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Marketing Attribution in B2B Companies:

Associating software and customer data to increase confidence in data-driven channel optimization decisions

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Project Work

presented as partial requirement for obtaining the Master Degree Program in Data-Driven Marketing

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MARKETING ATTRIBUTION IN B2B COMPANIES: ASSOCIATING SOFTWARE AND CUSTOMER DATA TO INCREASE CONFIDENCE IN DATA-DRIVEN CHANNEL OPTIMIZATION DECISIONS

By

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Master Thesis / Project Work presented as partial requirement for obtaining the Master's degree in Data-Driven Marketing, with a specialization in Digital Marketing and Analytics

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledge the Rules of Conduct and Code of Honor from the NOVA Information Management School.

Rafael de Oliveira Santana

Lisbon, 13 July 2023

ABSTRACT

To build a solid marketing and sales process, B2B companies invest in robust CRM and Marketing automation systems to help teams to identify and manage companies, contacts, interactions, sales opportunities and more. These systems offer several report types for different roles within the company, being the Marketing Attribution one of the most important to marketing leaders when analyzing what are the campaigns, channels and tactics that drive more revenue. This information is key when choosing which channels companies should allocate budget, but these tools can’t track all touchpoints in the buying journey, which can lead marketing leaders to make misleading decisions on where to invest their budgets. This research tested and analyzed an experiment applied in a prominent B2B company that added a layer of customer-level sourced data to what is tracked by the attribution tool, suggesting a hybrid attribution model that is able to identify hidden touch points and re-distribute the weights of credits attributed. To perform the study, an experimental research collected and analyzed data from a sample of 220 purchase paths, discovering that marketing attribution models widely adopted by companies can be significantly improved when granular user-level data is added to the view. It has significant managerial contributions as marketing leaders can do a better channel performance analysis and make more informed decisions when allocating investments.

KEYWORDS

Industrial marketing, Marketing attribution, Attribution modeling, Digital marketing, Data-driven marketing, Customer insights

Sustainable Development Goals (SGD):

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LIST OF ABBREVIATIONS AND ACRONYMS

B2B	Business to Business
CRM	Customer Relationship Management
CTA	Call to Action
CTR	Click-through Rate
MSI	Marketing Science Institute
ROI	Return on Investment
SBE	Small Business & Entrepreneurship
UTM	Urchin Tracking Module

1. INTRODUCTION

Internet has become a basic need in the life of most of population, with 60% of people with access in the world according to Our World in Data.org (2023); companies shifted their strategies to reach their targets in the digital environment, and digital marketing offered opportunities to organizations to reach customers, improve brand awareness and increase sales with lower costs (Dwivedi et al, 2021).

There are a huge number of strategies that can be used in digital marketing to help companies to create new customers, retain existing ones, expand their relationships and build loyalty. These strategies in place will require tactics that use channels such as social media, paid advertising, website, content blogs, search engine optimization, email and more. These channels are used together in a mix of touchpoints targeting the desired audience that helps the prospects to know the company, identify clear and hidden needs, discover how company's products can help to solve those needs, investigate fit and quality by doing online research, and finally deciding to become a client (Hidalgo, 2015).

Thes buying decisions can be particularly complex when purchases are made by people representing organizations. Companies acting in the B2B (Business to Business) environment need to deeply understand the buying process of their customers. Usually when a prospect identifies a potential solution for its company's challenges, there are several steps within the organization to validate it, given the complexity of the transaction and the associated value. (Marvasti et al, 2021).

In these buying processes, B2B marketing or Industrial marketing plays an important role in generating interest and influencing the audience. It is done not only by engaging with the market and generating leads, but also being a key player in the sales-marketing interface, generating demand, capturing revenue, and gaining competitive advantage (Hobbs, 2015; Sabnis, Chatterjee, Grewal, & Lilien, 2013). The presence of marketing in the selling process resulted in a shared responsibility for driving revenue to the company. Marketing attributable revenue became a key indicator to measure effectiveness and the contribution that marketing plays to company sales performance (Lundi & Marinova, 2014).

To track marketing and sales performance, a setup of tools and technologies is needed to store customer data, qualify leads, see evolution across the sales funnel, measure revenue and report campaign performance. A key tool to help B2B companies to track this process is a CRM platform (Heini, Sisko, Maarit, & Lipiäinen, 2015). Often CRM tools are integrated with Marketing Automation systems, that are known as the automated marketing decision support on the internet (Little, 2001), allowing marketing teams to deploy automated campaigns based on company's strategy.

To better understand the audience behavior and how they interact with the marketing activities across their buying journeys, these platforms offer marketing attribution systems that track the interactions prospects had with the company until becoming a client. These interaction events are referred to as touchpoints, and the whole set of them is referred to as user path (Leguina, Rumín, & Rumín, 2020).

Attribution models are an advanced set of analytics that is used to distribute suitable credit for the sale or conversion to each showcasing touchpoint of marketing channels (Moffett, Pilecki, & McAdams 2014). The most common models are rule-based and the most prominent is the last-click model, crediting 100% of the value to the last interaction a user clicked before a purchase conversion (Xu, Duan, & Whinston, 2014). There are other models largely adopted by companies, such as Time Decay, First Interaction, Linear attribution, Position based and multi-touch attribution. Depending on the position of touchpoints in the purchase path, different levels of credits are attributed, giving more relevance to interactions that might happen in the beginning, in the end of the journey, or distributed in personalized ways. This variety of models is available to help companies identify one that fits their customer behavior and better represents the relevance of touchpoints across the purchase path.

With the ability of capturing touchpoints across the buying journey and attributing credits to the most relevant ones, the reports provided by attribution tools are used by marketing professionals to identify the most effective tactics and channels (Econsultancy & Google, 2012), so they can take informed decisions when optimizing their strategies and the budget allocation to increase revenue contribution.

However, independently of the attribution tool or model used by companies, there are some facts that can lead these attribution reports to biased interpretations. Attribution tools track data by using UTM values, data from cookies and individual devices gathered from the interactions prospects have with touchpoints provided by the company. Conversions on organic or paid search campaigns, CTA clicks in social media posts or emails, form submissions in websites and landing pages, all these interactions are tracked by attribution tools and added to their channel performance reports.

But there are some customer behaviors that aren't captured by attribution systems. Today's buyers' purchasing processes are based on their own terms, and not company's terms (Holliman & Rowley, 2014; J¨arvinen & Taiminen, 2016). Prospects have the power to research by themselves, in the moment they want, not necessarily taking actions that can be measured by attribution tools. Buyers can research about companies and solutions by consuming podcasts, reading posts in social media, watching video reviews, reading comments from peers in communities, asking recommendations to colleagues from other companies and more. All these possible interactions can't be tracked by attribution systems as they don't require an identifiable action, such as a click or a submission.

These touchpoints that attribution systems struggle to identify are common to happen in the earlier stages of the buying path and are key to build awareness to the audience that, if there is a need that fits with the organization's solutions, prospects know who can help them. And once prospects are ready to buy, they will take action in the conversion channels to talk with the company – SEO, Paid search, direct traffic and more. This process is known as demand generation and demand conversion (Hidalgo, 2015), and consistent B2B marketing strategies use the channel mix to reach the audience in the different stages of their buying journeys.

B2B buyers spend the majority of their time in a buying path engaged in independent online research, spending 60% more time on autonomous research than meeting with potential suppliers (Gartner, 2020). Additionally, 77% of B2B buyers consume three or more pieces of digital content alone before contacting the company and asking for a sales conversation (DemandGen, 2020). With this scenario of research autonomy, trusting purely in the data offered by the attribution tools can lead marketing leaders to wrong interpretation about channel effectiveness (Danaher & Heerde, 2018). It is also known that attribution softwares over-weights the results of channels used to capture demand, such as Search and Direct traffic (Hongshuang & Kannan, 2013), not because they are responsible for the results, but because they are the path buyers take when they feel ready to buy.

A comprehensive literature review done in this study demonstrated that there is a need for further research in adding granular user-level data in these attribution models (Gaur & Bharti, 2020), and for the best of author's knowledge, there is no academic research that approaches how a marketing attribution system can report what are the non-trackable interactions a prospect can have with the content of a company, interactions that are key to drive demand to the conversion channels.

This research gap is especially important when we have an increasing pressure in companies to make marketing accountable for sales pipeline and revenue. Budget allocation decisions are critical to the success of marketing strategies, and according to a survey done by Econsultancy and Google Analytics in 2012, 72% of marketers consider a top benefit of marketing attribution reports is to be better able to allocate budget across channels. Doing it with information that covers the full buying journey, and not only what can be tracked in digital, is key to support marketing leaders in taking better decisions.

Supported by the research gap mentioned above of using granular user-level data in attribution models, and how B2B marketing professionals use the data provided by these tools, this study has the following research question: “How can B2B companies approach marketing attribution reporting by using software and customer provided data to identify the most effective channels?”. The objectives of the study are: 1) to verify if adding granular user-level data to the software-sourced attribution reports can help marketing professionals to visualize hidden touchpoints not captured by attribution systems; 2a) to check if data provided by customers about their buying paths can be used to identify channels where the demand was generated, 2b) to verify if software collected data can be especially useful to identify the channels where the demand is captured and converted to qualified lead.

This study expects to contribute to the marketing attribution topic discussion by developing knowledge in the existing research gap related to how granular user-level data can be captured and added to attribution models. For that, a hybrid attribution model composed by software and user provided data was created and applied in a company where an experimental research was executed.

The experiment was done in a global B2B company from the consulting services industry, focusing on the United States market. The company has a mature structure of CRM and Marketing automation tools, using a multi-touch attribution model that allocates credits in a linear way. 220 purchase paths were analyzed, dividing 110 members in the experimental group and another 110 in the control group.

To collect quantitative data, the experiment consisted in adding to the forms that the studied company uses to capture high intent leads, a free text field asking prospects to share how they heard about the company. It demanded prospects to remember how they discovered the company and type any early touchpoints that are in their memory and potentially weren’t captured by attribution tools, adding a layer of user-provided data to be combined with the existing marketing attribution reports. By adding this field, the studied company was able to get quantitative data directly from customers, and it was aggregated to what is provided by the attribution system and compared to the control group.

Additional metrics that were analyzed and compared between the experimental and control groups are related to: 1) the conversion rate of these forms to identify if there is a significant statistical change; and 2) user-level data provided without relevant information (e.g. no words, random typing) to check the impact of these inputs when compared to the full experimental sample.

This research document is composed of the following sections: literature review of the main studies related to Marketing attribution, followed by the conceptualization of an experimental research applied in a B2B company for analysis. With the practical experiment, an analysis of the results and recommendations is presented, finalizing with the managerial implications and conclusions.

2. LITERATURE REVIEW

This section proposes to verify the current state of research about marketing attribution, B2B marketing and channel effectiveness topics, identifying evolution, existing models and methods, best practices and any new developments, as well as an existing research gap to be explored by a practical experiment. For that, the following keywords were classified as relevant to this research: Marketing attribution, attribution modelling, marketing effectiveness, customer journey, B2B marketing, industrial marketing, channel effectiveness.

Marketing professionals always had the responsibility of reporting the success of marketing activities to stakeholders, demonstrating the effectiveness of the applied strategies and ensuring budget investments to the next cycles. The most used measure for evaluating digital marketing effectiveness is called ROI – Return on Investment (Goodwin, 1999). According to Flamholtz (1985), ROI is a financial ratio used to express profit in direct relation to investment. This concept came from the accounting area and before the rise of digital marketing, marketing performance was measured by the use of accounting tools such as balance sheets and income statements (Laverty, 1996). With the popularity of the internet and the adoption of digital marketing strategies by advertisers, other measuring capabilities were added to the possibilities of marketing reporting due to its high level of trackability (Goodwin, 1996). One of these reporting capabilities is Marketing attribution.

2.1. MARKETING ATTRIBUTION MODELLING

B2B marketing plays a critical role in finding potential customers and helping them to understand that the offered solution is the best for their companies' needs. Several strategies can be implemented in order to position the company as a trustable partner (brand awareness), help the audience to understand what the company does and how it can solve their challenges (demand generation), and be accessible and easy to be contacted when the prospect is ready to initiate the buying process (conversion) (Hidalgo, 2015).

This buying journey demands several touchpoints between the companies and the potential customers. To be able to understand the role each touchpoint and channel tactic plays in this journey, marketers need to find ways to track these activities and how effective they are across different marketing events, i.e. ads, shown prior to a conversion. These events are referred to as touchpoints, and the whole set of them is referred to as user path (Leguina et al, 2020).

The current scenario in B2B companies requires that marketing teams not only engage with the audience and generate leads, but also be a key player as the sales-marketing interface, generate demand, capture revenue, and gain a competitive advantage (Hobbs, 2015; Sabnis et al, 2013). Marketing attributable revenue became a key indicator to measure effectiveness and the contribution that marketing plays to company sales performance (Lundi & Marinova, 2014). This revenue accountability under marketing teams demands marketing to partner with the sales team by being part of the sales funnel.

Marketing and sales working together requires a setup of tools that allow both teams to record customer information, feed with new leads, qualify those leads (marketing funnel), track the sales opportunity generation process (sales funnel) and measure closed won revenue. In this process, marketing needs to report to the company the impact/contribution they had in the company's sales numbers. An essential tool to help marketing and sales teams to track this process is a CRM platform (Heini et al, 2015).

CRM tools are platforms defined as an integration of processes, human capital and technology seeking for the best possible understanding of a company's customers (Chen & Popovich, 2003). An acronym for Customer Relationship Management, they allow teams to store information about accounts, opportunities, contacts, leads and more. All interactions between the sales team and customers are hosted in the CRM, as well as all the marketing campaigns and the interactions with contacts and leads.

The data available in CRM platforms can be specially potentialized when integrated with a Marketing Automation platform. Little (2001) defines marketing automation as the automated marketing decision support on the Internet. These tools are systems dedicated to help marketing teams to communicate with customers and leads, allowing marketing teams to deploy automated campaigns based on the company strategy and specific criteria set by marketing.

To be able to track marketing and sales performance, these platforms have attribution systems that indicate the campaigns and channels that are responsible for generating leads and driving revenue. Attribution models appeared as a solution to marketing departments measure the effectiveness of their activities. Rentola (2014) stated that attribution models became an important topic for industry as it helps marketers to calculate ROI in multi-channel marketing decisions. Marketing attribution is a strategy of determining the value of marketing communications and allocating it to identified touchpoints along customer journeys (Kannan, Reinartz, & Verhoef, 2016; Moffett et al, 2014). Another definition for marketing attribution was mentioned by Kelly et al (2017), saying that marketing attribution assigns credits to customer engagements happening before a completed conversion. The importance of marketing attribution to companies is mentioned by the Marketing Science Institute (MSI) (2018), ranking attribution as the number one priority to marketing departments in that year.

The main models in place today are rule-based models and the most prominent used in companies is the last interaction, or last-click model, that ascribes 100% of the credit to the last interaction a user clicked before a purchase conversion (Xu et al., 2014). But other models became quite well known such as Time Decay, First Interaction, Linear attribution and Position based. On these models, different numbers of credits are attributed to touchpoints depending on their position in the purchase path, giving more relevance to early-stage, late-stage interactions, or distributed in personalized ways across the buying journey. This variety of models are used by companies to identify an option that fits the characteristics of their markets and audience, and better represents the relevance of touchpoints across the purchase path.

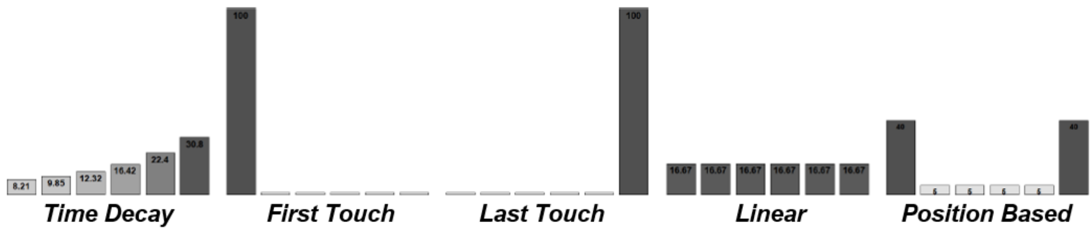

Figure 1 - Relevance given to touchpoints by different attribution models

2.2. Evolution of Attribution Models

Attribution models used for measuring marketing performance evolved significantly in the last two decades. Several studies were created to improve and propose new models to increase the confidence in the reported data. Early academic studies regarding marketing attribution and its models focused mainly on click-through rates (CTR) as an effective way to measure performance (Ansari & Mela, 2003). Later in the same period, other studies reported that CTRs were declining fast (Manchanda, Dube, & Goh, 2006), and Chatterjee, Hoffman, and Novak (2003) shared conclusions that only a small proportion of visits resulted in conversions. Other models were adopted in the coming years, which are called rule-based attribution models, also called first generation models. Leguina et al (2020) defines these models as a set of rules that attribute success of a conversion across different marketing events shown to the user prior to the conversion. The most common rule-based attribution model is the last touch, where ascribes 100% of the credit to the last ad the user clicked on before a purchase conversion (Xu et al, 2014). Other well-known rule-based models are Time decay, First click, Linear and Position based (Leguina et al, 2020).

Prior research indicates that heuristic models of attributing conversion to the last (or first) click can result in wrong conclusions (Abhishek, Fader, & Hosanagar, 2012; Li & Kannan, 2014; Xu et al., 2014). In recent years, other model frameworks emerged based on multi-touch attribution. These models are based on mathematical and statistical foundations such as linear regression, neural networks and other AI approaches to attribute credits to each interaction in a more personalized way to each journey. These data-driven models use as input data from previous advertising campaigns in order to identify an accurate distribution of the attribution across the different touchpoints present in those campaigns (Leguina et al, 2020).

Several frameworks and technologies were created and adapted to increase accuracy of these models, using regression, game theory-based approaches, VAR models, mutually-exciting point process models and hidden Markov models (Anderl, Becker, Wangenheim, & Schumann, 2015). Media industry companies such as Adometry, Convertro and VisualIQ also introduced a variety of attribution methodologies (Moffett, 2014). Multi-touch frameworks consider that more than one interaction can each have a fraction of the credit based on the true influence each impression has on the conversion (Lovett, 2009). These models allow attribution to understand buyers' path individually, taking into consideration the number of touchpoints, the time distance between each interaction, the carry-on factor from different channels, and attribute a personalized weight to the touchpoints. Nisar and Yeung (2017) mentions that these models deliver results much closer to reality, providing a better understanding of sales cycle length and purchase funnel.

2.3. Multi-touch attribution frameworks

Several frameworks were developed to take the most of multi-touch attribution. One of the models adopted by marketing attribution tools is the Shapley value. Molina, Tejada, and Weiss (2022) explored how this game theoretic model works and the possibilities to the industry. Based in a transferable utility game model, it is described as particularly helpful to deal with cases in which the position or repetition of channels are considered on the paths to conversion, resulting in different weights for each touchpoint across the journey.

But not only the position and the number of times a channel is placed in a buying path must be considered. According to Hongshuang and Kannan (2014), multi-touch attribution models must measure the incremental value of each touch point by estimating the carryover and spillover effects to improve the credits attributed to different channels. This has useful managerial implications for allocating marketing budgets across marketing channels and for targeting strategies.

With the developments of new algorithms and computer power, different algorithms were applied to support multi-touch attribution modeling, such as linear regressions, naïve bayes, random forest and support vector machines. Leguina et al (2020) applied all these models in a large dataset to analyze how they perform and analyze the accuracy of each approach in different use cases, suggesting that linear regressions deliver more accurate results than other models.

A relevant finding about multi-touch attribution models is available in Anderl et al (2015). Using Markovian graph-based data mining techniques, it was found that in touch points where the interaction is initiated by the customer, the contribution of channels such as paid search and direct type-ins is consistently overestimated. It raises the assumption that these attribution models are particularly good in measuring channels responsible for capturing conversions, and allocate more credits to the tactics commonly used for it.

2.4. USE OF MARKETING ATTRIBUTION FOR BUDGET ALLOCATION

B2B companies have an increasing pressure to prove return on investment in the marketing efforts and channels used to communicate with customers, and marketing attribution models are used to maximize marketing output and guide leaders to allocate budgets in different activities. Econsultancy and Google Analytics survey done in 2012 shows that 72% of respondent marketers consider a top benefit of marketing attribution reports is to be better able to allocate budget across channels.

Bhatta (2022) research showed that different models and touchpoint sequences can result in different attribution results. Data gathered from a B2B company showed that the customer journeys started with organic or paid search, that are channels initiated by the customer, convert better than any other journeys where the touchpoints are initiated by the company, such as paid advertisements. Channels used to convert prospects have an important role in capturing records that already have a good level of brand awareness and pro-actively take action to get in touch with the company, but the channels used to create awareness reach the audience in early stages of the purchase path, resulting in lower conversion rates and consequently, lower levels of credits allocated by the attribution reports, possibly leading marketing professionals to not accurate decisions when allocating investments to channels.

Marketing attribution is used not only in B2B companies, but across different industries and business models, playing a significant role in helping marketing teams to measure channel effectiveness. Retailing companies that require an Omnichannel approach are using attribution tools to understand buyer's path, and Méndez-Suárez & Monfort (2021) applied a calibrated structural equation from previous research to estimate the impact of advertising on web and store sales for an omnichannel retailer. In the main findings that can be applied not only under the retail industry, the study shows that when attribution models don´t consider simultaneous cross effects to different advertising media, they can influence marketing leaders to make incorrect decisions regarding where to focus investments.

Additional context to how marketing attribution data can be interpreted and used with caution was mentioned by Danaher and Heerde (2018), who proposed an attribution formulation based on the relative incremental contribution that each medium makes to a purchase, taking into account advertising carryover and interaction effects. The study approached the topic by using analytical derivations and studying simulated and empirical data. An important question raised is: 'should attribution be used for allocation? If a medium obtains an 80% weight in attribution, does it mean it should get 80% of the media budget?'. The study answer for this question is 'no', explaining that attribution is a descriptive summary of how much of a (relative) contribution each medium has made to a purchase and marketing leaders should use this metric with caution.

Marketing attribution models and reports are widely used by marketing professionals across different industries to measure channel effectiveness and help to make informed decisions about how to allocate their budget investments. Marketing Science Institute (2018) ranked attribution as the number one priority to marketing departments, showing a solid relevance of the theme to these professionals. A model that can provide a better understanding of the full purchase path consequently will help to take more accurate and confident decisions when allocating investments on channels.

2.5. FRAMEWORK

Analyzing other studies that covered the developed bibliography focused on Marketing attribution topics in the last years, we can see that there were rapid advancements in the theme, where different methods were created and different ways of using and viewing data were applied. This fast pace of developments resulted in a gap in formalizing how those frameworks work and naming common methods and terms (Bulhalis & Volchek, 2021). There are also some open fields in the topic to be researched related to the accuracy of the reports offered by these tools, as we can see in the review above some concern about data precision and interpretation by marketing teams.

An area for further analysis is the possibility of aggregating to attribution models a layer of data provided by the user that lives the purchase path to the attribution model. Gaur and Bharti (2020) research scanned through an extensive literature review in attribution modelling for marketing, covering academic works from 1990 to 2019, and identified and synthesized the techniques applied by different authors to solve the problem of attribution in the marketing literature. The research identified 21 studies under different categories of research, such as effectiveness, cross channel effects, carryover / spillover effects, and the different models / algorithms used by researchers, and recommended that future researchers focus their efforts on granular user-level data, as it was observed that all analyzed studies don't have user-level data.

A common aspect of these studies is the constant search for better models that deliver more accurate data to marketing leaders. It's common sense that accurate data is key to help business leaders to make decisions with a higher standard of certainty. Leguina et al (2020) worked in testing models to ensure the paper could contribute with a set of recommendations to build accurate efficient attribution models, ranking the best and worst algorithms performance in the study. Méndez-Suárez and Monfort (2021) researched specially the effects of simultaneous cross effects of different media, to help managers to avoid taking incorrect decisions from misleading calculations. Molina et al (2022) applied game theoretic models to increase data confidence by addressing the attribution problem that arises when the total benefits obtained by a marketing campaign must be attributed to the different channels involved in the campaign, which is considered by the authors a cornerstone of any multichannel marketing strategy. Hongshuang and Kannan (2013) study illustrated the importance of estimating the effects of interactions initiated by the company and by the user so that the attribution of each channel to the overall conversions can be better determined. Similarly, Bhatta (2022) showed that the customer journeys started with organic or paid search, that are channels initiated by the customer, convert better than any other journeys where the touchpoints are initiated by the company, such as paid advertisements. Danaher and Heerde (2018) showed how attribution can offer misleading insights on how to allocate resources across media. Across all those mentioned studies, the intention of increasing the accuracy of what is reported by these models is evident.

A fact that is not explored in these studies is the impact that non-trackable interactions have in the customer purchase path and how they should be added to the attribution reports. Although all the technology advancement, mathematical models and methodology enhancements seen in the reviewed studies, those attribution models don´t consider the non-trackable interactions and the contribution they have in a structured B2B marketing strategy. As recommended by Gaur and Bharti (2020), future research focusing on the use of granular user-level data can add significant contributions to these models.

In digital, not all activities can be tracked and it is related to new media formats and how people consume information today. According to Gartner (2020), 60% of the buying process is over before a buyer gets in touch with the company they want to buy. It demands marketing teams to create strategies to generate demand and make prospects get in touch with the company. Hidalgo (2015) defined marketing demand generation as the practice of aligning people, processes, content, and technology to that of buyers and their buying process. Today’s consumer buying behavior is autonomous and non-linear. Digitalization increased access to online information have made it easier for business-to-business (B2B) buyers to research, compare, and order offerings and, thus, transformed their buying processes and the overall marketing landscape (Edelman & Singer, 2015; Halchack, 2017; Steward, Narus, & Roehm, 2018).

Today’s digital channels include a wide range of online, word-of-mouth forums, discussion boards, chatrooms, forums and social networking websites (Mangold & Faulds, 2009). With that, in a well-built marketing demand generation strategy, companies need to create content and deliver it where the targeted audience is, adapting their format to how the content is consumed in those different channels. Reading a social media post but never clicking it, listening to a podcast while doing gym exercises, asking for references to peer colleagues in the industry in a social media closed group, or just contact directly the company as a returning customer after changing the employer, all these are common touchpoints a company can have with potential customers that must be considered in the demand generation strategy, but they aren’t captured by attribution systems. An additional layer of user-provided data can increase the accuracy of these models.

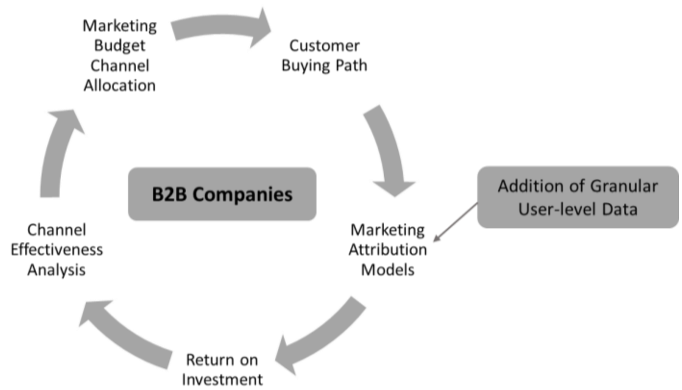

Figure 2 – Conceptual Framework: Use of granular user-level data in marketing attribution modeling

This study proposes to contribute to the theoretical discussion by testing a model that adds a layer of quantitative data provided not by the attribution tools and models, but by the potential customer that lived the buying path until the conversion point. The experiment is set to answer the research question "How can B2B companies approach marketing attribution reporting by using software and customer provided data to identify the most effective channels?"

The analysis of both data - prospect provided and marketing attribution reporting - has the potential to help marketing professionals to better understand the buyer path and how different touchpoints, even those not reported or tracked by attribution systems, can contribute to a conversion. This better understanding of the different touchpoints and how they are effective in generating demand and capturing conversions, can have significant managerial implications on how marketing professionals iterate their marketing strategies and allocate investments in channels with more confidence.

2.6. HYPOTHESES

B2B marketing professionals use attribution reports to track channel effectiveness and allocate budget (Econsultancy & Google Analytics, 2012), and if the proposed hybrid model adds touchpoints that weren't known by the standard attribution tools by using user-level data, as suggested by Gaur and Bharti (2020), there is a significant increase in the accuracy of these reports, helping marketing professionals to better understand channel effectiveness and take more informed decisions.

Hongshuang and Kannan (2013) showed the effects in attribution accuracy of interactions initiated by the company and by the user, and identifying the most effective channels for different moments in the journey can help marketing professionals to adapt the channel mix strategy to what is more effective in each moment. It covers since the early touchpoints promoted by the company to create awareness about an existing problem that a product can solve, until being easy to find when the prospect takes action to talk with the company, as defined by Hidalgo (2015) as demand generation and conversion. Considering the aspects previously presented, the following hypotheses are proposed:

Hypothesis 1: Adding granular user-level data provided by prospects can help attribution reports to visualize possible hidden touchpoints not captured by the attribution system.

Hypothesis 2a: Data provided by customers captured in the moment they convert in a high-intent form can be used to identify the channels where the demand was generated.

Hypothesis 2b: On the other side, marketing attribution system data can be especially useful to identify the channels where the demand is captured and converted to a qualified lead.

3. METHODOLOGY

To answer the research question “How can B2B companies approach marketing attribution reporting by using software and customer provided data to identify the most effective channels?”, an experimental research approach was used as methodology. Bell (2009) defines experimental design as the process of carrying out research in an objective and controlled fashion so that precision is maximized and specific conclusions can be drawn regarding a hypothesis statement.

As a field for research, a B2B company that acts in the consulting services industry was chosen, having the United States as the main market and supporting more than three thousand customer companies every year. The selling model of the company’s solutions demands that sales representatives connect with potential clients to identify needs, create customized proposals, negotiate and close deals. In this model, marketing team works to promote the company’s brand and solutions, generating leads and qualifying them across the marketing journey until they are ready for a sales approach.

To support the process, CRM and marketing automation tools are used to manage prospects data, interactions, evolution in the buying journey, and reporting results. To measure performance, a marketing attribution system is set and able to report a multi-touch model. These factors align the company with the object of study of this research, and considering the potential benefits they can obtain, the organization was identified as an ideal environment to run the experiment.

To analyze the results, quantitative research was executed using anonymized data from the company approached in the study. Aliaga and Gunderson (2002) describes quantitative research methods as the explaining of an issue or phenomenon through gathering data in numerical form and analyzing with mathematical methods; in particular statistics. It is particularly helpful to test hypotheses, find patterns and explore relationships between variables, helping researchers to draw conclusions from the data.

3.1. DATA COLLECTION

First of all, it is important to say that the company used as an environment for this research agreed in offering access to systems, applying changes in their conversion and reporting processes, and sharing anonymized data for analysis and conclusions of the study. To answer research question and prove / discard hypotheses, it was needed to collect data from the marketing attribution reports of the company under the experiment. Systems adopted by the company and used to collect data are market leaders and have a mature implementation in the company’s processes: Salesforce and Marketing Cloud Account Engagement. These tools allow a high level of personalization, but in general, to track marketing touch points the tool has the ability to pull data from social media channels, cookie and UTM parameters, analyzing the interactions to build the attribution reports.

The marketing attribution system in place, just like any other attribution tool, captures only data based on the touch points that can be tracked, so to be able to capture customer-provided data with the potential non-trackable touch points and build the hybrid attribution model, it was needed a change in the process on how the company convert leads in its submission forms. Conversion forms are a key asset in marketing conversion tactics, and according to Jarrett and Gaffney (2009), depending on the moment in the buying journey, prospects can be more or less likely to share the information that forms are asking. The updated forms were available in the website and landing pages used to capture high-intent prospects, as this audience is much more aware about the company and its solutions and consequently, more flexible in sharing information than prospects that are initiating the buying path.

High intent leads are prospects that are aware about their needs, the company and the products that can solve their challenges, and take action asking to be contacted by the company to get more details. Low intent leads are prospects that have some level of interest or awareness about what the company does, but still aren't ready to have a sales conversation and evolve the discussions to an opportunity. As the experiment proposes to help marketing professionals to identify effective channels and allocate their investments with more confidence, the research focused on high-intent leads that drives better conversion rates to opportunities and closed won deals.

To collect this data directly from prospects and add to the hybrid attribution model, a field was added in the conversion forms with the question "How did you hear about us?". This approach can be categorized as adding soft-data to the standard hard data provided by the marketing attribution tool. Hard data is a type of precise measurement, while soft data, which is typically abundant and much less expensive than hard well data, is described as a supplementary indirect measure that can be integrated to a model to increase confidence (Ahu & Journel, 1993).

This field was set as an open text field, allowing prospects to type the source they have in their memory. The use of a drop-down field could easily harmonize the data by offering a picklist of values, but it can bias the answers by the suggestion effect (Michael, Garry, & Kirsch 2012). Data treatment was done by using string matching automation, described by Hakak, Kamsin, Shivakumara, Gilkar, Khan, & Imran (2019) as a technique for solving problems of fields such as text mining, natural language processing, pattern recognition and more, so the data added to the open field without a scale or picklist values can be categorized and analyzed as quantitative data.

Once the company system was able to report both data provided by the marketing attribution system and the self-attributed inputs shared by customers in the new form field available, it was possible to build the hybrid marketing attribution model. This suggestion for marketing attribution reporting consists in adding to the reporting view the touch points captured automatically by the attribution system with the touch points mentioned by clients in the self-attribution field available in the conversion form. It allows marketing professionals to have an additional layer of information, comparing channels, finding similarities and discrepancies in data provided by both sources, identify relevant touch points along the buying path that weren't reported by the standard attribution system, and leverage it to take insights and conclusions about what is working in their channel mix strategies.

With the changes mentioned above applied and access to company's marketing attribution system data, the research collected data during 60 days, between May and June 2023, getting a total of 220 different buying paths so data could be analyzed with significant accuracy of results. To determine the sample size for this research, it was considered the total population of US companies with 100+ employees, as this number matches the ideal customer profile of the company used as a field for research in this study, and the maximum population that could be reached by the experiment. The American SBE Council (2019) and the United States Census Bureau (2019) show that there are 120,000 companies with over 100 employees. Considering a standard deviation of 0.055 and a confidence level of at least 90%, the ideal sample size is 220 cases.

Figure 4 – Data Collection Process

3.2. Experimental Group and Control Group

To run experimental research, it is necessary to have an experimental group that receives the treatment or experimental manipulation, and a control group that receives no treatment and is used for comparison (Check & Schutt, 2012). In this research, data was collected using the same research parameters to both groups: same region, time period, target audience and data collection instrument.

The experimental group is composed of 110 form completions in which the granular user-level data was captured by using the "How did you hear about us" field available in the high-intent forms. Also, the standard attribution system data was captured and analyzed.

The control group is composed of 110 form completions which the high-intent forms didn't have the user-level data captured, and only the standard attribution system data was tracked. This control group allows the researcher to compare data collected in both groups and evaluate the impact of the experiment in the group exposed to the variable.

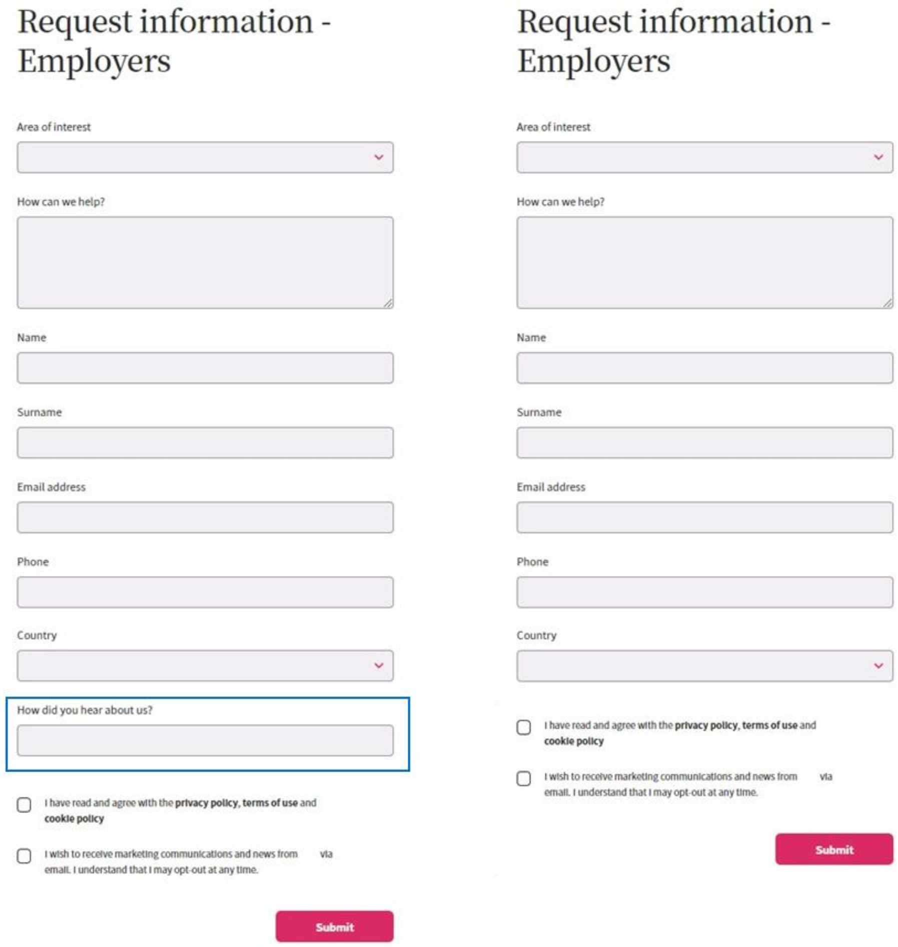

Figure 5 – High-Intent Conversion Forms: Experimental Group (left) and Control Group (right)

3.3. DATA ANALYSIS

After collecting data from the marketing attribution software with the touchpoints each purchase path had in experimental and control group, and the additional data inputs provided by users in the experimental group, the result was a combined dataset composed by the following variables: Form views, Date of conversion, Self-reported attribution value, multi-touch linear values, First-touch value, Last-touch value, touchpoint position, Date of Opportunity Creation, Number of Opportunities Created, Number of Closed Won opportunities, Date of Opportunity status change.

User-sourced data was treated and harmonized using string matching automation, this way the different text strings added by users to the open text field could be grouped in channel categories and analyzed as quantitative data. After that, the use of Power Pivot tables was applied to visualize quantitative credits attributed to different channels under the different data sources: software data and user-level data in the experimental group, and software data only in the control group.

The analysis focused on all records that converted in the high-intent forms and generated revenue for the company. It is particularly helpful to understand which channels reported by the attribution system and captured through the self-attributed field are helping to generate qualified leads and pipeline.

To analyze data, experimental and control groups have their datasets manipulated in the following way:

- In the experimental group, it was identified the percentage of credits that the attribution system assigned to channels. It was also collected the channels mentioned by users in the self-attributed field. These touchpoints collected from users were added to the purchase path reported by attribution tool, and the credits applied to these channels were scored in a linear way following the same logic used by the company's attribution model. This way, if a journey had 4 touch points identified by the attribution system and one touch point reported in the self-attributed field, each touch point received 20% of weight (20% x 5 = 100%). These data were plotted in bar charts to see the similarities and discrepancies in what was credited to channels by the software and user data, and later they were merged to represent the hybrid attribution model.
- In the control group, it was also identified the percentage of credits each channel received in a linear way from the attribution tool. This data was added to the same charts mentioned above, so experimental and control groups data could be compared.

Additional analysis was done to identify the relevance of invalid customer-provided answers to the overall experimental group sample. Any answers provided with null or irrelevant value was classified as non-Relevant and compared to the total number of touch points obtained in experimental group.

A last analysis was to determine if the additional field for capturing customer-provided data in the submission forms had a significant impact in the form conversion rates. For that, the average conversion rate of the forms was compared between the experimental and control group to find any significant difference.

4. EMPIRICAL STUDY

The sample obtained to analyze the results was composed of 220 purchase paths that were divided in 2 groups of equal size: experimental and control group. The data collected presented the following variables: Form views, Date of conversion, Self-reported attribution value, multi-touch linear values, touchpoint position, First-touch value, Last-touch value, Number of Opportunities Created, Number of Closed Won opportunities, Date of Opportunity status change. Results details can be checked in the coming sub-sections.

4.1. TOUCHPOINTS NOT CAPTURED BY ATTRIBUTION TOOL, BUT REPORTED BY USER-PROVIDED DATA

The suggested hybrid marketing attribution model has the intention to identify possible touchpoints along the purchase path that aren't captured by attribution softwares, and using granular user-level data, as suggested by Gaur and Bharti (2020), the experiment verified the differences obtained in a model that combines user-provided data and software-sourced data, compared to a control group that used an attribution model containing only the data captured by the attribution tool. The data obtained in the experimental group were segmented by what was captured by the attribution software only, and what was identified in the self-attributed report, in a way the channels captured and weights assigned to them could be compared.

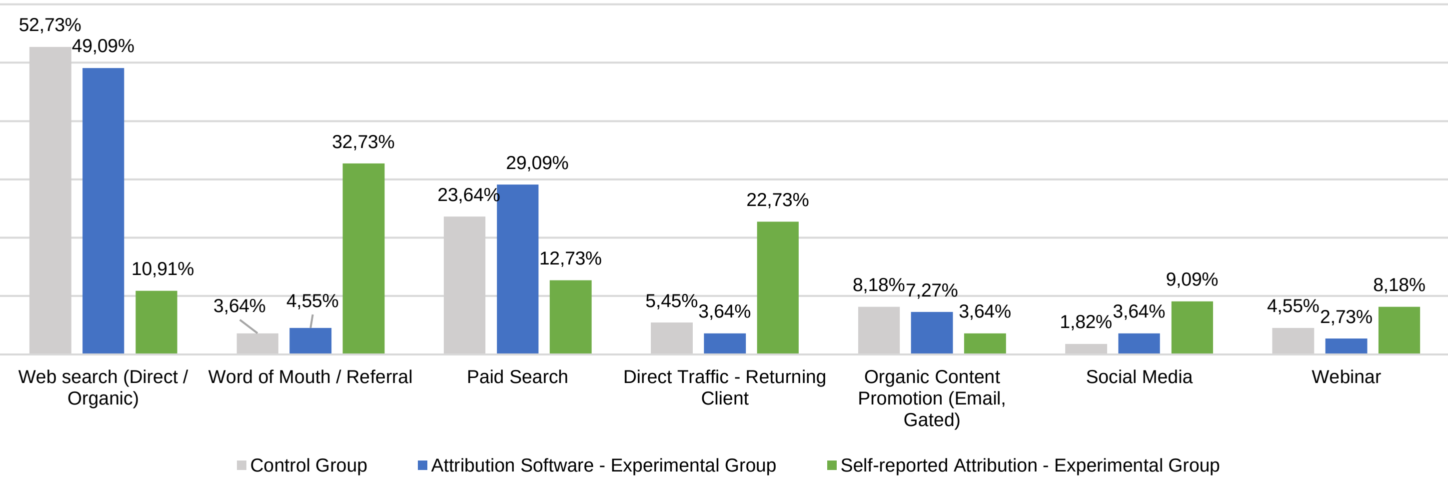

Figure 6 – Touch points and Credits Attributed by Data Source

When comparing data obtained in the control group and the experimental group focusing only on the software-provided touchpoints, there is a significant similarity across the different identified channels: high levels of credits attributed to web search (Direct / Organic) and Paid Search, allocating in average 5 times more weight in Web search and 2 times more credits in Paid Search than what was reported in the self-reported attribution; and low levels to channels such as Word of Mouth / Referral, Organic Content Promotion, Direct Traffic - Returning Client, Social Medias and Webinars.

It is clear that channels which attribution systems delivered the highest credits had lower weights when looking at the user-level sourced data. On the other hand, self-attributed data showed much more relevance in channels such as Word of Mouth / Referral, Direct traffic for returning clients and social media. In line with the first hypothesis, channels such as Word of Mouth / Referral, Direct traffic for Returning clients and social media received low levels of attribution credits by the attribution software, while they appeared consistently in the user-level sourced data.

According to Gartner (2020), 60% of the buying process is over before a buyer get in touch with the company they want to buy, and in this study, the attribution software presented challenges in reporting channels that customers interact without the need of a clear action that can be tracked: Word of mouth / referrals can happen in offline environment, in discussion forums, partner companies / influencers opinion and more; type-in Returning clients are a clear signal of customer loyalty, and self-reported data offers the ability to identify people that changed the company, but still returns to do business after joining a new organization; Social media interactions not necessarily demand an action from the customer, considering that posts can be seen and read without clicks or reactions.

These are channels that attribution software struggle to report as they can´t identify these touchpoints, but customer-provided data shows that these are effective channels that are worth to invest. Considering how marketing professionals use attribution reports to make decisions on channel budget allocation (Google, 2012), this finding represents a significant increase in data accuracy for informed decisions.

4.2. Differences in Credits Attribution – Experimental and Control Groups

After analyzing the data from different sources in an independent way, in the experimental group the user-level sourced data was combined with the marketing attribution sourced data in order to create the hybrid attribution model. For that, the touchpoints mentioned by customers were incorporated as additional touchpoints in the attribution tool purchase paths, and the credits assigned to channels were redistributed keeping the linear allocation model in place. This new combined model was compared with the same control group mentioned in the previous chart, so differences in channel allocation between both groups and attribution models could be visualized.

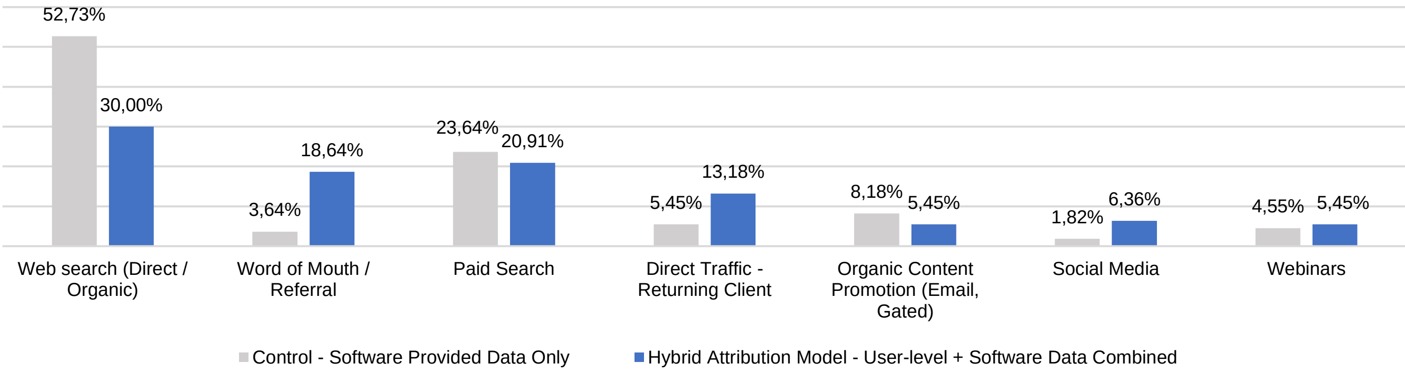

Figure 7 – Channel Attribution Performance: Hybrid Model versus Control Group

The hybrid attribution model used in the experimental group with combined data from software and users, showed a more balanced level of credits attributed to the identified channels along the purchase path. Web search channels demonstrated a reduction of 43% in credits attributed when compared with control group, 13% less in the paid search, and 33% less credits in organic content promotion. Channels such as Word of Mouth / Referrals, Direct traffic - Returning Clients and Social Medias presented a significant higher level of credits than what was presented in the control group. As the control group don´t have the ability of capturing granular user-level data, the attribution results for word of mouth / referral category and direct traffic for returning visitors were limited to the information captured by the tool, using cookie and UTM tracking data.

To validate if the results presented a statistically significant difference, it was applied a Student´s T Test for independent samples. A t-test for independent samples compares how significant are the means of two groups (Ross & Willson, 2017), and it was used to test two hypotheses: Null, to check if the means for the two samples are equal or very similar; and Alternative, to check if the means are not equal and significantly different.

In T test, if the p-value is less than the desired significance level, the null hypothesis is rejected. For this test, we used a significance level of 0,05 so a level of 95% confidence can be expected.

Attribution Channel	Mean-Experimental Group	Mean - Control Group	Standard Deviation - Experimental Group	Standard Deviation - Control Group	T Value	P Value	Hypothesis
Web search (Organic / Direct)	0,3000	0,5273	0,4606	0,5273	-3,5013	0,00056	Alternative - Significant difference
Word of Mouth / Referral	0,1818	0,0364	0,3875	0,1880	3,5421	0,00052	Alternative - Significant difference
Paid Search	0,2091	0,2364	0,4085	0,4268	-0,4842	0,6287	Null - No Significant difference
Direct Traffic - Returning Client	0,1364	0,0545	0,3447	0,2281	2,0758	0,03926	Alternative - Significant difference
Organic Content Promotion (Email, Gated)	0,0545	0,0818	0,2281	0,2753	-0,8	0,42464	Null - No Significant difference
Social Media	0,0636	0,0182	0,2452	0,1342	2,1789	0,03081	Alternative - Significant difference
Webinars	0,0545	0,0455	0,2281	0,2093	0,308	0,75837	Null - No Significant difference

Figure 8 – Student's T Test Applied to Experimental and Control Groups

The test showed that the results obtained between the two groups in the Web Search, Word of Mouth / Referral, Direct Traffic – Returning Client, and Social Media channels are significantly different considering the sample size and the possible variations in population. That means that the hybrid attribution model delivered in these channels statistically significant different results than what was reported by the standard attribution software in this experiment. The channels Paid Search, Organic Content Promotion and Webinars presented results in both groups that, in this sample, can´t be considered significantly different.

Considering the concerns related to reporting accuracy presented by Danaher and Heerde (2018) and Hongshuang and Kannan (2013), this analysis in the hybrid attribution model shows an approach that helps to increase reporting accuracy and reduce the risks of using misleading insights on how to allocate resources across media. If a budget allocation decision would be taken based only on the data offered by the marketing attribution system (control group), it could lead to decisions that would increase investments in Direct traffic and Paid channels, and reduce efforts in low performance channels, like Social media, communities and influence marketing. But with the user provided data available added to the attribution model (experimental group), a more balanced credit allocation result was obtained, it is possible to see the relevance these channels had to the conversion result, and budget allocation decisions can be improved.

4.3. Characteristics of User-level Sourced Data vs. Software-provided Data

To determine if attribution tools assign more credits to channels commonly used in tactics to capture and convert demand in late stages of the journey, while user-level sourced data assign more credits to channels used in strategies that generate demand in earlier stages of the purchase path, we distributed the channels in sequence considering the position they appeared the most in the purchase paths analyzed in this study.

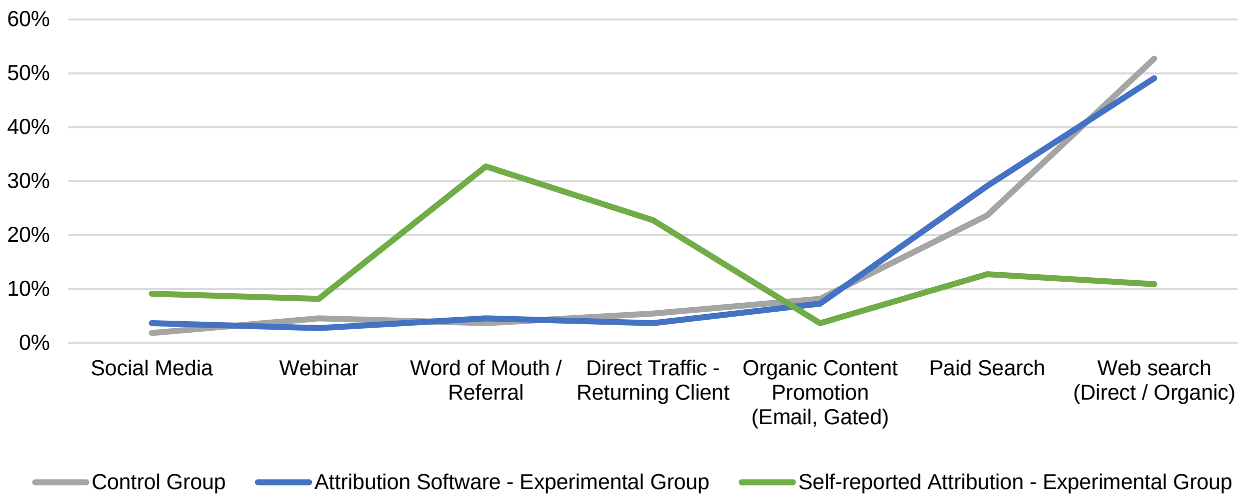

Figure 9 – Channel Attribution in Purchase Path: Demand Generation and Conversion Stages

In the left-hand side, it is possible to see the channels that appeared the most in the early stages of the purchase path according to the marketing attribution tool. In these channels, the user-level sourced data demonstrated higher levels of credits attributed than what was identified by the attribution software. In organic content promotion channels, widely used by the studied company to promote conversion call-to-actions, there is an inversion in the trending lines, and from that point the credits assigned by attribution tools have much more weight than what was self-reported by prospects.

Along the theoretical discussion regarding attribution channels, exists the understanding that different channels can lead buyers in the purchase path to different actions. Hongshuang and Kannan (2013) and Bhatta (2022) demonstrated how purchase paths initiated by the users have higher conversions and credits attributed than other touchpoints initiated by the company. As explained by Hidalgo (2015), there are channels that help companies to generate demand by educating the audience about specific needs, and there are channels particularly helpful to convert the created demand when prospects are ready to engage with the company. Both strategies are important in a Sales-Marketing Interface B2B environment (Hobbs, 2015; Sabnis et al, 2013).

Aligned with Bhatta (2022) and Anderl et al (2015), the study results showed that both experimental and control groups have more credits assigned by the attribution system to Web Search and Direct Traffic channels, which are well known for capturing or converting demand.

When looking at user provided data, it is possible to see that the channels reported by customers are especially useful for content consumption and awareness. They are the main touchpoints that come to the mind of users when submitting the conversion form, demonstrating the strong memory impact of these activities that happened in early moments in the purchase path, contributing to generating demand for the conversion channels. The results are in line to the second hypothesis, the different data sources used in the hybrid model are useful to help marketing professionals to understand which tactics or channels are generating more awareness and memory in the audience, contributing to demand generation strategy improvement, and which channels are used by prospects to get in touch with the company when they are ready to buy.

4.4. Proportion of Non-relevant Inputs to the Full Sample

Attribution model accuracy is key to help marketing teams to understand the performance of their marketing activities and identify opportunities for adjustment in the channel mix used in their strategies. It is known that B2B marketing professionals use attribution reports to track channel effectiveness and allocate budgets (Econsultancy & Google, 2012), and understanding in the hybrid attribution model what is the impact of the irrelevant inputs provided by users, is an important step to analyze if user-level provided data is a trustful asset.

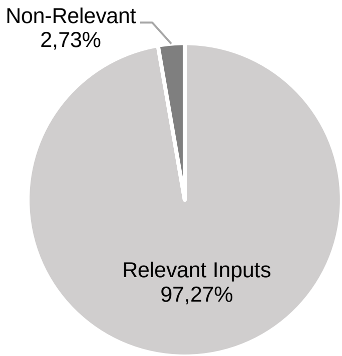

Figure 10 – Non-relevant Inputs in the Self-attributed Report vs. Full Experimental Sample

Non-relevant submissions added to the self-attributed report represent less than 3% of the full experimental group sample, not representing a significant statistical volume to influence the level of accuracy of the proposed hybrid model (<5%). Certainly, it is a metric that must be tracked to analyze differences over time to ensure accuracy in the attribution reports, but in this experiment it didn´t represent a risk to the sample.

4.5. Submission Form Conversion Rates

The experimental group had a variable added to the forms used to convert leads and evolve to a sales opportunity. As the number of fields in a conversion form can influence the conversion rate performance (Jarrett & Gaffney, 2009), it was compared the form completion rate between the experimental and control group to identify any significant changes.

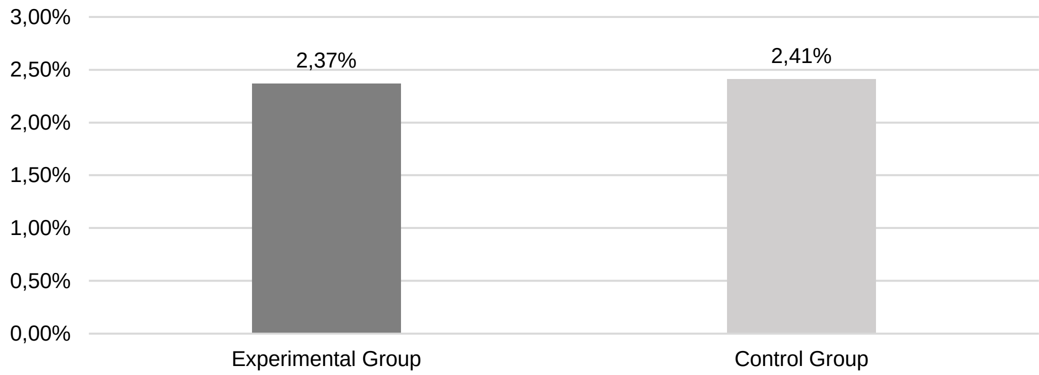

Figure 11 – Form Conversion Rate – Experimental Group vs. Control Group

Experimental group demonstrated a form conversion rate performance 0,03% lower than the control group, a variation that doesn´t represent a significant impact as result of the manipulation applied to the conversion form in the experimental group.

5. RESULTS AND DISCUSSION

5.1. Key Results Summary

This research was able to create data cuts in the experimental and control groups to identify how each data source contributed to the aggregated hybrid attribution model. It showed how software data allocated in both groups high levels of credits to channels such as Web Search (Direct / Organic) and Paid Search, while allocated few credits to channels such as Word of Mouth / Referral, Organic Content Promotion, Social Media and Webinars. There are channels that software allocated 5 times more credits than was reported by the user provided data.

On the other hand, user level sourced data demonstrated higher credit attribution in channels categorized by softwares as low relevance to the conversion result: Word of Mouth / Referral, Direct traffic for Returning Clients and Social medias. These touchpoints had low levels of credits added by the attribution system in both experiment and control groups.

The hybrid attribution model used in the experimental group showed a more balanced level of credits attributed to the identified channels along the purchase path. Web search channels demonstrated a reduction of 43% in credits attributed when compared with control group, 13% less in the paid search, and 33% less credits in organic content promotion. Channels such as Word of Mouth / Referrals, Direct traffic - Returning Clients and Social Medias presented a significant higher level of credits than what was presented in the control group. As the control group don´t have the ability of capturing granular user-level data, the attribution results in word of mouth / referral category and direct traffic - returning visitors were limited to the information captured by the tool, using cookie and UTM tracking data.

When data from both sources were combined to create the hybrid attribution model, it demonstrated a much more balanced credit allocation in the identified channels, and comparing to control group, some channels had a significant reduction in the relevance to conversion: Web search with 43% lower credit allocation, Paid Search with 13% lower credit allocation, and organic content promotion performed 33% below the control group. As contrast, channels as Word of Mouth / Referrals, Direct Traffic - Returning client and Social medias demonstrated higher level of credits in the experimental group that used the hybrid model: Social medias had 3,5 times more credits than control group, Word of Mouth had 5 times more credits, direct type-in for Returning clients presented almost 2,5 times more credits than control group. It is important to remember that the control group were able to capture this data by using cookie and UTM tracking data, but the ability of the tool to track these touchpoints is limited considering that in several situations these interactions happen without a trackable activity associated.

When applying a Student´s T Test to validate how significantly different or similar the averages obtained by the experimental and control groups were, a significant difference was confirmed in the following channels: Web search, Word of Mouth / Referral, Direct Traffic – Returning client, and social media. Paid search, Organic content promotion and webinars presented similar attribution results in both groups that aren´t considered statistically different.

Channels that had higher credit allocation in the user level sourced data are commonly used in touch points initiated by the company to create awareness and demand, or that are the result of word of mouth and customer loyalty. On the other side, channels with more relevance in the software-only sourced data are touchpoints commonly initiated by customers to get in touch with the company, showing how software tends to allocate credits to channels responsible for generating lead conversions. These different data sources used together in the hybrid model bring insights about how different strategies play complementary roles to generate demand and to capture conversions in a B2B environment.

When capturing user level provided inputs, it was identified that 2,73% of submissions were categorized as null or non-relevant, and these inputs couldn't be used in the hybrid model. It didn´t represent a significant statistical volume in this study to influence the level of accuracy in the hybrid model. Additionally, it tracked the form conversions rates in both groups to identify any negative influence of the form manipulation that was necessary to implement the hybrid model. The conversion rate difference was lower than 0,05%, not representing a significant impact to the conversion rate for the experimental sample.

The results above confirm the following hypotheses of this study: 1.) Adding granular user-level data from prospects to the standard attribution data helps attribution tools to visualize hidden touchpoints not captured by them; 2a.) The data provided by customers in the moment they convert in high-intent forms can be used to identify the channels where the demand was generated; 2b) Marketing attribution system data is useful to identify the channels where the demand is converted to qualified leads.

5.2. THEORETICAL CONTRIBUTION AND PRACTICAL IMPLICATIONS

5.2.1. Granular User level Data Increases the Accuracy of Marketing Attribution Reports

Based on the results of the study, the use of attribution system data combined with soft-data provided by prospects can increase the accuracy of marketing attribution reports in B2B environments. Channels identified through the process of capturing customer provided data can be added to the purchase path to deliver a better understanding of the buying journey, and the weights of credits attributed to each channel or tactic can be calibrated to better indicate the contribution each touchpoint had to the conversion result.

Focusing the study on the research gap identified and mentioned by Gaur and Bharti (2020) in the comprehensive literature review that was developed, the implementation of a marketing attribution model that uses granular user-level data in a B2B company showed significant improvements in the final attribution report. Leguina et al (2020) and Méndez-Suárez and Monfort (2021) studies tested models and different channel interactions effects in the purchase path with the purpose to build more efficient attribution models and more accurate calculations. This experimental research used the standards defined by those studies and added a layer of soft-data collected from users together to the multi-touch model to uncover any possible hidden touchpoints and recalibrate credits considering customers' inputs regarding what made them become a conversion. The hybrid model created as a result of collecting data from both sources was able to identify channels not reported by attribution tool and added them to the user path, and the credits allocated in the channels could be adjusted based on the inputs provided by prospects in the moment they get in touch with the company.

5.2.2. Better Understanding of Users' Paths Results in Better Channel Budget Allocation

Channel budget allocation decisions can be taken with more confidence. With a marketing attribution model that delivers a more comprehensive understanding of the purchase path, including possible hidden touchpoints that drive demand and revenue, marketing professionals can make more informed decisions and adjust their investments based on the most effective channels to different marketing strategies.

Some recent studies in the marketing attribution discussion field, including Bhatta (2022), Anderl et al (2015) and Hongshuang and Kannan (2013), mentioned how attribution systems can bias the report results and allocate more weight to some specific channels, such as direct traffic, paid and organic search. In this experimental research, we could see similar data obtained from the used software attribution, both in the experimental and control groups: over 80% of all credits were attributed to these channels. Trusting purely in this data could lead marketing leaders to take decisions aligned to what the attribution tool reported.

Danaher and Heerde (2018) stated that marketing attribution reports shouldn't be used for budget allocation, considering that attribution is a descriptive summary of how much of a relative contribution each medium has made to a purchase, and marketing leaders should use this metric with caution. The reality is that the majority of marketing professionals see as a top benefit of marketing attribution reports is to be better able to allocate budget across channels (Google, 2012), and this study experiment shows an approach that helps to increase reporting accuracy and reduce the risks of using misleading insights when allocating resources across channels.

In this experiment, if a budget allocation decision would be taken based only on the data offered by the marketing attribution system, it could lead to decisions that would increase investments in Direct traffic and Paid channels, and reduce efforts in channels such as Social media, communities and influence marketing. But with the user provided data available added to the attribution model, a much more balanced and informed analysis can be done, answering the research question that a hybrid attribution model that combines software and user level sourced data can help marketing professionals to take decisions with more confidence about which channels are relevant across the purchase path.

5.2.3. Ability to Identify Most Effective Channels to Demand and Conversion Strategies

Hybrid attribution model can be used to identify the most effective channels for demand generation and demand conversion strategies. Both sources play complementary roles: while the customer-provided data focus on the marketing activities and channels that made prospects take the decision to search the company and ask to talk to sales, the software-based data suggests which are the channels that are effective to capture these customers once prospects feel ready to have a sales conversation.

Considering what was stated by Bhatta (2022) and Anderl et al (2015), in purchase paths where the interaction is initiated by the customer, the contribution of channels such as paid search, organic search and direct type-ins is consistently overestimated by marketing attribution tools. It happens as these are the channels commonly used by prospects to find the company when they are ready to buy, and not necessarily the channels that are responsible for the conversion result. Hidalgo (2015) explains how demand generation and conversion strategies use different mixes of channels to reach the audience, creating awareness and understanding about solutions in earlier moments in the purchase path, until the final touch points to transform prospects in conversions once they are ready to do business with the company. These two strategies are important in a Sales-Marketing B2B environment (Hobbs, 2015; Sabnis et al, 2013).

The results of this study showed how attribution software prioritized credits to channels used to capture conversions: Organic Search, Paid Search and Direct Traffic channels. On the other side, analyzing user provided data, it was possible to see that the channels reported by customers are mainly used for content consumption and awareness, aligned with demand generation strategies. This information has managerial implications and can be used by marketing professionals to get insights on their different strategies and adapt channels to better generate or convert demand to companies' products.

The framework available in the figure below represents how marketing professionals can adopt the hybrid attribution model and use the data obtained from both sources to increase visibility in the touchpoints that influence the most in different moments of the purchase path. On the left-hand side are the channels and tactics that can be classified as highly effective in early stages of the journey, when demand is being created. This data obtained directly from prospects that lived the purchase path can bring additional understanding about the touch points that helped customers to create awareness about the company and the challenges its solutions can solve, and as a consequence led them to request a sales contact once they evolved to a conversion stage. On the right-hand side of the image are the conversion channels which marketing attribution tools are really effective to track, channels that are widely used by B2B companies in tactics to capture conversions and feed the sales pipeline. The combination of both data can bring significant insights to marketing professionals about channel strategy and budget allocation.

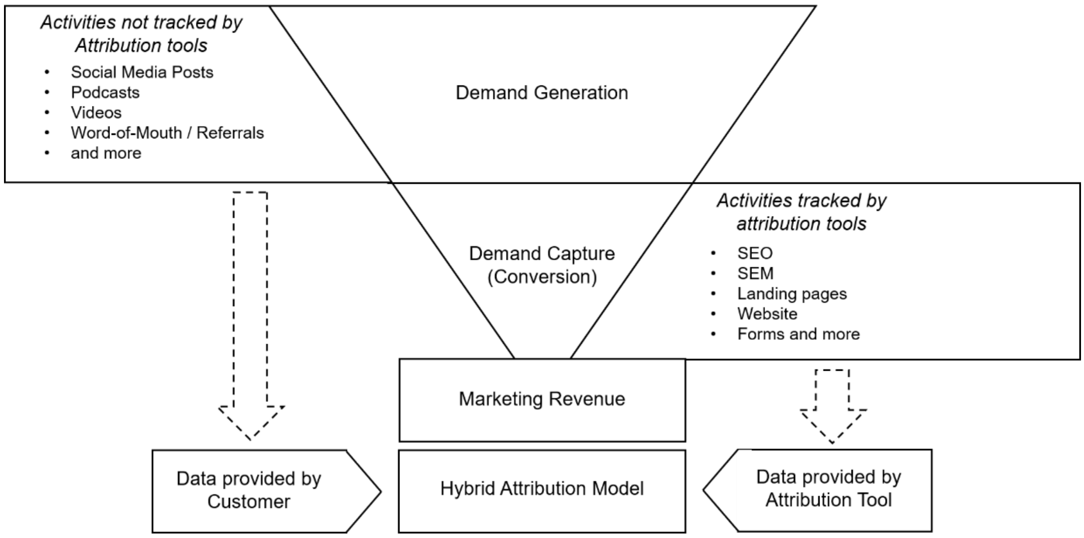

Figure 12 - Suggestion of Model for Hybrid Attribution Reporting

5.2.4. No Influence of Hybrid Attribution Model in Form Conversion Performance

The suggested hybrid attribution model doesn´t significantly influence the conversion rates of high-intent conversion forms used by B2B companies with high levels of sales and customer interaction in the sales process.

To implement the hybrid attribution model, an additional field was included to the high-intent forms to collect user-level data, and to confirm or discard that this new field had significant impact in form conversion rates (Jarrett & Gaffney, 2009), it was compared the form completion rate between the experimental and control group to identify any significant changes. Experimental group had a performance very similar to what was presented by the control group, indicating that it is possible to capture soft-data from prospects without significantly impacting the form conversion performance.

6. CONCLUSIONS AND FUTURE WORKS

This study was developed to answer the following research question: ‘How can B2B companies approach marketing attribution reporting by using software and customer provided data to identify the most effective channels?’. The initial assumption was that marketing attribution softwares aren´t able to capture touch points in the purchase path that are relevant to the final conversion result and it could lead marketing professionals that work in B2B organizations to make misleading decisions related to channel budget allocation.

The hypothesis was that adding granular user-level data by asking prospects to share how they heard about the company in the moment they convert in a high-intent form, would help attribution reports to visualize possible hidden touchpoints not captured by the attribution system. Additionally, the data provided by customers potentially could be used to identify the channels where the demand was generated, while marketing attribution system data could be especially useful to identify the channels where the demand is captured and converted to a qualified lead.

The experimental research applied in a B2B company showed that the use of granular user-level data increases the accuracy of marketing attribution reports, as channels not tracked by attribution tools can be identified in the user sourced data and be added to the customers’ purchase paths to deliver a better understanding of the buying journey. Additionally, the weights of credits attributed to each channel could be calibrated to better indicate the contribution each touchpoint had to the conversion result.

This better understanding of the purchase path results in more confidence to marketing professionals when taking decisions related to channel budget allocation. With a marketing attribution model that delivers a more comprehensive understanding of the purchase path, including possible hidden touchpoints that drive demand and revenue, companies can make more informed decisions and adjust investments based on the most effective channels to different marketing strategies.

Furthermore, the marketing attribution hybrid model applied in this study allowed us to identify the most effective channels for demand generation and demand conversion strategies, by using user-level and software data in a complementary way. While the customer-provided data results showed the marketing activities and channels that made prospects take the decision to search the company and ask to talk to sales, the software-based data suggested which are the channels that are the most effective to capture these customers once they feel ready to have a sales conversation. Marketing professionals can leverage this data to improve their channel mix by aligning them with the best strategies for each moment of the purchase path.

As this model didn´t have a significant impact in the conversion rates of the forms used by the studied company, the study also showed that capturing soft-data from prospects to enrich the purchase path isn’t a risk to form conversion rates.

This research was limited in proposing an attribution model that adds a layer of granular user-level data to the information captured by an attribution system used by a B2B company, which has a sales model that demands sellers and customers to interact to close deals. The research also was limited in applying the experiment using a multi-touch attribution system that assigns credits in a linear way across the touchpoints, other attribution models and frameworks weren´t applied. Future studies in this discussion field can apply the proposed hybrid attribution model in environments that uses other attribution tools, models and algorithm frameworks. They also can explore applying the suggested hybrid model in companies from other industries and business models, so new point of views and insights can be generated. This research worked with a sample that delivered a confidence level of 90% under the United States market, and future studies that focus on increasing the confidence to higher levels and other regions can generate additional perspectives to the discussion topic.

The combined use of software data with granular user-level sourced data can bring additional accuracy to marketing attribution reports, and relevant insights to marketing teams about their overall marketing strategy along the customers' purchase path. It can be particularly helpful to marketing professionals when taking investment decisions and allocating budget to different channels across the buying journey.

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8. APPENDIX

8.1. NOVA IMS ETHICS COMMITTEE - PROJECT APPROVAL:

NOVA IMS Information Management School

This is to certify that
Project No.: **DDMKT2023-4-208108**
Project Title: **Marketing Attribution in B2B Companies: Associating software and customer data to increase confidence in data-driven optimization decisions**
Principal Researcher: **Rafael de Oliveira Santana**

according to the regulations of the Ethics Committee of NOVA IMS and MagIC Research Center this project was considered to meet the requirements of the NOVA IMS Internal Review Board, being considered **APPROVED** on 4/24/2023.

It is the Principal Researcher's responsibility to ensure that all researchers and stakeholders associated with this project are aware of the conditions of approval and which documents have been approved.

The Principal Researcher is required to notify the Ethics Committee, via amendment or progress report, of
- Any significant change to the project and the reason for that change;
- Any unforeseen events or unexpected developments that merit notification;
- The inability of the Principal Researcher to continue in that role or any other change in research personnel involved in the project.

Lisbon, 4/24/2023

NOVA IMS Ethics Committee
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