiliate	515	948	179	156	227	248	230	1743	9	7	20	127	5	2245	***6659***
Display	41	560	84	30	78	77	155	21	853	0	2	260	0	578	***2739***
Email Paid	12	129	15	14	23	34	170	6	3	47	0	20	11	169	***653***
Social Media	796	364	35	13	27	503	48	33	1	0	1250	48	1	1207	***4326***
Retargeting	1270	3082	516	222	521	263	1351	109	169	38	81	3360	47	3192	***14221***
Other	108	246	23	14	36	24	130	8	2	16	2	45	208	262	***1124***
TOTAL	***21858***	***107294***	***8447***	***10857***	***18165***	***8721***	***40272***	***4350***	***1775***	***393***	***3055***	***10775***	***710***	***104884***	***341556***

Annex X: Transition Probability from 3rd Interaction to 4th Interaction, in percentage form

		4th Interaction														
		Facebook	DTI	SEO	Price Comparison	SEM	Referral	Email n/ Paid	Affiliate	Display	Email Paid	Social Media	Retargeting	Other	Conversion	***TOTAL***
3rd Interaction	Facebook	24.32%	20.27%	1.20%	0.71%	1.26%	4.97%	2.44%	0.89%	0.04%	0.02%	1.83%	2.94%	0.24%	38.86%	***100.00%***
	DTI	3.96%	46.14%	1.63%	1.01%	3.33%	1.58%	8.47%	0.57%	0.28%	0.07%	0.33%	2.00%	0.11%	30.53%	***100.00%***
	SEO	2.59%	31.58%	2.73%	3.35%	9.94%	2.43%	5.68%	1.31%	0.39%	0.03%	0.12%	2.41%	0.10%	37.34%	***100.00%***
	Price Comparison	1.38%	11.38%	3.79%	36.00%	6.10%	1.44%	1.73%	1.03%	0.09%	0.03%	0.08%	1.46%	0.05%	35.44%	***100.00%***
	SEM	1.61%	16.43%	7.43%	3.11%	28.37%	3.07%	3.65%	0.97%	0.15%	0.08%	0.10%	1.90%	0.11%	33.01%	***100.00%***
	Referral	11.98%	13.05%	2.76%	0.87%	2.28%	10.14%	3.70%	2.26%	0.41%	0.19%	2.88%	1.68%	0.11%	47.66%	***100.00%***
	Email n/ Paid	2.20%	24.74%	2.31%	0.53%	2.17%	0.86%	44.82%	0.57%	0.29%	0.23%	0.08%	2.90%	0.23%	18.06%	***100.00%***
	Affiliate	7.73%	14.24%	2.69%	2.34%	3.41%	3.72%	3.45%	26.18%	0.14%	0.11%	0.30%	1.91%	0.08%	33.71%	***100.00%***
	Display	1.50%	20.45%	3.07%	1.10%	2.85%	2.81%	5.66%	0.77%	31.14%	0.00%	0.07%	9.49%	0.00%	21.10%	***100.00%***
	Email Paid	1.84%	19.75%	2.30%	2.14%	3.52%	5.21%	26.03%	0.92%	0.46%	7.20%	0.00%	3.06%	1.68%	25.88%	***100.00%***
	Social Media	18.40%	8.41%	0.81%	0.30%	0.62%	11.63%	1.11%	0.76%	0.02%	0.00%	28.90%	1.11%	0.02%	27.90%	***100.00%***
	Retargeting	8.93%	21.67%	3.63%	1.56%	3.66%	1.85%	9.50%	0.77%	1.19%	0.27%	0.57%	23.63%	0.33%	22.45%	***100.00%***
	Other	9.61%	21.89%	2.05%	1.25%	3.20%	2.14%	11.57%	0.71%	0.18%	1.42%	0.18%	4.00%	18.51%	23.31%	***100.00%***

Note: top 2 values per row (without the column Conversion) in grey background.

Annex XI: Transition Probability from 4^{th} Interaction to 5^{th} Interaction, in absolute values

4^{th} Interaction	5^{th} Interaction: Facebook	DTI	SEO	Price Comparison	SEM	Referral	Email n/ Paid	Affiliate	Display	Email Paid	Social Media	Retargeting	Other	Conversion	***TOTAL***
Facebook	5612	4818	323	133	317	1014	794	213	13	11	424	825	56	7305	***21858***
DTI	3882	53437	1790	1062	3499	1331	10282	587	323	74	396	2273	151	28207	***107294***
SEO	227	2674	220	285	884	230	548	111	37	4	15	269	16	2927	***8447***
Price Comparison	204	1250	420	4066	729	170	242	120	23	1	10	195	7	3420	***10857***
SEM	304	3132	1309	533	5471	453	804	185	42	13	20	425	38	5436	***18165***
Referral	1051	1167	300	60	244	984	398	225	49	23	297	184	23	3716	***8721***
Email n/ Paid	856	9956	881	217	901	299	18581	194	133	114	41	1170	113	6816	***40272***
Affiliate	303	560	134	101	139	194	192	1228	9	5	19	82	1	1383	***4350***
Display	18	392	43	13	41	47	115	13	568	0	1	172	0	352	***1775***
Email Paid	13	80	6	5	13	26	94	10	0	36	0	12	9	89	***393***
Social Media	542	265	14	7	22	396	41	25	0	0	968	50	1	724	***3055***
Retargeting	961	2289	385	158	396	172	1157	91	169	12	40	2744	31	2170	***10775***
Other	64	132	14	7	23	11	104	5	0	8	0	39	133	170	***710***
TOTAL	***14037***	***80152***	***5839***	***6647***	***12679***	***5327***	***33352***	***3007***	***1366***	***301***	***2231***	***8440***	***579***	***62715***	***236672***

Annex XII: Transition Probability from 4th Interaction to 5th Interaction, in percentage form

	5th Interaction														
4th Interaction	Facebook	DTI	SEO	Price Comparison	SEM	Referral	Email n/ Paid	Affiliate	Display	Email Paid	Social Media	Retargeting	Other	Conversion	***TOTAL***
Facebook	25.67%	22.04%	1.48%	0.61%	1.45%	4.64%	3.63%	0.97%	0.06%	0.05%	1.94%	3.77%	0.26%	33.42%	***100.00%***
DTI	3.62%	49.80%	1.67%	0.99%	3.26%	1.24%	9.58%	0.55%	0.30%	0.07%	0.37%	2.12%	0.14%	26.29%	***100.00%***
SEO	2.69%	31.66%	2.60%	3.37%	10.47%	2.72%	6.49%	1.31%	0.44%	0.05%	0.18%	3.18%	0.19%	34.65%	***100.00%***
Price Comparison	1.88%	11.51%	3.87%	37.45%	6.71%	1.57%	2.23%	1.11%	0.21%	0.01%	0.09%	1.80%	0.06%	31.50%	***100.00%***
SEM	1.67%	17.24%	7.21%	2.93%	30.12%	2.49%	4.43%	1.02%	0.23%	0.07%	0.11%	2.34%	0.21%	29.93%	***100.00%***
Referral	12.05%	13.38%	3.44%	0.69%	2.80%	11.28%	4.56%	2.58%	0.56%	0.26%	3.41%	2.11%	0.26%	42.61%	***100.00%***
Email n/ Paid	2.13%	24.72%	2.19%	0.54%	2.24%	0.74%	46.14%	0.48%	0.33%	0.28%	0.10%	2.91%	0.28%	16.92%	***100.00%***
Affiliate	6.97%	12.87%	3.08%	2.32%	3.20%	4.46%	4.41%	28.23%	0.21%	0.11%	0.44%	1.89%	0.02%	31.79%	***100.00%***
Display	1.01%	22.08%	2.42%	0.73%	2.31%	2.65%	6.48%	0.73%	32.00%	0.00%	0.06%	9.69%	0.00%	19.83%	***100.00%***
Email Paid	3.31%	20.36%	1.53%	1.27%	3.31%	6.62%	23.92%	2.54%	0.00%	9.16%	0.00%	3.05%	2.29%	22.65%	***100.00%***
Social Media	17.74%	8.67%	0.46%	0.23%	0.72%	12.96%	1.34%	0.82%	0.00%	0.00%	31.69%	1.64%	0.03%	23.70%	***100.00%***
Retargeting	8.92%	21.24%	3.57%	1.47%	3.68%	1.60%	10.74%	0.84%	1.57%	0.11%	0.37%	25.47%	0.29%	20.14%	***100.00%***
Other	9.01%	18.59%	1.97%	0.99%	3.24%	1.55%	14.65%	0.70%	0.00%	1.13%	0.00%	5.49%	18.73%	23.94%	***100.00%***

Note: top 2 values per row (without the column Conversion) in grey background.