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Descriptive study of touchpoints determining the conversion of online consumers in a financial services context

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Abstract

Online advertising media is undeniably powerful. Though costly, it brings an unprecedented amount of awareness and yields great conversion rates that can be accurately tracked. This study revolves around the customer journey and tries to understand the steps customers undertake to complete a purchase. From every single touchpoint that leaves digital fingerprints on each different channel, to how they all interact and potentiate each other. Furthermore, what impacts the conversion itself, and what techniques can be utilized to our advantage, from retargeting to ad personalization and creative customization? Moreover, in the context of the particular financial institution studied, which attribution method would be the best fit when analyzing the whole picture? Results showed that the J-shape attribution was the technique most in line with their present objectives and is considered more accurate than their current method. In addition, specific formats to utilize display advertising efficiently and optimize conversion rates were discovered. Analysis and research showed repetitively that video display yielded greater results when compared to traditional banner advertising since they are more intrusive. Moreover, during this thesis, results showed that the channel that gave the highest conversion rates by far was affiliate marketing. It was thus recommended to the client to explore different affiliate techniques such as influencer marketing to exploit this powerful advertising method further. Additionally, efficient and simple implementations to maximize email conversions at a low cost were discovered, such as introducing promotions directly at the bottom of important recurrent emails already sent monthly by the institution to their clients. This approach will assure that the email will be opened and that it won't be perceived as spam by the consumer. Finally, the death of the cookie era was explained and recommendations on how to prepare for those new changes were made, including implementing APIs and utilizing Google's FloC as soon as possible. This thesis will touch on all the points mentioned prior and will give specific recommendations to the client on which processes and changes they can implement in their businesses to facilitate and maximize the conversion of credit cards.

Keywords: Customer journey, Touchpoint, Channel, Attribution methods, Retargeting, Personalization, Cookies, Omni-Channel, Banner-blindness, Conversion rates.

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List of abbreviations

- CR: conversion rate
- STDC: see-think-do-care
- AIDA: awareness-interest-desire-action
- KPIs: Key Performance Indicators
- NS: Natural Search
- PS: Paid Search
- Af: Affiliate
- OS: Other Sources
- Ds: Display
- Dr: Direct
- Em: Email
- PSo: Paid Social
- SEO: Search Engine Optimization
- SEM: Search Engine Marketing
- API: Application Programming Interface
- FLoC: Federated Learning of Cohorts
- PPIDs: Publisher Provided Identifiers
- LT or LC: Last Touch or Last Click
- FT or FC: First Touch or First Click
- AI: Artificial Intelligence
- CPM: Cost Per Thousand
- CTA: Call To Action
- CIC: Customer-Initiated-Channels
- FIC: Firm-Initiated-Channels
- WOM: Word Of Mouth
- NMC: Non-Multi-Channel
- GIGO: garbage in, garbage out

Foreword

This dissertation is part of obtaining the degree of Master of Science in Management. It revolves around online conversions and took 16 months to complete. With a BAA in Finance and a burning passion for the world of E-commerce, the combination of both in this project was a no-brainer. Additionally having an E-commerce background since the young age of 16, this project is a major stepping stone toward my goal of becoming a well-informed and educated E-commerce entrepreneur.

My drive for this study was to have the chance to poke around in massive datasets and explore what influences conversion. Digging around and discovering which results are possible to achieve when finding the strengths and weaknesses of each marketing channel, touchpoints, and advertising technique and exploiting them is an incredible opportunity.

Multiple hurdles were encountered in the making of this project. Data collection was an issue within itself. It required learning the multiple different platforms utilized by the client needed to aggregate the data for analysis, this step took months. Furthermore, the murkiness of those data lakes was cloudier than what was expected, finding the required data among millions of lines was a monk's work.

The subject of advertising, attribution as well as retargeting, and personalization is constantly evolving with rapid and drastic changes in the space. Researchers have studied and speculated about the best techniques and attribution methods for distribution merits efficiently and accurately towards each touchpoint of a customer journey. This project is no different, with its objective of understanding the most optimal ways of distributing the advertising budget of this financial institution in efficient channels with specific techniques to maximize their conversion rates.

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Chapter 1: Introduction

"Half of my advertising spend is wasted; the trouble is, I don't know which half." (Blake et al., 2015, p. 1). This quote from John Wanamaker is what sparked this research. It is a problem that all businesses face daily. Where are my investments well spent and where are they lacking? Where should I invest my resources to maximize my gains when it comes to advertising? This is not an easy question since so many variables need to be considered to have a chance of answering it correctly.

In this situation, there are two possible paths to try and give an approximate answer, the online world, and the offline world. This thesis plans to focus on the online world since there is an abundance of data points and entries to observe compared to the real world where way fewer things are being accurately tracked. When it comes to E-commerce, quality datasets are crucial; the more data you collect, and the more clearly it is organized, the higher the odds are of making educated decisions when it comes to having great returns on your investments. Currently, in the literature, there is a gap concerning optimal sequence orders of touchpoints in customer journeys as well as which specific advertising channel can obtain the highest conversion rates. This thesis had the opportunity to access a massive dataset coming from one of the country's most renowned financial institutions to try and fill that gap.

1.1. Context

In this section, many subjects will be briefly touched on prior to diving in deeper in later chapters.

The first step is to start by observing the customer journey, which entails tracking the entire path that customers follow from the moment they first interact with the product or brand, right until the end (Lee, 2010). The customer journey is composed of both channels and touchpoints, this in itself can be challenging to track accurately since the journey is not always linear but is more often than not, omnichannel. Omnichannel means having a multitude of different touchpoints through many different channels (some of them can even be offline, which makes it even harder to keep track) (Cortiñas, 2019). Thus to be able to track it accurately, you need to aggregate multiple different sources of data from different channels and then create a clear path to be able to analyze it efficiently (Cortiñas, 2019).

To achieve this, advertising techniques, also known as channels, need to be sorted out accordingly. These channels range from paid search, organic search, paid social, affiliate marketing, email marketing, direct, and even offline channels. Once sorted, channels need to be dissected in order to reflect the different touchpoints that were involved in the conversion. Touchpoints are the interactions the customers make during their purchasing process; they can be either online or offline. Identifying them is the easy part, the challenge is to then attribute them their individual impact on the whole conversion process. This means that once a clear journey is mapped out, each touchpoint and channel will need to be analyzed in order to try and decipher their individual influences on the conversion itself. Although challenging, this can be achieved by comparing the conversion rates of each channel and touchpoints involved in the journey and then comparing them to a plethora of different journeys. But this raises questions such as; does the impact of certain channels/touchpoints have more value at the beginning of the conversion funnel or toward the end? Knowing this will greatly influence how investments are conducted for online marketing by businesses.

Additionally, the way marketers will decide to observe and analyze the data they have collected and sorted will also impact the end results. Using either a single-touch model, multi-touch model, or even custom attribution models (that can include artificial intelligence), will give varying results. This indicates that different attribution methods will impact your final outcome, even if it is based on the same data entries. There is still no clear winner when it comes to attribution methods, and although some are considered better than others, the realistic answer is that every business needs to find the attribution method that fits best to their needs (Leguina, 2020). Marketers will need to test and compare different methods, and in certain cases might even need to create a custom one. In this thesis, multiple types of attribution methods will be juxtaposed with the objective of recommending the attribution technique that best fits the needs of this financial institution.

The subjects mentioned prior all have varying degrees of influence on the final conversion itself. But, external factors also need to be considered, for example, the incoming changes in the data collection process, such as the death of the cookies, will greatly impact how data will be obtained in the near future. This attests that new measures must be put in place by businesses to prepare for this drastic change. Additionally, subtle things such as the speed of the servers, the quality of the website, and the frequency of advertising, can't be ignored and need to be accounted for. All the subjects mentioned in this section will be discussed in deeper detail in the following sections of this thesis.

1.2. Study objectives

In this research, a stack channel dataset with more than half a million data entries will be aggregated and analyzed. Each touchpoint will be categorized and observed to figure out which ones have the more significant impact on conversion. Additionally, different combinations of certain touchpoints will be compared to find if there are specific combination orders that yield more meaningful results. Is there a specific order within the customer journey that converts better than others? Which individual channels will bring higher conversion rates at different moments in the journey and why? This researches goal is to find which investments are the most efficient and which ones are barely worth investing in, in the context of this particular financial institution. To reach this goal, subjects such as; different advertising methods, website quality, consumer psychology, personalization, innovative attribution techniques, and many others will be touched on to have a general idea of all the potential factors that can affect the outcomes. In short, the objective of the study will be to try and shine a light on which individual channels/touchpoints (or combinations) yield greater results for online conversion.

1.3. Research question

To what extent touchpoints or combinations of touchpoints are related to online conversion when it comes to acquiring new clients for financial products?

Chapter 2: Literature review

In ascending order, the themes go as follows; “The customer journey (pre-purchase to post-purchase)”, “Modeling customer journey” and “Modeling online customer journey”. The themes mentioned previously all equally contribute to the understanding of which factors impact online conversions.

2.1. The customer journey (pre-purchase to post-purchase)

“Marketing’s primary objective is to reach consumers at the moments, or touchpoints, that influence their purchasing behavior” and to pinpoint that moment, the whole process needs to be understood (Saravanakumar & SuganthaLakshmi, 2012, p. 4445). The customer journey consists of tracking all the customer’s interactions, from the first time they hear about the product/brand, right until the conversion (Lee, 2010). Each individual goes through different types of journeys before the conversion occurs and to understand them, those paths need to be categorized as either a single-channel journey or an omnichannel journey (Cordeiro, 2018). Then the journeys themselves are composed of both channels and touchpoints. Channels can be offline or online and refer to which advertising method was utilized. These advertising methods range from organic search, direct search, paid search, social marketing, affiliate marketing, and emails. Within those channels, there are individual interactions that the customer made (for example clicking on an ad) called touchpoints, they occur in a step-by-step fashion and are like digital fingerprints (Matoulek, 2018).

Touchpoints as well can be either offline or online and are called external or internal touchpoints respectively. To ensure organizations select cost-effective channels and utilize mechanisms and techniques that truly affect the choice of customers, the complex customer journey needs to be analyzed as a whole (Ford, 2018). Furthermore, to understand what happens to journeys composed of touchpoints occurring in the same channel or touchpoints happening in different channels, effects like the crossover and spillover will be explained and taken into account. Additionally, other variables affect conversions such as website quality, the repetition effect, and others. Thus to gain a comprehensive understanding of the customer journey, every subject mentioned prior will be explained in order in the following section.

2.1.1. Single channel journey

"As the name suggests, with single-channel customer engagement, brands message and interact with their customers via only a single unique channel, such as email or SMS, not both" (Kearl, 2021, para. 2). Single channel journeys may entail considering the last interaction before conversion, the last non-direct link clicked, the last AdWord clicked, or even the first interaction in a conversion. In this case conversion of customers occurs in a single touchpoint (Harris, 2018). Firms usually use measurements such as customer feedback to determine single channel journeys, even though such measures do not capture the entire customer experience or journey (Lemon & Verhoef, 2016). These measurements entail considering specific aspects of the customer journey such as perceptions of customers at specific times for a single purchase. Nevertheless, Priest (2017) argues that single channel customer journeys fail to capture the overall customer experience that leads to conversion since each touchpoint across the journey matters. Besides, considering a single channel impedes organizations from isolating impactful marketing activities from ineffective ones to ensure proper resource allocation (Priest, 2017).

2.1.2. Omnichannel journey

Since the customer journey involves consumers interacting with organizations through various channels, firms must consider omnichannel marketing to enhance the effectiveness of advertisements in reaching potential consumers (Anderl et al., 2015). Cortiñas et al. (2019) emphasize that customer journeys are increasingly displaying omnichannel behavior by using multiple distribution channels to finalize their purchases. Besides, customers can use all distribution services within the available channels or partially use the distribution services of a single channel to buy products (Cortiñas et al., 2019). Thus, omnichannel customer journeys entail considering all the channels the consumer interacts with before the conversion. This includes highlighting the role of the first and final interaction in the conversion, as well as determining the impact of interactions in between using data modeling (Forrester Consulting, 2012). Lemon and Verhoef (2016) argue that consumers have multiple interactions in different channels to form complex journeys, which requires firms to consider omnichannel management (Priest, 2017). Ji et al. (2016) highlight the importance of utilizing various advertising channels for online conversions.

Since consumers use more than a single channel to find information online before buying a product Dhar and Weinberg (2016) emphasize that firms should consider omnichannel marketing techniques to enhance the interaction, spillover, and carry-over effects (which will be explained later). These effects will be described later, but in short, they occur when customers visit a website again after the initial visit by using either the same channel or a different one.

Nevertheless, omnichannel marketing should occur cohesively to achieve organizational goals in which each channel should play a specific role (Shao & Li, 2011). Therefore, while it is challenging to control and manage omnichannel customer journeys, firms should create and deliver positive customer experiences across omnichannel journeys by integrating different business functions (Lemon & Verhoef, 2016). But regardless of the selected marketing channel, budget allocation relies on the effectiveness of the channel (Gaur & Bharti, 2020).

Furthermore, within the omnichannel journey itself, touchpoints can be divided into two categories, either external or internal. External touchpoints happen in the offline world, like someone going to your store, and internal ones are considered interactions in a process online (Transformation, 2019). In short, these categories are synonyms with offline touchpoints and online touchpoints.

To explore the role of each touchpoint, marketers can consider utilizing predictive probabilistic approaches to model customer journeys. Techniques such as

Game theory and the Markov model are complex but valid options. The game theory consists of using the Shapley value (which is found by implementing an overwhelming number of operations in a system) to examine the contribution of each touchpoint to the final purchase (Priest, 2017). Compared to the Markov model which is a system based on mathematical probabilities that helps stakeholders understand the shift from path to path throughout the customer journey (Matoulek, 2018). This model considers that subsequent events in the journey rely directly on preceding ones (Balzter, 2000). These models can predict the potential for conversion using historical data about purchases and website visits but are hindered by the inability of stakeholders to quantify the predictive power of those techniques (Moe & Fader, 2000).

2.1.2.1. Offline channels

Over the last decade, we've seen a large movement from offline channels to online ones, and in 2017, online advertising revenue overtook TV advertising for the first time (Abhishek et al., 2017). Regardless, offline touchpoints are still essential but are a bit more tricky, since they don't leave traces as online touchpoints do with their cookie trail. If you want to track them, you have to do it the hard way. But even though they might be harder to track and account for, they are necessary for the understanding of the consumer journey as a whole. If you only take into account online touchpoints, then you only have half the story since customer journeys are progressively nonlinear (Murphy, 2017). The customer could in fact do the whole conversion process online, but he could also ask a friend for advice, directly call the store for information, see an ad on TV, or hear information on the radio (Murphy, 2017). In those cases, when traditional media drives consumers to online stores,

> marketers can look for an increase in direct website track and correlate this with the timing of an online campaign. It's not a perfect science, but the data suggests that companies are getting better at it (Murphy, 2017, p.27).

Even though offline touchpoints are harder to track, they can't be overlooked and marketers should find out ways to effectively track those interactions and connect them to their libraries of data to take them into consideration. For example, if a customer calls your business, an online ticket could be created with his information and linked to the library of data for later analysis. The ROPO effect, meaning research online, and purchases offline is frequent and thus lots of data points could be missing in the journey.

> The interactions with the offline environment influence the online behavior and vice versa. In terms of offline data, online campaigns can invoke conversions offline and they should be tracked precisely by conversion paths (Matoulek, 2018, p. 20).

The general issue with attribution is the quality and completeness of your data itself. By taking into account offline touchpoints, you are taking a step in the direction of a more clear and more complete customer journey.

2.1.2.2. Online channels

When it comes to online advertising, multiple different channels offer each different strengths and weaknesses. To observe and confirm those advantages and disadvantages, data collection needs to be done efficiently. Yet a business can gather all the data they want, but without key performance indicators, it will remain numbers on a sheet. Thus to uncover results from the data collected, the right KPIs need to be put in place (Bond, 2022). The existence of different campaigns and campaign objectives varying from search campaigns, social campaigns, and display campaigns to objectives such as brand awareness or acquisition suggests that firms can use various KPIs to evaluate the effectiveness of their campaigns. One major KPI that will be utilized to analyze the dataset in this analysis is conversion rate. It is “calculated by simply taking the number of conversions and dividing that by the number of total ad interactions" (Google ads help, 2022). In 2022, “the average conversion rate across Google Ads is 4.40% on the search network and 0.57% on the display network.” (Bond, 2022 p. 8). But when it comes specifically to the industry touched on in this thesis, the financial industry, the average conversion rate is 4,17% for search and 0,80% for display ads (Bond, 2022).

On a separate note, techniques such as cross-selling and up-selling are also great in online advertising and can be utilized in different channels right before the conversion. These well-known marketing techniques are aimed “to raise the value of a single sale transaction” (Kubiak, 1970, p. 2). Cross-selling consists of offering additional items that complement the initial purchase while Up-selling offers the customer to buy more of that item or a more costly version of the item (Kubiak, 1970). These methods are used by companies such as Amazon and show great results (Kubiak, 1970).

2.1.2.2.1. Display advertising

First and foremost, display advertising consists of banners, images, text, etc., showcased on different platforms, websites, or apps. In fact, there is a plethora of different types of display ads such as banners, native, animations, interactive content, video content, infographics, and more. (Indeed, 2021). As opposed to the other formats mentioned previously which are self-explanatory, native ads are different since they differ from traditional display advertising (Sirrah, 2019). Contrary to traditional display ads which appear outside the feed, native advertising is part of the feed (Sirrah, 2019). Though this format yields higher click rates, the trade-off is in brand recognition (Aribarg, 2020).

Over time, they have evolved to be more obtrusive and harder to ignore; in fact display advertising is not limited to banners and images, for instance, by including audio and video features, they become more noticable (Goldfarb & tucker, 2011). Sadly for advertisers, there is increasing use of programs in browsers to help users block advertisements. These programs or "ad blocks" make it challenging to obtain accurate data (Kannan et al., 2016). Yet, display advertising is far from dead, since 2013, Google has been estimated to have exposed over 90% of internet users worldwide to display ads, “with more than a trillion impressions served to over 1 billion users every month” (Google Display Network, 2013).

Furthermore, “different ad formats influence consumers in distinct ways" (Abhishek et al., 2012, p.1). For instance, display advertising is considered more effective during the initial stages of the customer journey than other forms of advertisement (AdRoll, 2016). Mere exposure to display advertisements results in increased online search activity (Xu et al., 2014). Customers usually engage in online searches to collect additional information about the brand and the offered product they just saw (Ghose & Todri, 2015). Moreover, exposure to display advertising increases the intent of customers to purchase by about 7.1%, which highlights the positive effect of display advertisements (Ghose & Todri, 2015). Kannan et al. (2016) also find that the longer the exposure to display advertisements, the higher the likelihood of customers visiting the website.

However, over the years, display advertising has dramatically decreased in response rates mainly due to a phenomenon called “banner blindness” (Hollis, 2005). This incident consists of customers actively trying to avoid banners by simply overlooking them, which renders them almost futile in a sense (Hollis, 2005). Furthermore, in the digital age, attention span has been affected negatively, dropping from 12 minutes 10 years ago to an average of 5 minutes today (Subramanian, 2018). But the decision to scroll down or to quit a web page is made in 10 seconds (Subramanian, 2018). “Marketers will have to contend with the reality of shrinking attention spans to modify and adjust their product campaigns and promotions.”(Subramanian, 2018, p. 5). Wu (2017) mentions that we currently exist in an attention economy. Thus when trying to maximize the investments made in display advertising, the format chosen needs to be more intrusive to yield greater levels of success.

2.1.2.2.2. Search advertising

Search advertising consists of bidding on keywords to showcase advertisements on search engines according to queries (Blake et al., 2015). Search ads also known as paid search, sponsored links, or search engine marketing (SEM) are a massive part of online advertisement. In 2020, in the US, the total search advertising industry revenues totaled almost 60 billion USD, and paid search accounted for approximately 40% of it (Perrin, 2020). Needless to say, paid search is where a lot of companies invest their online advertising budget. This precise form of advertisement is based on the search queries of the consumer, hence it allows only showing the most relevant ads to the user (Jeziorski & Segal, 2015). “It is viewed as the most effective kind of advertising because of its very precise targeting”(Jeziorski & Segal, 2015, p. 2).

These kinds of advertisements really focus on the intent of the customer, which is a great strategy because it also avoids uninterested shoppers (Blake et al., 2015). In this channel, keywords can be divided into two categories, branded or generic (Rutz, 2011). For example, a search query could be broad like “hotel”, which falls in the generic category, or brand-specific like “Hilton hotel” which is considered branded keyword (Rutz, 2011). According to Tunuguntla (2022), generic keywords have higher costs (bids) than branded ones since several businesses are all competing for the same ones. Although more expensive, generic can have the benefit of affecting subsequent branded searches, which branded keywords can’t do (Rutz, 2011).

Although less expensive than generic keywords, branded keywords have higher probabilities of being clicked than their counterpart (Tunuguntla, 2022). Additionally, “for brand-keyword advertising, it is obvious that the user searched for the brand name and hence is well aware of it, making brand-keyword advertising redundant” (Blake, 2015, p.22). Moreover, branded queries in paid search can easily be substituted with natural search (Yang, 2010). Regardless, those keywords are precious and competitors desire similar ones and in most situations cannot resist stealing traffic by bidding on your brand’s keywords (Tunuguntla, 2022). This creates what is called “the prisoner's dilemma”, in this case, “a company and its competitor would both be better off not buying any brand keywords, but each cannot resist the temptation to pinch away some of their competitor’s traffic” (Blake et al., 2015, p. 22). Arguments can be made that buying keywords through paid search is a form of defensive strategy against other bidders (your competitors) (Tunuguntla, 2022).

In his work, Rutz mentions

> how consumers would initially engage in generic (possibly, product category-related) searches, and then, move towards branded keyword searches in subsequent periods as they progress through the decision-making funnel (Rutz, 2011, p.3).

Search advertising is a powerful channel since it affects the consumer profoundly across all different stages of the funnel/customer journey (Abhishek et al., 2012).

Also, the paid advertisement offers crucial information allowing the marketer to track multiple variables, ranging from which ads the customer clicked, the time it was clicked, the total amount spent or the bidding prices, etc. to help him evaluate the efficiency of his ads (Blake et al., 2015). In effect, when using paid search, the marketer is presented with a lot of data on the visitor who clicked on its ad, like the geographic area of the user, his time zone, what product he clicked on, etc., and thus can utilize that information to make better-educated decisions on future spending (Blake et al., 2015). But while it seems like a flawless plan to target consumers based on their queries, “In many cases, the consumers who choose to click on ads are loyal customers or otherwise already aware of the company’s product” (Blake et al., 2015, p. 2). This has to be taken into account since it seems on paper that these paid advertisements are bringing in tons of new customers when actually, some of them would have probably ended up on that website anyways by using different channels. The average amount of new clients in this channel will be explained in the analysis section.

2.1.2.2.3. Organic search (Natural search)

In digital marketing, there are multiple channels through which you can show your ads to reach your intended consumers, such as; affiliation, paid social, direct, email, organic, etc. According to its definition, “It refers to users' visits to the advertiser’s webpage coming from a search engine not promoted content” (Leguina et al., 2020, p. 6). These “not promoted” links are called organic links and are usually more trusted by customers than promoted links (Katona, 2013). This means that advertisers tend to want to capitalize on that search engine ranking by using methods called search engine optimization, or SEO for short.

Yet, contrary to the other channels, organic search is an interesting one since it is considered a “free” channel by most. Though organic search might not cost anything to start, it needs to be optimized to yield great results (Berman, 2013). The reality is that over the years SEO has become a multi-billion dollar business (Katona, 2013). “In the absence of sponsored links, the organic ranking is improved by SEO if and only if the quality provided by a website is sufficiently positively correlated with its valuation for consumers.” (Berman, 2013. p. 644). This suggests that there are some costs when it comes to natural search due to SEO that needs to be accounted for in the long run to better allocate budgets when it comes to online advertisement.

2.1.2.2.3.1. Search Engine Optimization (SEO) & their potential hidden costs

There are two options to reach the consumer in search engines, either with organic search (SEO) or with paid search, also known as SEM (search engine marketing) (Rentola, 2014). Although the algorithms that dictate which ads will appear first are ambiguous, multiple factors can be taken into account to optimize your visibility as well as your odds of being highly ranked on search engines. According to “Mozlow's hierarchy of SEO needs”, named after Maslow's pyramid (Appendix 1a), SEO is primarily affected by “crawl accessibility, compelling content, optimized keywords, great user experience, share-worthy content, the title, URLs, and the description” (Crawford, 2019, p. 7). These criteria mentioned prior are all relevant in ranking your content in the top results of the search engine, and the better the ranking, the greater the opportunity for a marketer to obtain a visitor on its website, or even a conversion (Rojalin, 2020). When establishing an online marketing budget it is vital to consider the potential “hidden” costs of SEO, since most businesses consider this channel free because it is organic. For example, they need to consider the costs of hiring an SEO consultant, optimizing the website, and creating pertinent content. In particular, a firm may need to hire an SEO consultant to acquire the necessary expertise or skills and ensure the success of the SEO campaign (Nash, 2020). Seeking external services like website optimization and content creation requires the firm to incur some costs depending on the length of the agreement such as annual or monthly contracts (Nash, 2020). Furthermore, firms can “can choose to invest in SEO effort to promote their site in organic listings as well as bid for sponsored links” (Berman, 2013, p. 649). When using a search engine, the consumer has a choice between organic links, which tend to be more trusting, or sponsored ones which appears first (Katona, 2013). Thus, it is essential to consider this in SEO costs before initiating the SEO campaign to ensure its success.

2.1.2.2.4. Direct search

The direct channel occurs when a customer enters directly your URL in the search bar (Google analytics help, 2022) or if your website was previously bookmarked (Sharma, 2022). But data will also appear in this channel if a visitor came from a link that wasn’t tagged.

> “Links like this are often shared via text messages, personal emails, or a business communication platform like Slack. Furthermore, if the medium is equal to ‘(none)’ and the traffic is unidentified, it will also be considered direct. This is the main reason why this channel is sometimes inflated when it comes to the number of visits (Comber, 2020, p. 11-12).

But usually, when conversions happen in this channel, it is most likely because they are returning customers, but it doesn’t exclude the possibility of being new clients either. If a client first went through a natural search, for example, they could decide to take a shortcut on their next visit and directly type the business URL (Sharma, 2022).

2.1.2.2.5. Social Media Marketing

When social media arrived in our lives, it not only changed the way we can express ourselves, but it also unlocked unprecedented opportunities for marketers (Bostanshirin, 2014). Platforms such as Twitter, Facebook, Instagram, TikTok, YouTube, Reddit, etc. have multiple millions of users that are eager to consume content (Bostanshirin, 2014). Usually, the type of content posted on those platforms is more creative, distinct, and trustworthy, and relies primarily on attention (Bostanshirin, 2014).

When looking at Facebook, the age of users ranges from 25-34 and the same goes for Instagram (Bernhart, 2022). But if you are looking to get the attention of the younger demographic, Tiktok and Twitter are the platforms with their largest age group being from 10-19 and 18-29 respectively (Bernhart, 2022). For older demographics, look no further than Pinterest, ranging from 50-64 (Bernhart, 2022). This means that depending on the target audience you are looking for, different platforms will answer your needs more efficiently.

2.1.2.2.5.1. Paid Social

When it comes to paid social, or just social media in general, it is a chance to expand your competitive edge by boosting your brand awareness as well as your online traffic (Bostanshirin, 2014). This can be achieved through this channel by promoting paid ads on platforms like Facebook or Instagram (Ertemel & Ammoura, 2016). “Paid social media advertising is primarily being used to support branding-related efforts” (Vizu, 2013, p. 5). Multiple advantages are associated with paid social media ads (Taylor, 2013). Firstly, it effectively gets the attention of customers through the use of creative content and it amplifies brand visibility (Taylor, 2013). Secondly, it is also considered cost-effective since it is a relatively cheaper form of advertisement when compared to traditional marketing (Taylor, 2013). Thirdly, it can generate valuable leads when the content is shared by users once promoted (Taylor, 2013).

2.1.2.2.5.2. Organic social

Organic social primarily relies on share-worthy quality content. The goal is to organically spread awareness by inciting people to share your content on their social network. “In making social media users share its promotional content with people in their network it means that it has gained support from a trusted source and possibly will be regarded highly by the recipient” (Bostanshirin, 2014, p. 786). Content that has been shared by someone you personally know is definitely more trusting of a source than when it comes from the business directly (Bostanshirin, 2014). Sharing content with friends and family falls into the category of “word of mouth” (WOM) but in the online space (Bostanshirin, 2014). The type of content in this section can be unique promotions to users of this platform, or sneak peeks at an upcoming project the business is currently working on (Saravanakumar & SuganthaLakshmi, 2012).

2.1.2.2.6. Affiliate marketing

Affiliate marketing is a very powerful marketing technique that essentially boils down to creating a beneficial situation for both parties involved (Duffy, 2005). Usually, the advertiser offers to pay the affiliate in some way in exchange for some exposure, either upfront and/or a percentage of revenues for each new customer brought. A typical affiliate marketing situation would be the affiliate creating some sort of content like a Youtube Video, a podcast, a blog post, or a comparison website and then talking about the products or services the advertisers are offering. “Affiliate marketing is basically transmitting personal selling to an online environment” (Jurišová, 2013, p. 106). This is a situation where the affiliate is greatly incentivized to promote as much and as convincingly as possible the product/service of the advertiser since their revenues are directly tied to the number of new customers they bring.

Furthermore, Vladimira mentioned in her paper that “to the relation of the company - customer it brings another man who has nothing to do with the company, and therefore the recipient considers him a better reference to classic advertising” (Jurišová, 2013, p. 106). Additionally, this method of marketing is great because it has very little upfront costs. The business will pay the affiliate a percentage or a fixed price on every new client he/she brings, the business will then most likely turn a profit for each new customer in the long run.

> Affiliate marketing combines the value of personal sales and technology solutions offered by online marketing. To companies with lower budgets, it provides an opportunity to increase profits and raise awareness of its brand (Jurišová, 2013, 106).

> The key to successful affiliate marketing lies in the construction of a win-win relationship between the advertiser and the affiliate. Affiliate marketing is likely to become the principal mainstream marketing strategy for e-commerce businesses in the future (Duffy, 2005, p. 161).

Like Duffy mentioned in his research (2005) this method might become the "go-to" advertising technique for most businesses since this channel yields powerful results when it comes to conversion at relatively low costs.

2.1.2.2.6.1. Influencer affiliate marketing

"The new influencers are beginning to tear at the fabric of marketing as it has existed for 100 years, giving rise to a new style of marketing that is characterized by conversation and community" (Carrabis, 2008, p.1). In short, influencer affiliate marketing consists of identifying influential users and inciting them into approving a brand or a product through their social media activities (De Veirman, 2017). Then through similar affiliate contracts like those mentioned above, a win-win relationship can be initiated where the affiliate talks and approves your product and gets rewarded by the number of new customers brought.

This advertising method creates a different level of trust since the "ad" is not coming directly from the business itself, but from a person that isn't "directly" connected with the person trying to sell you something (Jurišová, 2013). "The added value of the affiliate marketing business is just an input of an objective person who has no relationship with that company, thus is becoming for a potential customer more objective reference" (Jurišová, 2013, p. 110). Thus they can give their personal opinions, be less biased than the advertiser in question, and showcase in detail the product/ service. Moreover, another benefit for the business is being able to target the affiliates' audiences specifically. For example, by establishing an affiliate relationship with a financial YouTuber, you can guarantee that most of the viewers will definitely be interested in finances and in the recommendations from that persona. “For global thinking companies, affiliate marketing should become the most important communication and sales channel” (Jurišová, 2013, p. 110).

This particular method of advertising can sometimes tie in with a fairly old phenomenon that is resurging in recent days with the online business environment called parasocial relationships (Goldschmidt, 2003). “Parasocial interaction is a perceived interpersonal relationship on the part of a [...] viewer with a mass media persona” (Perse & Rubin, 1989, p. 60). This situation is pretty common when it comes to streaming platforms like YouTube, Twitch, or other social media platforms. This suggests that with these sorts of relationships, a certain level of trust is developed (at least one-sidedly) between the viewer and the influencer. This ties in directly with affiliate marketing since the viewer is listening to the influencer’s point of view and thus is more likely to follow through with their suggestions of products/services.

2.1.2.2.6.2. Referral marketing

> Online referral marketing, for example, is a business practice that rewards customers who successfully refer other customers to a website or upon completion of a sale usually via their own social contacts (Guo, 2012, p. 373).

Common examples are companies such as Paypal and American Express that incentivized their users with financial rewards to recommend the service to other users (Buttle, 1998). Multiple businesses use the “refer a friend” technique and reward their users with points or cash, credit card companies are no exception to this (Buttle, 1998). This method of advertising is a form of affiliate marketing, but is open to everyone. As an alternative to business-to-consumer marketing, referrals as well as affiliates utilize an approach called consumer-to-consumer (Guo, 2012). “New online referral strategies leverage consumer-to-consumer interactivity, taking new forms such as blogs, news groups, product reviews, and social networking sites" (Guo, 2012, p. 373). Like affiliate marketing, this method of advertising is effective and isn't costly (De Bruyn, 2008). Thus this method, as well as affiliate marketing, guarantees that each dollar spent on this brought new clients since this is a "pay per performance" technique, they only have to pay at the conversion (Guo, 2012). In the database of this financial institution, the referral marketing was classified in the channel "other sources".

2.1.2.2.7. Email marketing

Email marketing is considered by many to be one of the strongest channels of E-marketing (Jenkins, 2008). This channel is primarily used to send promotions to users (Jenkins, 2008). "Among its benefits point to "high response rates" and "low costs" of email marketing and believe that these advantages "are rapidly turning email marketing into an invaluable tool" (Bostanshirin, 2014, p. 785).

Yet this channel has deficiencies. The first one is the most obvious, customers can decide to place this mail in their spam folder or simply ignore the mail and leave it unopened (Jenkins, 2008). This can be avoided by employing "different channels and methods of marketing to increase the chance of success." (Bostanshirin, 2014, p. 785). As Bostanshirin said, the key is to redirect those customers through a different channel later in their journeys to prompt conversion. The second issue is that there needs to be consent from the recipients to receive those emails from the marketers (Bostanshirin, 2014). Meaning unless consent was received, no emails can be forwarded to the customer (Jenkins, 2008). The email list then needs to be built over time from agreeing customers and cannot be purchased from a third party without informed consent from their part again (Office of the privacy commissioner of Canada, 2022).

2.1.2.2.7.1. Spam emails

There is a fine line between keeping a customer informed on promotions and spam. According to Campaign Monitor, spam emails are "unsolicited, irrelevant emails that land in your inbox" (Campaign Monitor, 2017,). The spam folder needs to be avoided by marketers above all (Campaign Monitor, 2017). The first rule to avoid this folder is to only send emails to people who have consented to it, this is the reason to avoid purchasing third-party email databases (Campaign Monitor, 2017). Then, the email needs to be personalized (Campaign Monitor, 2017). This is easy to implement since the financial institution got those email addresses through first-party data collection, meaning they also have their names. Furthermore, avoiding spam words like "100% free" or "Act now" is key, since spam filters are on the lookout for those (Campaign Monitor, 2017). Finally, the amount of email sent monthly need to be accounted for, a good ratio could be twice a month (Lynch, 2021). This ratio could be augmented if the business has appealing content or regular promotions (Lynch, 2021).

2.1.3. Touchpoints

Touchpoints refer to the general interactions between users and merchants such as impressions or visiting specific sites (Matoulek, 2018). Firms use touchpoints to understand exactly when customers purchased a product across their journey (Cordeiro, 2018). Research highlights the importance of multiple touchpoints in influencing conversions throughout the customer journey (Kannan et al., 2016). Since a purchase may occur after customers interact with many touchpoints, this emphasizes the importance of using different channels for advertisement (Priest, 2017).

However, there is a gap in the literature when it comes to the value each touchpoint individually brings to the whole conversion process. This is due to the level of complexity associated with such a task. To assign weight to a single touchpoint in the whole customer journey implies finding the weight of every touchpoint simultaneously. Additionally, Harris (2018) demonstrates in his work that the challenge of attributing conversions to specific customer touchpoints is a difficult task, and this has led to the development of multiple different attribution models. This ties up with the subject of the attribution problem which will be explored further later in this research. Yet, technological improvements have been made to be able to predict the next touchpoint in a journey (Hassani, 2021).

Nevertheless, it is challenging to understand the effect of individual channels, the interaction between channels, and the channels that result in conversions. Leguina et al. (2020) argue that organizations can deal with these challenges by dividing the customer journey into two categories. The first is external touchpoints corresponding to user activities outside the marketing channel and the second is internal touchpoints corresponding to user activities within the marketing channel. “An example of an external touchpoint could be a kiosk where a customer comes in contact with a company's product, services [...], outside in the physical world” (Transformation, 2019, p. 1). On the other hand, an example of an internal touchpoint would be “steps of interaction in a process” (Transformation, 2019, p. 1). Organizations can then consider the external journeys leading to conversions and those not leading to conversions; the same principle can be applied to the internal journey.

2.1.4. The carry-over, spillover & interaction effects

Vendors use these effects to understand cross-channel attribution as the effect affects the immediate and enduring effectiveness of marketing channels (Dhar & Weinberg, 2016). The carry-over effect occurs when a user visits a website again using the same channel used initially to access the site (Anderl et al., 2015). The spillover effect occurs when website users visit the website again after the initial visit using a different channel (Anderl et al., 2015). Although these effects are different, both the carry-over and spillover have similar uses and influences (Dhar & Weinberg, 2016). Finally, the interaction effects measure the effects of advertising and it occurs when more than one multiple independent variable simultaneously affects the dependent variable (Dhar & Weinberg, 2016). Vendors usually use modern AI and machine learning-based techniques to model the interaction effect (Priest, 2017).

2.1.5. What other factors can affect online conversion?

It is clear that several different variables influence online conversions. Kannan et al. (2016) demonstrated that the device(s) used by customers affects conversions online, but so does demographic data such as age group, gender, location, user interests, etc. (AdRoll, 2016). Many additional factors have an impact on the customer journey and the odds of conversion such as the frequency of advertisements and the quality of the website or the ad.

2.1.5.1. The frequency of advertising & the repetition effect

Moreover the number of interactions throughout the customer journey or the number of visits to a vendor's website (including the factor of if it's their first visit or not) influence conversion (Kakalejčík et al., 2018). In fact, the number of previous visits influences future buying behavior since this conduct demonstrates recurring interest (Kakalejčík et al., 2018). In particular, past visits affect the subsequent visits in which customers use the same (carry-over effect) or a different channel (spillover effect) to return to a website (Anderl et al., 2014). Specifically, a higher number of past exposure increases the tendency of consumers to purchase a product in the long term. Although, "there are studies that show that impacting a user more than 10 times does not lead to higher conversion rates" (Romero, 2020).

The repetition effect can be divided into 2 categories, recall and attitude toward the brand (Schmidt, 2015). "Low involvement and spaced exposures enhance repetition effects on attitude toward the brand [...] and massed exposures enhance the repetition effects on recall" (Schmidt, 2015). From there, either the wear-in or the wear-out effects can take place (Moorthy, 2005). The wear-in effect is positive from the customer's point of view up to a certain point (Moorthy, 2005). This effect includes feelings like learning and habituation (Moorthy, 2005). The wear-out effect is the opposite, creating feelings of boredom and redundancy with advertisements having either no effect or even negative ones on the client (Moorthy, 2005). To put this into perspective the shape of the repetition effect would be like an inverted U curve (Schmidt, 2015). This means that the repetition effect is in effect “until familiarity and learning are saturated”, further advertisements will lead to negative effects (Schmidt, 2015). That specific point where the customer is at the perfect level of exposure has never been found and is considered the holy grail (Schmidt, 2015). Regardless, during the analysis of this thesis, by utilizing the carry-over effect, the tipping points where clear diminishing returns in conversion rates will be analyzed in each channel according to the specific dataset of this financial institution.

2.1.5.2. The quality of the website and the ads

Furthermore, the quality of the website has a great impact on the customer since it is their first impression of the business. Specifically, Kuan et al. (2008) argue that the system quality dimension has a positive effect on the intention of customers to purchase a product initially. But the opposite is also true, Kuan et al. (2008) demonstrate that website systems that impede customers from finding product data and buying products result in negative perceptions about the websites, which influences them to switch to a different website.

Additionally, researcher David Crête mentions that the quality of an ad greatly matters and is equivalent to the subjective evaluation of the global experience. Results show that the quality of the ad can predict the attitude of the consumer towards it (Crête, 2016). Today, everybody is bombarded with ads on all platforms from businesses trying to sell you things, the quality of the service you’re showcasing is extremely relevant to outshine the competition. The quality of the ads and the website are the first impressions the consumer has about your business and first impressions are important.

2.2. Modeling the customer journey

To model the customer journey properly and to properly evaluate the effectiveness of advertising, an understanding of how the customer thinks during the different psychological stages of the journey is paramount. Hence, in 1990, the hierarchy of effects model was created and promoted the “cognition-affect-conation” model (Barry & Howard, 1990). Over the years, other researchers took inspiration from this model and created their own adapted versions. Models like STDC, AIDA, and the marketing funnel were produced to try and get an even clearer understanding of each individual stage a customer goes through during its purchasing process (Skyword, 2020). Each of those models will be explored in the following section. Comprehension of these models will then be helpful for dissecting the journey in stages giving marketers the ability to target customers at more timely moments.

2.2.1. Hierarchy of effects models

According to Rathod (2011) advertising was considered initially as a way of increasing company sales. Today, stakeholders in the advertising industry use the hierarchy of effects framework to evaluate the effectiveness of advertisements (Weilbacher, 2001). In a comprehensive exploration of advertising studies, Barry and Howard (1990) demonstrate the idea that customers go through several stages toward a sale. They proposed a hierarchy of effects to understand and explain media advertising. The two researchers highlight the importance of the order of sequence of the three hierarchy stages or the *cognition-affect-conation.* Starting with “think, feel, do” or “feel, do, think” stages, in ascending order (Barry & Howard, 1990). Besides, they considered alternative order hierarchies of effect but they disregarded the conation-cognition-affect and conation-affect-cognition models due to the unlikelihood of advertising affecting behavior first without past affect or cognition (Barry & Howard, 1990).

Regarding the way advertising functions, Vakratsas (1999) examined the literature and found that advertising influences “cognition, experience, and affect” (Vakratsas, 1999). The research shows that practical advertising approaches affect the mind of customers and thus helps organizations avoid wasting their resources (Ambler, 1999). In particular, while the evidence does not support the existence of advertising hierarchies, three crucial transitional effects between purchase and advertising help us understand the functioning of advertising and the response procedure. As mentioned, these effects are “cognition, affect, and experience”. Other factors such as information processing abilities and motivation, mediate individual reactions to advertising, which in turn influences a person’s reaction to advertising. The researchers suggest that the three dimensions should be used to evaluate the effects of advertising in which some intermediate variables matter more than others. These variables are based on several factors including competition, target audience, product life cycle, and the effect of other marketing approaches (Vakratsas, 1999).

Overall, the approach of the hierarchies of effects frameworks is too simple, as they do not integrate other effects in the purchasing process. Regardless, stakeholders can use it for behavior prediction or use it as a conceptual tool for general guidance (Barry & Howard, 1990). Moreover, experience is implicit because consumers can enter the consumption process with some knowledge that influences the choice of a specific product or brand. Data processing among consumers can cause positive or negative behavior such as buying or not. Thus this framework should be used as a heuristic model for general guidance but remains too simplistic to explain the new shift the digital world has recently caused. Digitalization has caused a shift in paradigm regarding how customers think and reach decisions. This created a totally new environment and a complex customer journey with a massive amount of potential variables to account for. Therefore, other more recent models have been added to the literature, such as STDC, AIDA, and the marketing funnel.

2.2.1.1. STDC (see-think-do-care)

Since it is essential to understand the entire customer journey, advertisers can use different models to try and master it. The see-think-do-care (STDC) is one of the models that can be utilized for that purpose (Jílková, 2019). The “see” dimension concerns the first contact in which customers engage in research about the vendor (Kaushik, 2015). Thus, it is in the firm's best interest to describe itself adequately. In the “think” dimension, the vendor should demonstrate to customers why the business solves the customer’s problems better than their competitors (Matoulek, 2018).

Conversions occur in the “do” dimension, in which the vendor must ensure an efficient and seamless checkout mechanism to avoid negative perceptions just before the sale (Kaushik, 2015). Regarding the “care” dimension, vendors should ensure that customers are highly satisfied to retain them in the future. Furthermore, in the “care” aspect, vendors should try and establish a relationship with their customers after the conversion, this can affect the repurchase rate and thus increase the overall lifetime value.

2.2.1.2. AIDA (awareness-interest-desire-action)

Vendors can also use the “awareness-interest-desire-action” (AIDA) framework to understand the steps customers undertake to complete a purchase (Matoulek, 2018). For the “awareness” part, vendors focus on introductory activities such as describing the company and the goods (Matoulek, 2018). This stage is directly linked with display advertisement since the whole purpose of those ads is to bring a customer from a disengaged state to one where they are aware of your business and product (Abhishek et al., 2012). The “interest” phase entails catching the attention of potential customers while the “desire” stage involves the firm highlighting the benefits of its offerings to influence customers to complete purchases (Matoulek, 2018). Finally, the customer completes the order in the “action” stage, however, the company needs to make sure that the transaction itself is effortless (Matoulek, 2018).

2.2.2. Marketing funnel

As established prior, comprehension of consumer behavior is paramount to understanding the different stages occurring during the customer journey. Nowadays, the marketing funnel (also known as the decision funnel or purchase funnel) “is a visualization for understanding the process of turning leads into customers" (Skyword, 2020) (Appendix 2a). Starting with the largest end of the funnel, the awareness stage is composed of awareness marketing campaigns and consumer research (Colicev, 2019). During this stage, trust is established between the consumer and the business through different channels (Colicev, 2019). This is the lead generation stage (Skyword, 2020).

“Once leads are generated, they move on to the interest stage, where they learn more about the company, its products, and any helpful information and research it provides" (Skyword, 2020, p. 9). This is the phase where businesses can create relationships with their customers and target them with ads (Colicev, 2019).

The third phase is consideration (Colicev, 2019). Here customers are considered prospects and businesses can send them additional information about their offerings through email marketing while continuously targeting them with curated ads (Skyword, 2020). Free trials or discounts can be offered to customers at this stage (Colicev, 2019).

To leap from the 3rd to the 4th stage, customers need to show interest in your brand, this can be observed by items being added to their carts for example. This stage is called the intent phase (Colicev, 2019). This is where the brand needs to showcase why its product/service is superior to the ones offered by its competitors (Skyword, 2020).

Evaluation is the fifth and before the last stage. At this point, customers are weighing the pros and cons and making final decisions about the product/service (Colicev, 2019). At this point, the results from the 4th phase can be observed on whether or not the business made a good case against the competition and proved that its offerings are superior (Skyword, 2020).

Finally, the sixth and final stage is the purchase (Colicev, 2019). This is when the client made the decision to buy the product/service, and the conversion happened (Skyword, 2020).

Researchers debate on which model is more accurate, or if any of them is even relevant at all to this day (Skyword, 2020). Regardless, all these different models clearly show that customers go through different psychological stages during their journeys. Regardless, a discovery has been made in a research paper by Abhishek et al. (2017), “that advertisers should spend a relatively larger fraction of their advertising budget on the stage of the purchase funnel that they believe has a higher baseline conversion rate” (Abhishek et al., 2017, p. 493). For example, if a marketer is aware that the level of brand awareness appears to be more significant than the standard conversion prospect in the consideration stage, he should raise the amount spent on brand advertising (Abhishek et al., 2017).

2.3. Modeling the online customer journey

Attribution models are used to distribute the merits of conversion to touchpoints. They can be divided into two categories, single-touch models and multi-touch models. Single-touch models, which are used by 83% of businesses (AdRoll, 2017), consider one touchpoint, while multi-touch models consider multiple touchpoints and split the merits (Forrester Consulting, 2012). A plethora of different models can be utilized ranging from, time decay model, position base model, linear, custom models, and even models that include AI and machine learning. All the significant models will be explored and compared further in this section.

But ever since TV advertisements or print, attribution always had big issues (Abhishek et al., 2017). Today, for the first time since, online ads offer the opportunity to tackle this issue thanks to individual-level data. But due to a lack of transparency, the problem is far from solved. Furthermore, a lot of data tracking comes from cookies (third-party data) which helps marketers target and retarget customers with personalized advertisements. Yet the era of cookies is coming to an end due to data-privacy regulations. Different alternatives are emerging like APIs or prioritizing first-party data. Thus to gain a comprehensive understanding of attribution as a whole, every subject mentioned prior will be explained in order in the following section.

2.3.1. Attribution models

"Attribution modeling analyzes every single step a user took before conversion and assigns value to each individual marketing step along the way" (Swan, 2020). However, the choice of the model influences the attribution itself because numerous channels and touchpoints can be accounted for or dismissed (Harris, 2018). Finding an accurate attribution model that fits the businesses' needs will help uncover the effectiveness of each advertising campaign in different channels (Priest, 2017).

But the attribution itself is limited by the rules of the attribution model and the accuracy of your data (Abhishek et al., 2012). Furthermore, researchers have found that utilizing different common models yields radically different results when looking into ad effectiveness (Abhishek et al., 2012). This suggests that depending on which attribution technique is chosen, different levels of ad effectiveness will be shown in the results (Abhishek et al., 2012). This is a massive finding since most businesses utilize single-touch models, and switching their attribution method could yield totally different outcomes of ad effectiveness.

There is a gap in the literature when it comes to agreeing on an "ultimate model", different researchers have different opinions on the matter. However, it is commonly agreed that single-touch attribution models are outdated and that businesses should adopt multi-touch attribution models instead. The common consensus is that businesses should adopt attribution techniques that fit their needs. Consequently, depending on your business, choosing an adequate attribution model is crucial since it will skew the results and analysis accordingly.

2.3.1.1 Single-touch attribution models

Single-touch models are pretty simple, they attribute conversions or sales to a single touchpoint. These models usually only consider either the first interaction (called first-click or first interaction) or the last one (known as last-click or last interaction) (Forrester Consulting, 2012). In 2017, 83% of businesses utilized these methods of attribution. More specifically, 44% of businesses use the last-click attribution model and 39% of them use the first-click model (Adroll, 2016). These single-touch attributions are easy to implement for businesses, but according to AdRoll, these methods are “hindering their decision-making ability” due to their simplicity (Adroll, 2016, p. 3).

2.3.1.1.1. First-click & Last-click

Although similar, their main difference lies in which channel is considered, for example, last-click usually gives all the credits to the direct channel (Google attribution modeling example, 2022). While on the opposite side, the first-click method usually gives merits entirely to the paid search channel (Google attribution modeling example, 2022). In short, these methods give 100% of the credit for a conversion to either the first or the last thing that was clicked.

Studies demonstrate that simplistic attribution models, such as first-click or last-click, underestimate the role of specific channels in the final conversion (AdRoll, 2016). For example, last-click attribution is biased toward search engine advertising as it overestimates the contribution of other channels like direct (Kannan et al., 2016). Additionally, Priest (2017) argues that these models are inaccurate and flawed because of their failure to provide a real picture of the customer journey. The issue is that most businesses don’t realize that this attribution method is considered outdated, thus they don’t even contemplate other potential attribution techniques to analyze their data.

2.3.1.1.2. Last Non-Direct Click (same touch) attribution

When looking at the analytics help center from Google, they define the last non-direct click as “100% of the conversion value to the last channel that the customer clicked through from before buying or converting.” (Google Analytics Help Center, 2022, para. 15). This particular model is known to disregard both attributes and direct traffic (Google, default MCF attribution models, 2022). Furthermore, it is automatically selected when it comes to analysis in non-multi-channel (NMC) funnels (Google, default MCF attribution models, 2022). Moreover, being the default method from google (when it comes to NMC funnels) means that this attribution technique can be a great guideline to compare to different outcomes coming from other channels (Google, default MCF attribution models, 2022).

2.3.1.1.3. Last Google Ads Click attribution

This attribution method is pretty self-explanatory, like the last-click attribution techniques, it attributes all the merits of the conversion to the last-click, but in this case, specifically, it's attributed to the last google ads click (Google, default MCF attribution models, 2022). Google refers to it as a model that “attributes 100% of the conversion value to the most recent Google Ads ad that the customer clicked before buying or converting” (Google, default MCF attribution models, 2022). In short, this method touches the paid search channel and attributes all the merits of the sale to it (Google, default MCF attribution models, 2022). This particular method can be utilized when a business desires to figure out which google ads converted the most clients (Google, default MCF attribution models, 2022).

2.3.2.2. Multi-touch attribution models

Contrary to the simplistic approach of single-touch models, the multi-touch attribution model considers the effect of various touchpoints on the final conversion. These kinds of models are more powerful than single-touch ones because it enables firms to link conversions to various marketing channels, which results in optimized marketing campaigns (Ji & Wang, 2017). These models value the cumulative effect of most advertising activities throughout the user journey on customer behavior (Matoulek, 2018). Yet, “the accuracy of an attribution model is limited by the assumptions of the model, and the quality and completeness of the data available to the model” (Sapp, 2016, p. 1). Additionally, all these models have a flaw that is usually overlooked, they “assume that ad exposure does not change user behavior in other ways, such as driving additional website visits, generating branded searches, or creating awareness and interest in the advertiser" (Sapp, 2016, p. 1).

Advertisers can use any of the several options of multi-touch models including; linear models, time decay models, position-based models, data-driven models, etc., to fit their needs (Forrester Consulting, 2012). Furthermore, Berman (2018), also mentions that businesses will end up spending less on digital marketing when more advanced attribution techniques are used due to better allocation of resources.

2.3.2.2.1. Position base (U-shaped) attribution

Position based (or sometimes described as U-shaped) consists of merging both first-click and last-click attribution models together (Google, default MCF attribution models, 2022). In this case, rather than attributing 100% of the conversion to either the last or the first click, it will split them and award 40% of the credit to the last click and 40% to the first click (Google, default MCF attribution models, 2022). Then the remaining 20% will be distributed between the touchpoints that happened in the middle (Google, default MCF attribution models, 2022). This specific attribution technique is useful when the business "value touchpoints that introduced customers to your brand and final touchpoints that resulted in sales" (Google, default MCF attribution models, 2022). This method would distribute merits to each channel, as followed; paid search would receive 40% from being the first interaction, then direct would receive 40% for being the last, and channels such as paid social or email would share the remaining 20% (Google, attribution modeling example, 2022).

2.3.2.2.2. Linear attribution

The linear model, although part of the multi-touch attribution techniques, remains pretty simple. This specific model distributed equally the credits to "each channel interaction on the way to conversion" (Google, default MCF attribution models, 2022). This makes sense in a way since every single touchpoint leading to the conversion had an effect on the conversion itself, but the potential issue is that they might not all have equal influence. In their default MCF attribution model section, google mentioned that this particular method can be useful when the business's campaigns are aimed toward awareness (Google, default MCF attribution models, 2022). For example, when focusing on the consideration process, every single touchpoint is considered equally important (Google, default MCF attribution models, 2022). This suggests that channels ranging from paid search, paid social, direct, and email would be implied and would split the merits of the sale with 25% each (Google, overview of attribution, 2022).

2.3.2.2.3. Participation attribution

This attribution method is particular, it attributes 100% to every unique touchpoint in the journey (Adobe Analytics tool center, 2022). “The total number of conversions is inflated compared to other attribution models. Participation deduplicates channels that are seen multiple times.” (Adobe Analytics tool center, 2022). This method is great for having a more visual comprehension of how many times a client is exposed to a given interaction (Adobe Analytics tool center, 2022). It is used by media companies for understanding content velocity (Adobe Analytics tool center, 2022). Moreover, “Retail organizations often use this model to understand which parts of their site are critical to conversion” (Adobe Analytics tool center, 2022).

2.3.2.2.4. J-shaped & Inverse J attribution

Starting with the J-shaped, it consists of attributing 20% of the credit to the first interaction, then 60% to the last one, and the remaining 20% is then split between the middle touchpoints (Adobe Analytics tool center, 2022). If there is only one touchpoint, 100% of attribution is given to the last touchpoint and if there are 2 touchpoints in the journey it is divided 25% to FT and 75% to LT (Adobe Analytics tool center, 2022).

Then the opposite is done for the inverse J, meaning that 60% is given to the first touchpoint, 20% to the last, and the remaining 20% is divided equally into the points in between (Adobe Analytics tool center, 2022). The same logic is applied with journeys of 1 or 2 touchpoints, but inverted (Adobe Analytics tool center, 2022).

These sorts of models work well for marketers who want a balance approached while prioritizing touchpoints considered finders and closers. If the business prioritizes finders more, then they shall go with the inverse J model and vice versa (Adobe Analytics tool center, 2022).

2.3.2.2.5. Time decay attribution

When it comes to the time decay attribution model, Google explains that this method can be useful, but only if the time period observed is limited during the consideration phase (Google, default MCF attribution models, 2022). "This model is based on the concept of *exponential decay* and most heavily credits the touchpoints that occurred nearest to the time of conversion" (Google, default MCF attribution models, 2022). In this particular case, the short period of time in question mentioned earlier usually consists of 30 days, this means that the further in the past the touchpoint is, the less credit it will be allocated (exponential decay) (Google, default MCF attribution models, 2022). When compared to touchpoints made the day of the conversion, the ones made 7 days before will receive 1/2 of the merits, then 14 days prior will be allocated 1/4, etc. This method follows the formula "2^(-t/halflife), where t is the amount of time between a touchpoint and a conversion". (Adobe Analytics tool guide, 2022). "The exponential decay continues within your lookback window (default of 30 days)." (Google, default MCF attribution models, 2022). This method seems to be utilized in specific situations, where a business for example made some short-lived promotion campaigns (usually around 24-48h), and wants to attribute more merit to those when compared to touchpoints that happened weeks ago (Google, default MCF attribution models, 2022). When pinpointing which channels yield the most credit in this attribution model, the answer lies in the customer journey. Usually "the *Direct* and *Email* channels would receive the most credit because the customer interacted with them within a few hours of conversion"

(Google, Attribution modeling example, 2022). This suggests that other channels that occurred prior to the customer journey like paid social for example would receive exponentially less credit (Google, Attribution modeling example, 2022).

2.3.2.2.6. Data-driven attribution model

The first hurdle you can encounter with data-driven attribution models is getting all the data ready for analysis (Shao, 2011). These models emphasize the importance of conducting data analysis first, before selecting the relevant model for attribution. Once the analysis is done correctly, then the specific attribution model can be chosen accordingly (Matoulek, 2018). Leguina et al. (2020) find the data-driven model to be more accurate than the other models because the initial data analysis helps vendors identify the value and importance of a specific model.

The data-driven model utilizes “statistical techniques such as predictive analytics and machine learning” (Swan, 2020). Additionally, the analysis requires data such as interaction information, user attributes, conversion data, etc (Shao, 2011). Yet, marketers must be aware of the GIGO principle (garbage in, garbage out), meaning the data must be pristine before even thinking of starting the analysis stage. But do you even have enough data to use these attribution models? “For the method used by Google Analytics, 400 conversions with path length higher than 2 interactions and 10 000 paths undertaken in the last 28 days are required”, which is pretty attainable for big established companies (Matoulek, 2018, p. 21).

From there, specific users across multiple devices need to be identified. For this step, you can either choose a deterministic model (high accuracy) or a probabilistic method (Matoulek, 2018). In the deterministic method, cookie IDs are combined with the login data of the user (which is probably the most important data when talking about cross-device attribution) to make sure that you don't confuse one customer journey across multiple devices from multiple individual customer journey (Matoulek, 2018). In the probabilistic option, the goal is the same, to avoid the confusion mentioned prior, but marketers try to identify users across multiple devices with IP addresses, geolocalisation, web user behavior, etc. (Matoulek, 2018). Due to the help of machine learning models, they can identify and single out consumers online with the different types of information mentioned prior, similar to the deterministic method (Shao, 2011). Although this method is powerful, it will probably be greatly impacted by the incoming changes concerning third-party data collection (cookies). It will be interesting to observe how data-driven attribution models will adapt to the new third-party data norms. Since this method relies so heavily on cookies to work, other ways of obtaining this third-party data will need to be explored in order for this attribution method to function properly.

2.3.2.2.6.1. Custom attribution models

Custom attributions are highly-adaptable models that “use statistical methods such as Markov to quantify the fractional credit per channel and extrapolate and create rules for how revenues are assigned to specific touchpoints moving forward” (Swan, 2020). This method is usually a good alternative to all those different models since it is directly built on your data and is curated according to your needs (Swan, 2020). But this method requires a lot of data collection from multiple different sources, time, funds, and the knowledge of being an issue with the current models of attribution in the first place, which isn’t the case for the majority of modern businesses.

Although this method might not be an option for every business, Google also offers custom models. While more simplistic and not using AI technologies, businesses can still create their own models and adjust the lookback window, the credits attributed by interaction type, and apply custom rules (Google CM360, 2022)

2.3.2.2.6.2. Artificial Intelligence-based models

AI-based models use machine learning and rely on identifiers such as browser language, operating system, browser types, geolocation, and IP address to connect the customer (Matoulek, 2018). These models use collaborative filtering involving customer events such as purchases, item views, or adding to cart (Szabo & Genge, 2020). Furthermore, by using machine learning it is possible to map the path to purchase (Priest, 2017). These AI-based models work by considering and examining complex human behaviors and scrutinizing the effect of numerous touchpoints to identify influential advertising channels and then distribute the merits of a conversion accordingly (Priest, 2017).

2.3.3. The attribution problem

In today's digital world, disaggregated individual-level data is now at the disposition of marketers (Abhishek et al, 2017). This particular kind of data now offers "the possibility of determining the effectiveness of an ad on an individual customer at a specific time" (Abhishek et al, 2017, p. 494). Yet, in his work, Harris (2018) demonstrates the challenge of attributing conversions to specific customer touchpoints, which has led to the development of multiple attribution models. Furthermore, Berman (2015) elaborates on the subject of uncertainties advertisers face when publishing online advertising campaigns. He explains that by using multiple different platforms to publish a campaign, the targeted population is overlapping, which can create inefficiencies, and result in poor performance of that campaign. This can also create questioning from advertisers about the campaign's effectiveness, which may influence them to reduce their allocated digital marketing budget due to a lack of proof of performance. Berman (2015) also mentioned that the purpose of attribution is to better assign the marketing budget in order to optimize allocation with each different publisher. Consequently, researchers came to the realization that inadequate methods of attribution create flawed results and flawed analysis, which leads to poor budget distribution (Abhishek et al., 2012).

In essence, the attribution problem comes from "quantifying the influence of each ad on a consumer's purchase decision" (Abhishek et al., 2012, p. 1). But the issue doesn't stop there, it also " focuses [...] on accurate and stable interpretation of the influence of each user interaction to the final user decision rather than just user classification" (Shao & Li, 2011, p. 1). This issue is in part so difficult to solve due to a lack of transparency in online advertising causing an asymmetry of information (Abhishek et al., 2017). Furthermore, the whole ecosystem of online advertising is so complex and includes so many participants, each with different incentives, that this results in a surge of data fragmentation, which then expanded the gap of information asymmetry (Abhishek et al., 2017). With this lack of transparency that’s here to stay, marketers need to figure out ways to tackle this issue with different attribution methods that are more complex. This has opened the door to custom models and artificial intelligence technologies.

2.3.4. Retargeting with third-party data

Ghose and Todri (2015) describe retargeting to be an online marketing technique in which advertisers use previous customer actions to target the customers specifically. Retargeting is a powerful technique that utilizes the data they have collected from the first visit, called third-party data or cookies (Iftikhar & Khan, 2017).

By utilizing retargeting marketers can then tailor advertisements explicitly to those interested consumers, this is called personalization (Goldfarb & Tucker, 2011). Also called one-to-one marketing, personalization implies tailoring offers to customers' preferences, whether it's an ad, a page, a product, or a service, based on data collected prior about the customer, with cookies. (Bostanshirin, 2014). For example, if the consumer looked at specific products while on the website, these product images can be used to create an enticing ad for that particular customer later (Goldfarb & Tucker, 2011). This way, customers receive customized messages that yield substantial impacts in contrast with common content (Bostanshirin, 2014). Notebaert and Attuel-Mendès (2014) note that vendors must focus on customer personalization. Achieving this entails using the customer relationship management (CRM) approach in which firms use databases to offer tailored services based on customer needs (Notebaert & Attuel-Mendès, 2014). This tactic builds a particular one-to-one relationship with the client “by understanding the needs of each individual and helping satisfy a goal that efficiently and knowledgeably addresses each individual‘s need in a given context" (Bostanshirin, 2014, p. 788). Overall, personalization is a significant differentiator when comparing online advertising to traditional media (Bostanshirin, 2014).

But if cookies were to be removed from the equation, marketers would be declined crucial information about the customer’s interest and internet activity that is necessary for retargeting ads. Sadly advertisers will need to adapt to this new standard with the death of the cookie era approaching rapidly. There is a gap in the literature on which next steps businesses will need to take to adapt to this situation since it is so recent. Multiple paths can lead to retargeting for businesses, but which one will be the most commonly used to adapt to those changes is still unclear. Potential options offered today for targeting customers without cookies include first-party data, APIs and FLoC, PPIDs, and contextual targeting.

2.3.5. Data issues: The death of the cookie era

Cookies in this case are not the ones you eat, they “are small text files stored in a web browser on the user's device” collected by organizations (Matoulek, 2018, p. 6). The content of those cookies is then sent to the servers for later analysis (Matoulek, 2018). Those cookies are digital footprints and are invaluable to predict the needs of consumers to then retarget them later in the journey with personalized ads (Cinar & Ateş, 2022). The definition of third-party data consists of all “information collected by an organization that does not have a direct relationship with the data subject” (Cinar & Ateş, 2022, p. 10).

Even though advertisers can track customers to better understand the effectiveness of their online advertising, modern browsers allow users to delete cookies (Kannan et al., 2016). Therefore, cookie deletion poses challenges in differentiating new customers from past ones (Kannan et al., 2016). When customers delete cookies, they make it challenging for advertisers to register specific touchpoints in the customer journey (Kannan et al., 2016). Additional factors such as the feature of blocking advertisements or preventing tracking by other websites influence accurate attribution (Kannan et al., 2016). Cookies are relevant because browsers today offer unique identities to users based on their cookies, which they pair with the user login details to offer valuable information regarding cross-device attribution (Matoulek, 2018). Thus, cookie deletion affects attribution accuracy significantly through traffic over-reporting (Lee, 2010).

Nevertheless, the issue with cookies is not limited to user deletion, in fact, their inevitable demise is approaching in the near future (Bergen, 2021). Significant changes are anticipated concerning the way firms use cookies and data-tracking tools. Efforts by major search engines are made in order to phase out third-party cookies to address consumer privacy concerns and comply with regulations (Bergen, 2021). Due to breaches and continuous misuse of those data, countries around the world are tightening the screws and establishing data protection legislation (Cinar & Ateş, 2022). The reality is that invasive "personal data collection leads to privacy violations" (Cinar & Ateş, 2022, p. 1). The phasing out of cookies will make it more challenging for vendors to track data accurately, which will necessitate additional advertising expenditure and investments in other channels to counterbalance these changes. Google has announced its intention to gradually withdraw completely cookies on Chrome by 2023 (Cinar & Ateş, 2022). Furthermore, Apple has already put in place its Intelligent Tracking Prevention (ITP for shorts) on its browser Safari (Cinar & Ateş, 2022). This ITP blocks "third-party cookies by default" and requires users' consent to track them along their journeys (Cinar & Ateş, 2022). Regardless, in 2021, reports coming from IAB's state of Data reveal that investments in third-party data grow continuously (Cinar & Ateş, 2022). This is due to incomprehension from businesses of the inevitable death of the cookie era (Cinar & Ateş, 2022).

This will be a massive change that will require a period of adaptation for most businesses. Without the use of cookies, businesses will need to find new ways to track accurately their customers along their journeys. This simple change in data tracking will ripple across the entire industry. Different alternatives will need to be implemented and tested to observe which method is superior to the other ones. To avoid being "left behind", the key is to adapt quickly. Businesses need to implement different tactics as soon as possible to seamlessly keep obtaining those precious pieces of information about their customers. In fact, there will be a pivot when it comes to the importance of first-party data. Since no changes are foreseen in the future about this data collection method, first-party data will become crucial to businesses. Thus businesses will need to improve their first-party data collection as well as implement new methods such as the ones mentioned below to fill the gap of knowledge that will be created by the death of cookies.

2.3.5.1. Different alternatives to third-party data targeting (cookies) in the future

The death of cookies will have a massive impact on the online marketing industry. Fierce competition arises between AdTech companies to find what will replace third-party data when it comes to accurate targeting (Cinar & Ateş, 2022). Multiple alternative options are available to track the user, but it is too early to know which one will prevail (Cinar & Ateş, 2022). What is certain is that businesses will need to adapt rapidly to this change, and different alternatives of third-party data collection will need to be tested and implemented in order to receive similar data about the customer as before.

2.3.5.1.1. First-party data

In the new coming age, first-party data probably will be prioritized instead, since they are considered by leading AdTech companies to be more transparent (Cinar & Ateş, 2022). Gathering this data effectively will thus become a priority for businesses (Rycroft, 2022). But this raises other issues, the collection of those data will grow exponentially and so will their responsibility to protect them (Cinar & Ateş, 2022). Transparent programs will need to be put in place to establish a trusting relationship with the consumer (Cinar & Ateş, 2022). Furthermore, Google mentions how vital these relationships will become over time and says that they will continue to support first-party data collection on their platforms (Google, 2021). Although first-party data is a great alternative, it might not be sufficient to paint the “whole picture”. Additionally, this collected data will need to be protected by individual businesses, which will entail additional costs.

2.3.5.1.2. APIs & FLoC

Google declared its plan to introduce APIs that preserve privacy while enabling advertisers to track data (Bergen, 2021). These privacy-preserving APIs will “prevent individual tracking while still delivering results for advertisers and publishers” (Google, 2021). APIs or Application Programming Interfaces “are mechanisms that enable two software components to communicate with each other using a set of definitions and protocols” (Amazon web services, 2022). Google then followed by mentioning that they don’t believe people should need to accept being followed across the internet to enjoy relevant ads and that marketers shouldn’t have to track those consumers to reap the benefits of digital advertising (Google, 2021). They spoke about “advances in aggregation, anonymization, on-device processing, and other privacy-preserving technologies offer a clear path to replacing individual identifiers” (Google, 2021).

They also mention in their blog post that their “latest test of FLoC shows one way to effectively take third-party cookies out of the advertising equation and instead hide individuals within large crowds of people with common interests” (Google, 2021, para. 1). FLoC or Federated Learning of Cohorts is an API made for Chrome that will “provides a privacy-preserving mechanism for interest-based ad selection” (Dutton, 2022, p. 1). Its algorithm will periodically figure out different “interest cohorts'' based on search histories. Marketers will then have the option to add code on their respective websites to help the data-collecting process for Adtech companies (Dutton, 2022). FloC could also be used with machine learning to predict conversion rates based on specific cohorts.

A concrete example of how FloC works can be established in 6 steps. First, the FloC creates a model with multiple thousands of cohorts (Dutton, 2022). Then it will calculate which browsing history fits best with which cohorts (Dutton, 2022). Afterward, the advertiser will be able to observe cohort activity on their websites and share this data with Adtech platforms, the ad publisher platforms will do the same (Dutton, 2022). Once the Adtech company receives the cohort data, it will “select ads appropriate for the user’s cohort” (Dutton, 2022, p. 20). Finally, the publisher will showcase the relevant ads to the users (Dutton, 2022). Google will make these tools accessible to the public for testing in the coming months (Google, 2021). This would be a solution for them, not having to compromise advertising and monetization while giving a safe experience for Chrome users (Google, 2021).

2.3.5.1.3. Google's Publisher-Provided Identifiers (PPIDs)

PPIDs are identifiers given to customers by ad publishing companies that are then associated with their logged-in information (Google Ad Manager, 2021). The issue is that it can’t be linked unless the user signs in (Rycroft, 2022). At last, Google gave an option for publishers to pass those PPIDs to partners (Google Ad Manager, 2021). This option will allow advertisers to give personalized ads through custom audience segments made by the publishers themselves (Rycroft, 2022). This option seems promising since customers are classified constantly into custom audiences with different interests, which is crucial for retargeting, but this method appears to require some work upfront to obtain “similar” results as cookies. Thus businesses will need to take this into consideration and put additional effort, time, and money into this method of data collection.

2.3.5.1.4. Contextual targeting

This method refers to utilizing web page content analysis to search for specific keywords and sentences (Rycroft, 2022). Contextual targeting does not utilize personal data but could take advantage of data such as the time of browsing or the device used through the publisher (Andrews, 2016). Furthermore, marketers could analyze what the visited website is about, for example, finance, and then machine learning could be used to forecast which pages are a better fit for targeting and at what specific time (Rycroft, 2022). This method could potentially pinpoint customers' interests but is limited in its targeting options (Andrews, 2016).

2.4. Literature review summary

To recap the second chapter of this thesis, what was learned during this research about the customer journey is that it is challenging to track accurately. From the pre-purchase phase to the post-purchase, the customers don't take linear approaches to reach the conversion. Omnichannel journeys better reflect this situation by considering multiple different channels simultaneously such as display ads, paid search, natural search, affiliate marketing, etc. Additionally, it was established that offline touchpoints create gaps in the tracking of the journey, and actions to convert those interactions into online data points (such as email confirmation after phone calls for example) should be utilized to paint a more accurate and complete picture of the journey. The inner workings, strengths, and weaknesses of every channel were observed and their simultaneous usages of them proved efficient with the usage of the spillover effect. Also, it was established that journeys with multiple touchpoints depict interest from the consumer. Furthermore, other factors such as the frequency of ads were mentioned in relation to the carry-over effect.

Moreover, modeling of the customer journey was observed through different models to better understand each mental stage a customer goes through during their journeys. All the models had different compositions and stages, but they all agreed that the consumer goes through awareness phases, consideration phases, and action phases. It was also concluded that different channels affect the consumer differently depending on which phase he currently is in his journey.

Furthermore, multiple attribution models were dissected and the overall conclusion was that multi-touch attribution is considered more accurate since it accounts for various touchpoints. The attribution problem was explained and essentially boils down to transparency and the difficulty of attributing accurate weights to each ad on the consumer's final decisions. It was concluded that inadequate methods of attribution create flawed results and analysis which lead to poor budget distribution. In addition, the benefits of retargeting and personalization were shown, such as how they create a tailored experience for customers that leads to higher conversion rates. But the subsequent section mentioned incoming data issues due to the death of cookies that will change how targeting and retargeting are done in the future. Finally, alternative techniques such as first-party data or APIs were explored to prepare businesses in anticipation of the inevitable shift in third-party data.

Chapter 3: Methodology

3.1. Context

Due to the constant evolution of E-commerce, businesses now more than ever are eager to know how to maximize their marketing spending. For those companies, it is paramount to understand how your marketing investments work and which ones yield greater results. Every dollar needs to be maximized to its fullest potential. Thus, this study aims to add understanding to the subject, by comparing channels, touchpoints, and understanding the Omnichannel customer journey to a deeper level when it comes to the financial industry.

The following sections will try to address some of the limitations mentioned earlier in the literature review about the value of individual touchpoints. Although the task of finding the exact weight of every individual touchpoint in a journey is almost impossible with current methods, a different approach will be utilized to help fill this gap in knowledge. This approach will focus on the sequence of the different touchpoints in the journey. It was established earlier that different channels have different impacts depending on when and where in the journey the customer currently is. Multiple different sequences will be compared to try and find some optimal combinations, where channels can maximize their leverage as well as their impact on the customer's decision to convert.

After extended discussions with the financial institution explaining the purpose of this research and its benefits, they accepted the collaboration. A company computer was granted for the study, as well as the logins necessary to access all the data collection platforms needed for the analysis.

The financial institution in question is a bank, so it was mutually agreed upon that credit cards should be the product to focus on during the research and that the application form filled out would be the principal conversion metric to analyze. The main objective was to find data that was directly related to the conversion of credit cards. But this institution offers so many different credit cards implying a multitude of different forms that this needed to be limited as well. It was decided that the analysis's primary focus would be, but not limited to, forms called CCIA (Credit Card Instant Approval). Since credit cards need to be approved by verifying the customer's credit history, this form gets approved by a system instead of a human and is easier to track in the journey since the approval is instant. Lower than the financial industry average CR should be expected since this isn't an ordinary product and has some barriers to entry.

However, due to their massive dataset, the time frame couldn't exceed a couple of months since most platforms' have entry limits. A frame of 6 months was decided on, from November 1st, 2021 to April 30th, 2022. This thesis started in 2021, so at the time of the analysis, it was the most recent 6-month time frame that data was collected efficiently, subsequent to some new methods implemented by the financial institution considered more accurate.

3.2. Type of data

The type of data, in this case, was secondary data. Once access to their dataset was granted, the next step was figuring out where everything was located. Sifting through the different platforms to find the correct data was crucial for the analysis.

3.2.1. Data sources

Due to limitations from aggregating platforms, an estimate of the number of data entries needed to be fixed. In this case, due to the abundance of data offered by the institution, a number of around half a million data entries was set.

3.2.1.1 Beezwax

Beezwax is a platform that offers custom software for multiple purposes to businesses. The financial institution primarily utilized it for tracking campaigns accurately. Thus the data extracted from this platform was the campaigns about credit cards. What were the types of campaigns, their reach, the audience targeted, and their invested budget was observed, but for obvious reasons, the budget could not be shown in this thesis (Appendix 3a).

3.2.1.2. Facebook Ads

Obviously, the Facebook Ads platform was used to gather information about the paid social channel, more specifically which kind of social campaign and what was the targeted audience. Their ideal target audience includes; people with a university education, between the age of 21-49, living in Quebec, Toronto, or Vancouver. Additionally, their interests should ideally be focused on family activities, having a pet, practicing or showing interest in team sports, displaying interest in finance or the housing market, etc. All these interests and socio-demographic criteria are currently available options for targeted advertisements through social media platforms. Only advertisements concerning credit cards were taken into account.

3.2.1.3. Google Ads

Ads done through Google displayed important information about the keywords used and helped paint a cohesive picture of the search channel. A lot of information was found on search ads campaigns. but only the campaigns regarding credit cards were extracted and considered. This platform also helped paint a clear picture of their targeted audience. Additionally, the best keywords could be ranked and their CPC and CPM could be observed.

Google also has a section called campaign manager 360. This tool was used to differentiate the goals of each credit card campaign, most of them being consideration campaigns.

3.2.1.4. Adobe Analytics

This platform was the one primarily used by the bank for data collecting, thus it gave a lot of different types of information. Adobe Analytics also allows the creation of tables, graphs, and flow charts, which are useful visualization tools. But the data that was extracted was principally anything that had to do with conversion rates. Being so flexible, this platform permitted the extraction of data such as; the different types of channels, different device types, geolocalisation, language spoken, time zones, time spent on the platform, page visits, campaign types, audience, first visits, etc. This was the platform that allowed the most data extraction and a great level of precision for manipulation. Yet the dataset in there wasn't always perfectly categorized and needed to be cleaned.

3.3. Data extraction, cleaning, and aggregation

Data extraction consisted of taking the data from the previously mentioned platforms and transferring them either to Adobe Analytics or Power BI. Then the next step consisted of ensuring that the data taken from those different platforms could effectively be aggregated since some datasets offered “crooked” or insufficiently accurate data. In fact, lots of data entries coming from Adobe Analytics were classified as “unspecified or unavailable”. This was problematic since in some cases, the unspecified data was the most significant entry. Thus cleaning and specifications were in order, other alternative metrics or segments were selected to fill those gaps and in some cases, the “unspecified” entry needed to be ignored.

3.4. Final dataset

Finally, the data needed to be aggregated all in one place, in Power BI and Adobe Analytics. This process took several months of data gathering and back and forth with the financial institution to make sure they could maintain their anonymity. In the end, multiple charts were created on both platforms.

On Adobe, these tables ranged from; devices type, to the language spoken, worldwide localization, to differentiating old clients from new ones, etc. Furthermore, graphs and flowcharts were generated here to give a more visual picture of the customer journey and what it entails.

Power BI is a platform that allows massive datasets to be analyzed. Thus an entry of over 500 000 lines was created from every stack channel in the customer journey. This gave an incredible overview of each individual customer journey. Additionally, the journey could be classified by the order of channels visited or by conversion rates.

3.5. Data Analysis

Finally the analysis could be started. The crossover and spillover effects could be seen and dissected and will be analyzed separately. This analysis aims to observe different customer journeys with different combinations of channels and touchpoints and try to look at what affects each channel and compare different conversion rates. In this section, we are only looking at the completed forms as a conversion rate. This dataset includes a total of 518,764 individual visits from customers shopping for a credit card. It is important to note that different touchpoints don’t mean different channels, it is possible to have a multitude of touchpoints in the same channel (Anderl et al., 2015). The analysis of this section will be limited to data entries with a minimum of 50 visitors, data entries with less than 50 visitors will be left out. Some exceptions of unique and interesting results were still observed around 30 visitors when necessary. This was done to potentially recommend the institution of pushing those combinations further when great results were seen.

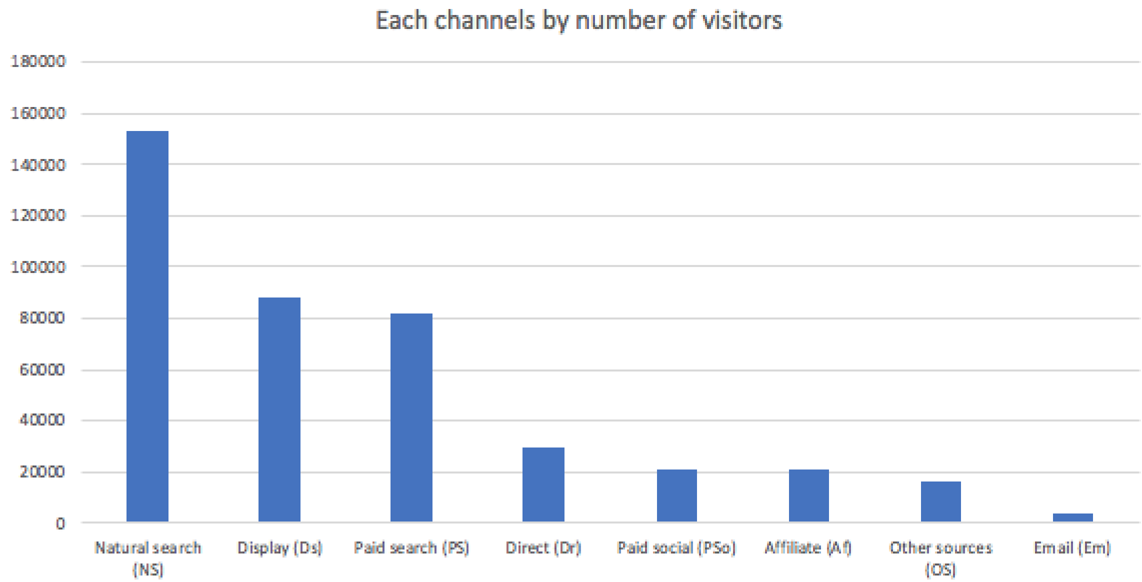
The second and last part of this analysis will consider data taken from the platform Adobe Analytics. This financial institution uses this platform to aggregate a multitude of other data coming from different platforms to have a more easy visualization of the results. In this section, it was possible to discern how many consumers coming from each individual channel were either loyal or new. Also, the type of devices, the pages viewed, the number of paged views, the average time spent on a page, and many more analyses were inspected. In this program, it was also possible to compare different attribution models and compare their results. Knowing that this specific bank used the attribution method “last click”, comparisons were useful to help determine if another method could yield more accurate results. This level of flexibility could only be possible on Adobe Analytics, compared to Power BI which can analyze more entries but offers less flexibility.

Chapter 4: Analysis section

4.1. Analysis from Power BI

When combining every single stack channel (from single ones to combined ones), an overall conversion rate of 3.53% was obtained, meaning a total of 18,313 forms were completed across all channels. The conversion rate in this analysis is credit card application forms completed divided by the number of visitors. Moreover, by separating the entries into their respective individual channels, it will be possible to observe and analyze which ones contributed more to the overall conversion. Furthermore, the carry-over and spillover effects will be evaluated separately to see which specific channels react more to each effect. This will give intel on which combinations are considered optimal for conversion. Additionally, each section will focus primarily (but not exclusively) on journeys starting with the channel analyzed. Moreover, the channels will be analyzed in ascending order of the number of visitors, the following graph gives an overview of every channel in that order. The visualizations such as graphs were generated in Excel for convenience.

1. Every individual channel ranked by the number of visitors



4.1.1. Natural Search (NS)

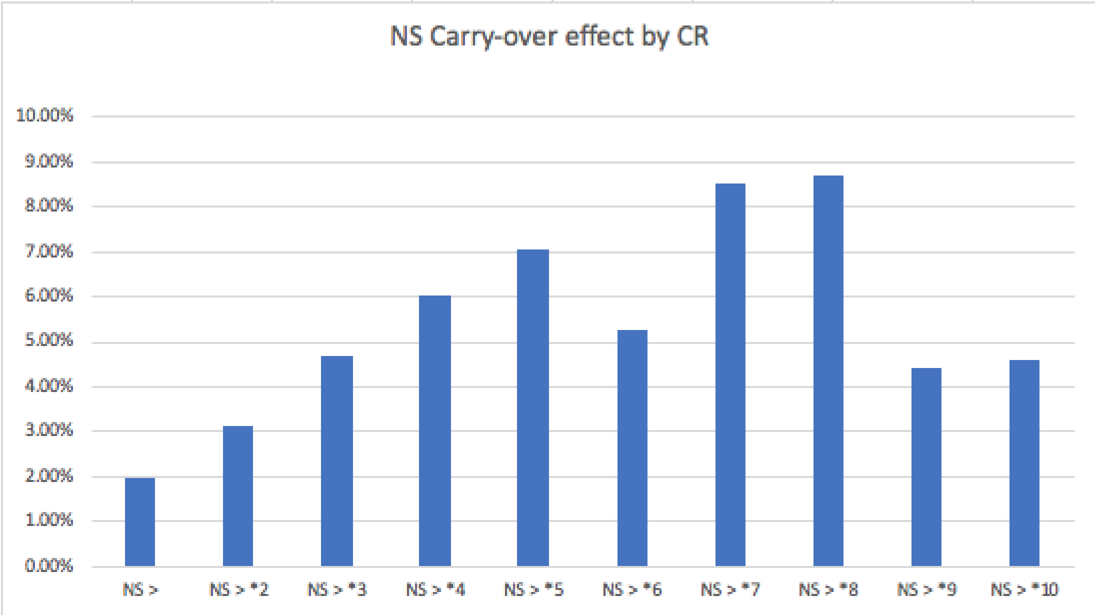
As seen in the previous graph, the first stack channel is “natural search” (NS) with 152 707 visitors, a conversion rate (CR) of 1,95%, and thus 2976 credit card application forms completed. Natural search is at the top of the charts (when comparing channels with a single touchpoint) which is usual since this institute has been established for a while and thus has acquired great notoriety over the years. When comparing the CR of natural search with the average CR of 3.53%, it is 1,58% under.

Furthermore, having a high number of natural search visitors is great, this implies that the business has great notoriety and that consumers are usually aware of its existence. This means that the financial institution receives a great number of visits daily at a “low cost”. Nevertheless, when it comes to the natural search channel, what also needs to be taken into consideration is that part of that traffic is actually clients looking for additional information about their existing purchases/accounts. By looking at the second analysis section done further in this thesis on Adobe Analytics, around 30,12% of customers coming through this channel are loyal customers. Loyal customers mean that they are already clients of this institution and thus probably less interested in conversion.

4.1.1.1. The Carry-over Effect

Starting with its definition, the carryover effect occurs when a customer visits the site again using the same channel (Anderl et al., 2015). In the following carry-over effect sections, when describing a channel that is combined with itself, it will be noted as “*X* > **y*”, *X* being the channel and *y* the number of touchpoints in that channel. Thus “NS > *3” signifies that the journey was composed of the natural channel three times in a row. The same nomenclature will be used for the carry-over effect of other channels with their respective abbreviations.

2. <u>How Natural Search's conversion rate is affected by the Carry-over effect</u>



This graph shows the conversion rate by stack channel of natural search. When observing this effect, natural search combined with itself once yields 3,14%, almost more than double the conversion rate than by itself. The carry-over effect shows a progressive growth over subsequent journeys until "NS > *6". At the 6th point, there seems to be an exception, a CR of 5.28% was observed which is 1,76% less than what was obtained at the 5th touchpoint (CR of 7,04%). Yet when looking at "NS > *7" as well as "NS > *8" even greater CRs are obtained with 8,53% and 8,70% over 211 and 138 visitors respectively.

When comparing all journeys composed of only the NS channel, from 1-10 touchpoints, the first "tipping" point is at the 6th point. But real diminishing returns are observed between the 7-8th touchpoints with an increase of only 0,17%. The diminishing returns continue to appear from 9-10 with a drop of -4,26%. This is the first example of this effect's limit; there is a threshold where substantial diminishing returns can be observed, it appears that this happens in natural search starting approximately at the 6th touchpoint, whereas the real tipping point happens at the 9th in this channel. Once the journey reached 9 touchpoints in the same natural search channel, the CR is 4,44%, which is less than the 3 touchpoints mark. Overall, the average CR across all-natural search carryover journeys (with over 50 visitors on this average) is 5,44% which shows that this effect works well in this channel.

4.1.1.2. The Spillover Effect

When looking at the spillover effect, meaning when a user visits the website again but through a different channel (Anderl et al., 2015), we can see that natural search is a great enabler.

3. The Spillover effect on journeys starting with Natural Search (with 2 touchpoints)

Journeys starting with NS	Nbr of touchpoints	Nbr of Visitors	CR	Nbr Form filled
NS > PS	2	8163	4.64%	379
NS > OS	2	623	5.46%	34
NS > Dr	2	697	4.88%	34
NS > Af	2	370	28.11%	104
NS > Ds	2	182	12.09%	22
NS > Em	2	104	2.88%	3

With only one additional touch point, the average conversion rate jumps to 9,68%. When observing commonly combined channels, “NS > PS” or the opposite “PS > NS”, CRs of 4,64% and 5,38% a great jump is noticeable, when considering that by itself NS had 1,95% CR. The most impressive combination in the spillover effect for two touchpoints remains “NS > Af” with an astounding 28,11% CR over 370 visitors.

4. The Spillover effect on journeys starting with Natural Search (with 3 touchpoints)

Journeys starting with NS	Nbr of touchpoints	Nbr of Visitors	CR	Nbr Form filled
NS > NS > PS	3	990	4.95%	49
NS > PS > NS	3	970	6.49%	63
NS > PS > PS	3	652	10.58%	69
NS > NS > OS	3	121	4.96%	6
NS > OS > NS	3	112	8.93%	10
NS > Dr > NS	3	96	10.42%	10
NS > NS > Dr	3	83	4.82%	4
NS > Af > NS	3	64	23.44%	15
NS > OS > OS	3	59	8.47%	5
NS > NS > Af	3	53	37.14%	20
NS > Af > PS	3	37	54.05%	20
NS > Af > Af	3	35	34.29%	12
NS > OS > PS	3	35	5.71%	2

More proof of the power of the spillover effect is depicted, for example when analyzing the different combinations of journeys starting NS and PS with 3 touchpoints, CRs range from 4,95%-10,58%. Overall, journeys with 3 touchpoints starting with NS have a CR of 16,48%. The highest result implies Affiliate marketing again with the journey “NS > Af > PS” yielding a CR of 54,05%. Though the number of visitors is low in this journey, a total of 37, it would be interesting to see this journey on a larger scale.

5. The Spillover effect on journeys starting with Natural Search (with 4 touchpoints)

Journeys starting with NS	Nbr of touchpoints	Nbr of Visitors	CR	Nbr Form filled
NS > NS > PS > NS	4	229	9.61%	22
NS > NS > NS > PS	4	221	11.31%	25
NS > PS > NS > NS	4	220	7.27%	16
NS > NS > PS > PS	4	127	16.54%	21
NS > PS > PS > NS	4	119	13.45%	16
NS > PS > PS > PS	4	106	12.26%	13
NS > PS > NS > PS	4	96	10.42%	10
NS > NS > OS > NS	4	34	5.88%	2

The efficiency of the spillover effect continues when digging deeper into customer journeys of 4 touchpoints. In every case, channels other than NS or PS are rare. When comparing the different orders of touchpoints in those journeys, the order with the highest CR of 16,54% was “NS>NS>PS>PS”. This showcases that the order matters since varying levels of success were obtained when the different sequences were observed varying from 7,27% to 16,54%.

6. The Spillover effect on journeys starting with Natural Search (with 5 and more touchpoints)

Journeys starting with NS	Nbr of touchpoints	Nbr of Visitors	CR	Nbr Form filled
NS > PS > NS > NS > NS	5	80	6.25%	5
NS > NS > NS > PS > NS	5	75	14.67%	11
NS > NS > NS > NS > PS	5	65	10.77%	7
NS > NS > PS > NS > NS	5	61	8.20%	5
NS > PS > NS > PS > NS	5	33	12.12%	4
NS > NS > PS > NS > PS	5	30	10%	3
NS > NS > PS > NS > NS > NS	6	38	10.53%	4
NS > NS > NS > NS > PS > NS	6	33	12.12%	4

Finally, the data get limited at this point, only combinations of NS and PS can be observed from journeys of 5 and 6 touchpoints. Yet by paying attention to different sequences, CRs vary from [6,25% -14,67%] for 5 points and [10,53%-12,12%] for 6 points. The sequences with the highest CR are “NS > NS > NS > PS > NS” and “NS > *4 > PS > NS”.

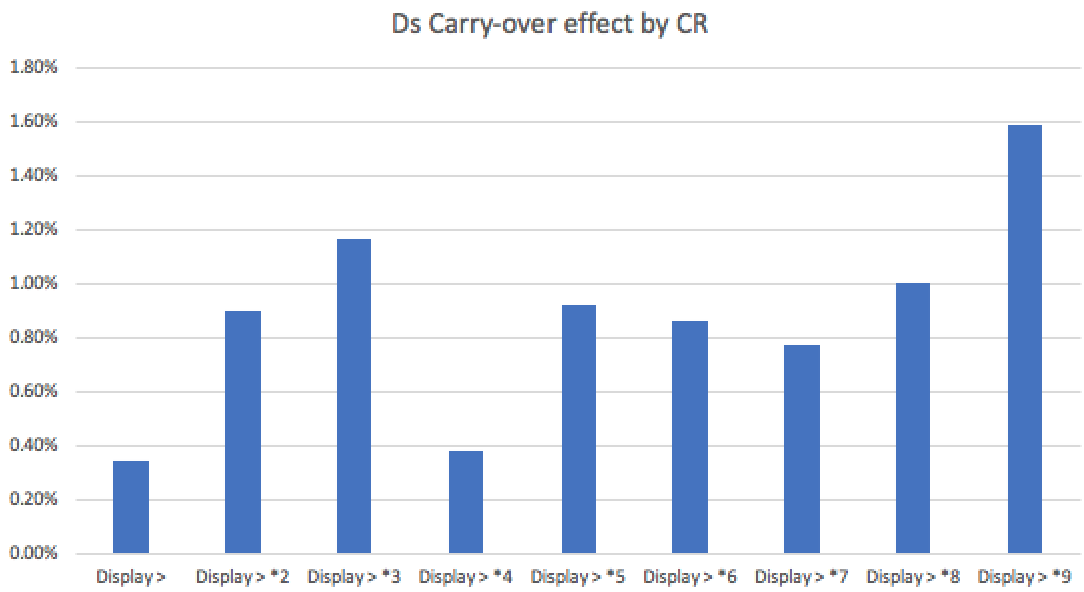
In short, the results found in NS are that the carry-over effect yields great results in this channel and that the tipping point of diminishing returns happens very late in the journey (at the 9th touchpoint). Additionally, the spillover effect showed that the NS channel is a great enabler and depicts great results of CR when combined with other channels, especially with Af.

4.1.2. Display advertising (Ds)

When comparing each channel by their number of visitors, the second place was attributed to display advertising. As mentioned prior, this channel’s advertisement can greatly vary in format, from banners, images, videos, and more (Indeed, 2021). With 88 051 visitors in 6 months, only 302 forms were completed in that period, meaning a CR of 0,34%. In the case of display advertising, it is expected to have low conversion rates, since its purpose is to create awareness. Starting by limiting the campaigns to the ones on the subject of credit cards, it was observed that all their campaigns from that platform are in the form of banners.

4.1.2.1. The Carry-over Effect

7. How Display's conversion rate is affected by the Carry-over effect



This analysis showed that the carryover effect in this channel isn't as efficient, it rapidly showed diminishing returns with each additional touchpoint. When observing the difference in CR from "Ds >" to "Ds > *2", a small increase of 0,56% was noted. The same scenario happened from 2 touchpoints to 3 with an increase of 0,27%. But the initial tipping point was rapidly obtained at the 4th touchpoint with a decrease of -0,79%. From there at the 5th and 6th touchpoints, CRs are considerably low considering that the customer has been targeted up to 6 times! In this case, the diminishing returns of this effect appear at the 4th touchpoint in the display channel. The conversion rate dropped significantly and after the 4th point, even though it slowly climbs back up, even at the 8th touchpoint its CR is 1% which is less than it was at the third point. Although this effect does work on this channel, it doesn't yield great effects. This ties in with the phenomenon called banner blindness, meaning over time consumers have learned to ignore those ads which renders the banner ads almost futile (Hollis, 2005). In fact, if you bombard the customer with similar ads the wear-out effect can emerge implying a negative effect on the customer's perspective.

4.1.2.2. The Spillover Effect

8. The Spillover effect on journeys starting with Display (with 2 touchpoints)

Journeys strating with Ds	Nbr of touchpoints	Nbr of Visitors	CR	Nbr Form filled
Ds > NS	2	183	6.56%	12
Ds > PS	2	124	14.52%	18
Ds > OS	2	100	10.00%	10
Ds > Dr	2	89	5.62%	5
Ds > Af	2	51	23.53%	12

As seen in the data, when consumers start their journey with display ads, they can come back through multiple different channels. Sadly in the data set, no journeys starting with display advertising over 30 visitors made it to 3 touchpoints. Thus by focusing on journeys with 2 touchpoints in this section, it is observable that the display channel is clearly a great enabler. When combined with any channel other than itself, CRs go from [2%-20%] over the average with just 2 touchpoints. Again, the strength of affiliate marketing is displayed in combination with display with the highest CR of 23,53%. As mentioned prior, the consumers targeted with display ads at the beginning of its journey will be more inclined to inform themselves about the business later. This was shown by the combination "Ds > NS" having the highest number of visitors from all the 2 points combinations.

In short, the results found in display advertising is that this channel doesn't yield great CRs since its main purpose is awareness. Additionally, the carry-over effect works with this form of advertising and shows diminishing returns at the 4th point, but the effect is still limited by the poor CR and doesn't increase the rate considerably. However, the spillover effect showed better results on this channel and confirms that display advertising is a great enabler when it is at the beginning of the customer journey. Great combinations include “Ds > PS” and “Ds > Af”.

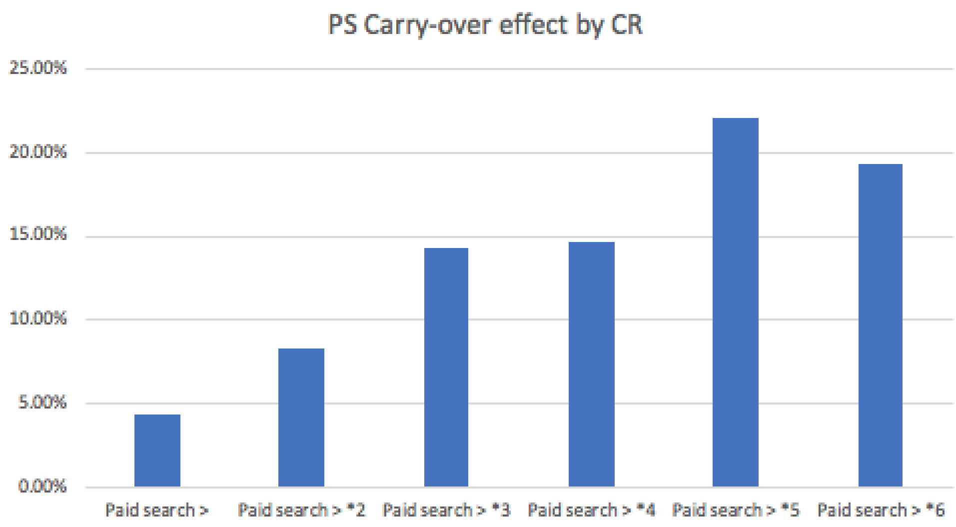
4.1.3. Paid Search (PS)

Third, by ascending order of visits, we have “paid search”. With 82 319 visitors and a 4,37% conversion rate. Over the 6 months period, 3600 credit card forms were completed. It is clear that this method yields great results since it is almost 1% over the average conversion rate of 3,53% with only a single touchpoint. It needs to be noted that further in this analysis, it was found that the amount of new customers in this channel is around 70,68%, meaning that 29,32% are already customers of this institution.

By looking through their Google Ads platform, it is possible to see which generic keywords and branded keywords were used. Then in Adobe Analytics, it was possible to observe which ones yielded the greatest amount of interaction and conversion. For the branded keywords, variations of their name and acronyms are in first positions, 1-8th (which can’t be shown for anonymity). But further down the list, generic keywords, like “direct brokerage”, “Canada immigration”, “mortgage calculator”, “retirement advisor”, “how to invest your money”, “travel insurance” and “mortgage rate” are yielding a great number of clicks in the hundreds of thousands.

4.1.3.1. The Carry-over Effect

9. How Paid Search’s conversion rate is affected by the Carry-over effect



When combined with itself, the conversion rate almost doubles from the first to the second point, and again from the second to the third. Little difference is noticed from the conversion rates perspective from the 3rd to the 4th touchpoint. However, a significant increase of 7,44% happens from the 4th to the 5th point. The journey of “PS > *5” seems to be the peak of the carry-over effect with a CR of 22,11%. It can be assumed that the customer keeps entering similar queries into the search engine until they're “educated enough” on the subject to decide if the product/ service is a fit for them. Yet the tipping point of diminishing returns is directly observed at the 6th point with a decrease of -2,81% in CR. Overall, the average CR across all paid search carryover journeys is 13,83%. This shows that this channel reacts well to this effect and also demonstrates the opportunity for retargeting.

4.1.3.2. The Spillover Effect

10. The Spillover effect on journeys starting with Paid Search (with 2 touchpoints)

Journeys starting with PS	Nbr of touchpoints	Nbr of Visitors	CR	Nbr Form filled
PS > NS	2	8145	5.38%	438
PS > OS	2	396	21.46%	85
PS > Af	2	258	24.03%	62
PS > Dr	2	225	15.11%	34
PS > Ds	2	137	6.57%	9
PS > PSo	2	66	18.18%	12
PS > Em	2	33	9.09%	3

When combined with additional different channels, the strength of the paid search channel can be observed. This channel interacts well with others and yields high CRs no matter the combination. Its lowest comes from the journey “PS > NS” with 5,38% CR over 8145 visitors and its highest reaches 24,03% when combined with Affiliate marketing.

11. The Spillover effect on journeys starting with Paid Search (with 3 touchpoints)

Journeys starting with PS	Nbr of touchpoints	Nbr of Visitors	CR	Nbr Form filled
PS > NS > NS	3	1002	5.59%	56
PS > PS > NS	3	612	9.15%	56
PS > NS > PS	3	652	9.36%	61
PS > PS > OS	3	55	27.27%	15
PS > OS > PS	3	53	16.98%	9
PS > NS > Af	3	37	56.76%	21
PS > OS > NS	3	36	5.56%	2
PS > Af > NS	3	33	18.18%	6

When moving to the 3 touchpoints journeys starting with paid search, multiple great combinations appear. Combined only with natural search, the rates vary from 5,59% to 9,36%, with the greatest sequence, in this case, being “PS > NS > PS”. Then when 3 different channels are in a single journey, rates vary immensely. Starting from the bottom in order of conversion rates, the sequence “PS > OS > NS” had the worst CR of all these 3 touchpoint journeys with 5,56%. Then it gets interesting when comparing the sequence “PS > Af > NS” and “PS > NS > Af” composed of the exact same channels but in a different order had a difference in CR of 38,58%. This is another concrete example of how much the order of the touchpoints matters. It appears that journeys ending with affiliate marketing yield amazing CRs. This statement will be further emphasized during this analysis by showcasing other examples.

12. The Spillover effect on journeys starting with Paid Search (with 4 or more touchpoints)

Journeys starting with PS	Nbr of touchpoints	Nbr of Visitors	CR	Nbr Form filled
PS > NS > NS > NS	4	194	5.15%	10
PS > NS > NS > PS	4	150	13.33%	20
PS > PS > NS > PS	4	133	6.02%	8
PS > PS > NS > NS	4	125	8%	10
PS > NS > PS > NS	4	115	9.57%	11
PS > NS > PS > PS	4	107	9.35%	10
PS > PS > PS > NS	4	105	7.62%	8
PS > NS > NS > NS > NS	5	56	12.50%	7
PS > NS > PS > NS > NS	5	37	5.41%	2
PS > PS > NS > NS > NS	5	35	11.43%	4
PS > PS > PS > PS > NS	5	32	15.63%	5
PS > NS > PS > PS > PS	5	32	12.50%	4

Journeys with 4 to 5 points starting with PS only included the NS channel. This is a bit of a shame since having more examples of different journeys would have been great to have in this dataset, but it gives the opportunity to focus on different combinations. When looking at the difference sequences starting with PS, a general thing to note is that journeys ending with NS usually tend to give lower CRs than the ones ending with PS. This is not always the case, but by calculating the average conversion rate in this table of the ones ending with NS, a CR of 9,41% compared to 10,30% ending with PS. This is only the case for journeys starting with paid search. But the same argument can be made when looking at every journey having 2-5 touchpoints. In every case, when the last touchpoint was NS, CRs were lower than journeys ending with PS. And when comparing their overall CRs from all journeys ending with NS, a CR of 9,88% was obtained compared to journeys ending in PS, with 14,27%. Arguments could be made that NS converts less overall than PS, but these results came from all kinds of different journeys with all kinds of combinations of channels in different orders. Either way, the best sequences for 4 touchpoints and 5 are “PS > NS > NS > PS” and “PS > NS > PS > PS > PS”.

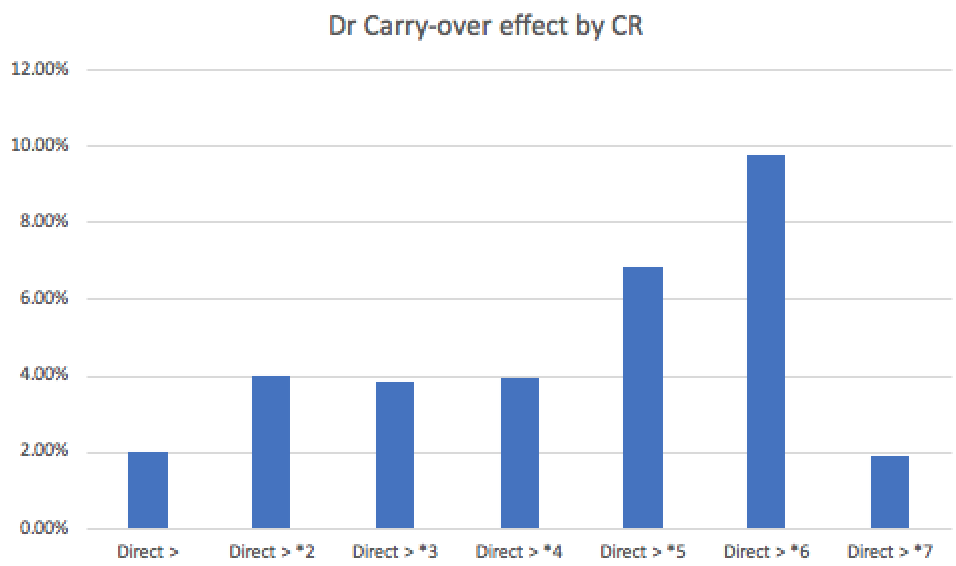
In short, the results found in paid search were that this channel is very powerful for conversion. In fact, it showed amazing results when combined with the carry-over effect by more than quadrupling its CR by the 5th touchpoint. From there diminishing results were observed. Additionally, this channel also works very well with the spillover effect, especially in combination with affiliate marketing. PS had a great range of sequences to analyze and demonstrate that the order of touchpoints matters greatly with wide CR ranges from [5,15% - 13,33%] with the same channels but in different orders. Overall, though this channel is expensive, it remains one of the strongest for conversions of credit cards.

4.1.4. Direct (Dr)

In this channel conversion rates aren't necessarily high since it is highly likely that this visitor is already a client. Further down in the adobe analysis section, it was established that 33,75% of visitors are already clients. But if the touchpoint made wasn't the first one, it could mean that this is not a recurring client that just decided to "take a shortcut". Nevertheless, this situation doesn't exclude the possibility of conversion, since conversions were clearly observed in this channel.

4.1.4.1. The Carry-over Effect

13. How Direct's conversion rate is affected by the Carry-over effect



In the direct channel, the CR doubles from the 1st touchpoint to the 2nd, then diminishing returns can be observed at the 3rd and 4th touchpoints. But when observing the 5th and 6th points the CR drastically increases with 6,86% and 9,76%

conversion rates respectively. But the real tipping point appeared at the 7th touchpoint, where the CR -7,87%. Overall, the average CR across all direct search carryover journeys is 4,62%. Which displays that the carry-over effect has potential in this channel.

4.1.4.2. The Spillover Effect

14. The Spillover effect on journeys starting with Direct (with 2 touchpoints)

Journeys starting with Dr	Nbr of touchpoints	Nbr of Visitors	CR	Nbr Form filled
Dr > NS	2	738	7.05%	52
Dr > PS	2	255	14.12%	36
Dr > Ds	2	97	15.46%	15
Dr > OS	2	94	5.32%	5
Dr > Af	2	74	50%	37
Dr > Em	2	31	3.23%	1

When looking at the spillover effect, when direct was combined with a different channel, for instance, natural or paid search, its conversion rate was greatly superior. The scenario is different when the direct channel is in second place in the journey for example “NS > Dr” (4,88% over 697 visitors) or with “PS > Dr” (15,11% over 225 visitors). In this case, these customers might not be recurring ones, for example, a person clicks on a listing coming from either a natural or a paid search, then afterward comes back directly and converts. Nonetheless, the highest 2 touchpoint combination was “Dr > Af” with a CR of 50%. This sequence shows yet again the power of the affiliate marketing channel.

In short, the results found in the Dr channel were that the carry-over effect is efficient, showing great CRs in this channel up to the 6th touchpoint. Additionally, this channel also reacts well to the spillover effect and does incredibly well in combination with the Af channel.

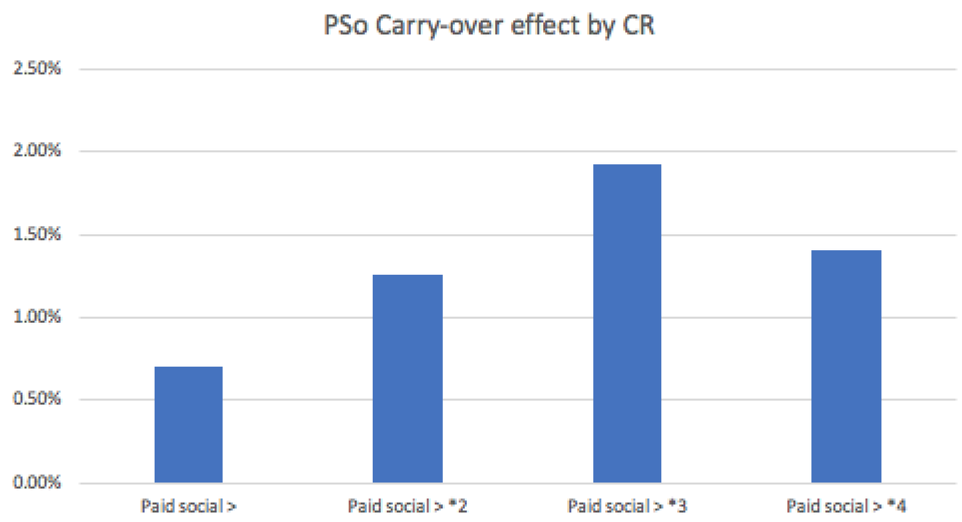
4.1.5. Paid Social (PSo)

In this data set, we can see paid social at the 5th position in terms of visits with 21 165 visitors, but with a 0,71% conversion rate. It is important to note that different social media campaigns are created for different purposes. In the dataset found of Facebook ads, almost every campaign was classified as consideration campaigns, which are not used for conversion. In the case of this financial institution, creating awareness is a crucial part of advertising credit cards. They need to explain to the customer why their credit cards are better a fit for their specific needs than the ones offered by their competitors. This implies a lot of education.

By digging into their different social media advertising platforms, it was observed that this particular financial institution, purely invests in this channel through Facebook, and no investment is placed on other platforms like Twitter, Tiktok, or even Instagram. This is not an optimal social media advertising strategy, since demographics differ from each platform.

4.1.5.1. The Carry-over Effect

15. How Paid Social's conversion rate is affected by the Carry-over effect



When observing the carry-over effect, the conversion rate almost doubles from 1 to 2 touchpoints, rising from 0,71% to 1,26%. The conversion rate keeps rising at the 3rd touchpoint with 1,93% over 259 visitors, but the tipping point of this effect seems to be at the 4th point. As the graph depicts, the CR dropped -0,52%, this drop might not seem big, but considering that CR for a single touchpoint was 0,71%, it remains substantial. The carry-over effect doesn't appear to be very powerful in this channel since the incremental increases were relatively small and the tipping point appeared early in the journey. Overall, the average CR across all paid social carryover journeys is 1.33%.

4.1.5.2. The Spillover Effect

Few data entries containing paid social media as the first touchpoint were included in the dataset. Thus it isn't really possible to evaluate the potential of this effect in this channel. One touchpoint of a journey starting with PSo was recorded and it was "PSo > PS" which yielded an amazing CR of 30,88% over 68 visitors. Another combination observed was "PS > PSo" with a CR of 18,18% over 66 visitors. Not much can be deduced from this section of the paid social channel analysis concerning this particular effect, but it seems that the sequence "PSo > PS" yields greater conversion rates.

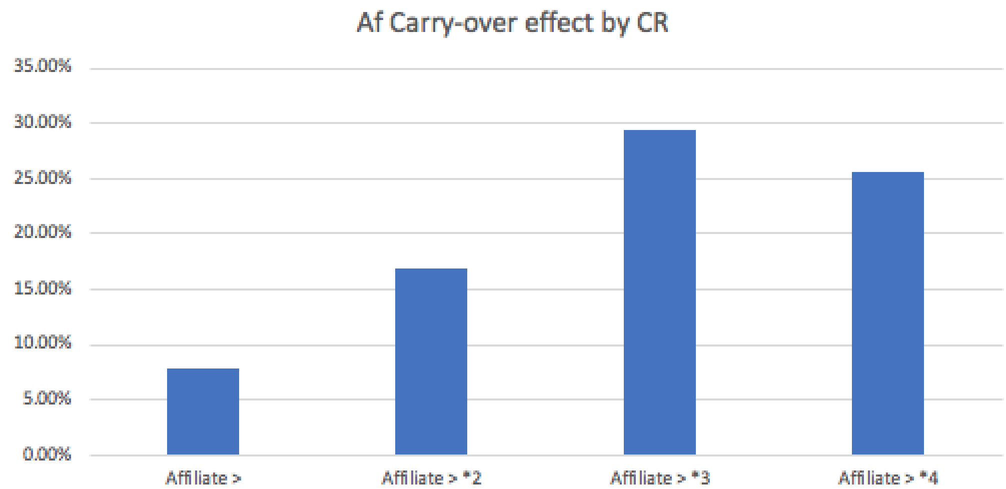
In short, the results found in PSo were that the carry-over effect barely had any influence on this channel. Additionally, due to a lack of data about this channel, no conclusion could be drawn from the spillover effect. However, it was observed that the financial institution only advertises on Facebook ads when it comes to social media advertising, but it was established earlier that they aim to target an audience ranging from [21-49] years old. This is slightly problematic since the average age range of users on Facebook is [25-34] (Bernhart, 2022), thus it would have been interesting to see data coming from different platforms to compare CRs.

4.1.6. Affiliate marketing (Af)

From what was observed from the dataset, the financial institution utilized the following aggregators for their affiliate marketing; Borrowell, Milesopedia, Ratehub, Weymedia, Fintel Connect, and Hardbacon. Additionally, the platforms such as Moving2Canada, MoneySense, and Immigrer.com are also affiliated partners. Overall, in Power BI, affiliate marketing was at the 6th position with 20 735 visitors with an outstanding base conversion rate of 7,75%, meaning 1 607 forms completed. The results of this channel are impressive since from one single touchpoint, it has more than double the average conversion rate of 3,53%. This reflects arguments made prior that people are more inclined to trust a business's product/service when the recommendation comes from someone else.

4.1.6.1. The Carry-over Effect

16. How Affiliate's conversion rate is affected by the Carry-over effect



We can definitely see the power of affiliate marketing when it comes to conversion in the database of this financial institute. By comparing the conversion rate of this single touchpoint channel, to other single touchpoint channels, Af is in first place with a 7,75% CR compared to PS with 4,37% in second place. Then when this channel is combined a second time with itself, it yields a CR of 16,88% over 1 528 visitors. This can be depicted as either the same source speaking of the business' products on two different occasions or two different sources speaking of the same product. From 2 to 3 touchpoints CR reaches 29,32% over 307 visitors. But diminishing returns were starting to be noticeable at the 4th point. When comparing it to the 3rd point, the 4th gave a CR of 25,53%, which is still a great rate, but -3,79% less than the previous point. Overall, even though diminishing returns were observed relatively quickly, the average CR across all affiliate carryover journeys is 19,87%, which still shows that this effect works well on this channel.

4.1.6.2. The Spillover Effect

17. The Spillover effect on journeys starting with Affiliate (with 2 or 3 touchpoints)

Journeys starting with Af	Nbr of touchpoints	Nbr of Visitors	CR	Nbr Form filled
Af > NS	2	420	25.48%	107
Af > PS	2	253	22.92%	58
Af > OS	2	169	68.64%	116
Af > Dr	2	86	45.35%	39
Af > Ds	2	54	24.07%	13
Af > Em	2	30	23.33%	7
Af > NS > NS	3	64	17.19%	11
Af > NS > Af	3	37	43.24%	16

Additional proof of the power of affiliate marketing can be observed in the financial institution's database when looking at the spillover effect. When looking at the table above, combinations of 2 touchpoints starting with Af have CR varying from 22,92% all the way to 68,64%. The highest conversion rate observed in all the datasets was found with the combination of "Af > OS" with a CR of 68,64% over 169 visitors. Moreover, when looking at 3 touchpoints journeys, the sequence "Af > NS > Af" gave the best results with a CR of 43,24%.

Regardless, when combined with an affiliate channel, pretty much any channel yields great CR results. The average CR of all journeys starting with affiliate marketing is 33,78%. This can be compared with journeys that include the Af channel as a touchpoint with an average CR of 38,90%. When combining both, meaning calculating the average of every journey that includes the Af channel, a CR of 36,07% is obtained, meaning that over a third of every customer that passes through this channel during their journeys end up converting.

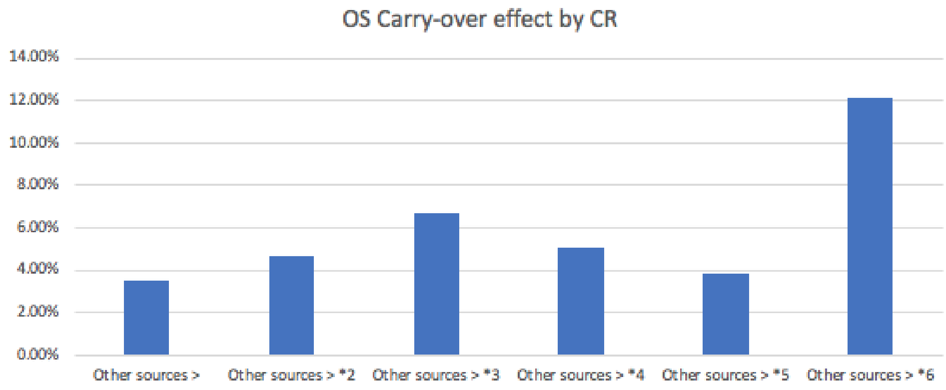
In short, the results found in affiliate marketing were positively surprising and showed the real power of this channel. For the carry-over effect, although diminishing returns were observed relatively quickly, amazing results were obtained with each additional touchpoint doubling the CRs up to the 4th point. However, the real surprise was when affiliate marketing was used with the spillover effect. In fact, this channel had the best conversion rates and showed amazing results when combined with any of them. This channel was only composed of aggregator websites, but it would be interesting to compare these results to influencer marketing. Overall this channel is undoubtedly the most powerful for conversion.

4.1.7. Other sources (OS)

Other sources is in the 7th position which isn't surprising considering that this category is composed of all the other channels that were either too small to calculate by themselves (small blogs referrer), or that couldn't be identified properly. However, "internal referrer" was also classified in this category. Sadly it is a bit of a tote as far as data collection goes in this institute. Better data classification needs to be considered and implemented in this channel to make more educated decisions and analyses in the future. The data shows us that for 16 012 visitors (560 forms completed), thus the CR is 3,5%, which is almost exactly the same as the average CR of 3,53%.

4.1.7.1. The Carry-over Effect

18. How Other Sources are affected by the Carry-over effect by Conversion rate



When observing the graph above, the carry-over effect shows some growth for journeys of 1 to 3 touchpoints. Starting with a base CR of 3,5% and reaching 6,65% at the third point. However, diminishing returns happen immediately at the 4th and 5th points with a decrease of -1,62% and -1,18% respectively. But the 6th point seems to be an exception with a CR of 12,12%. Overall, the average CR across all OS carryover journeys is 5,97%. This is abnormally high due to an anomaly at the 6th point with a CR of 12,12%, without taking this data point into account, the average CR would be closer to 4,73%. Overall the carry-over effect showed reasonable results but achieved a tipping point quickly. Regardless it is difficult to draw any concrete conclusion since its composition remains unclear. It would be interesting to be able to identify and compare every individual element that composes the OS to get a clearer understanding of these results.

4.1.7.2. The Spillover Effect

19. The Spillover effect on journeys starting with Other Sources (with 2 touchpoints)

Journeys starting with OS	Nbr of touchpoints	Nbr of Visitors	CR	Nbr Form filled
OS > NS	2	606	9.08%	55
OS > PS	2	366	30.33%	111
OS > Af	2	185	52.97%	98
OS > Ds	2	105	7.62%	8
OS > Dr	2	70	2.86%	2

Since "other sources" are composed of multiple different channels, results with different touch points vary greatly. This can be observed when taking the combination of “OS > NS” with a CR of 9,08% and comparing it to “OS > PS” with a CR of 30,33%. Regardless, the massive impact of affiliate marketing can again be noticed when combined with this channel, “OS > Af” with a CR of 52,97% over 185 visitors. This again shows the influence that the affiliate channel has over conversion rates.

20. The Spillover effect on journeys starting with Other Sources (with 3 touchpoints)

Journeys starting with OS	Nbr of touchpoints	Nbr of Visitors	CR	Nbr Form filled
OS > NS > NS	3	92	6.52%	6
OS > NS > OS	3	71	5.63%	4
OS > OS > NS	3	63	4.76%	3
OS > PS > PS	3	50	18%	9
OS > PS > NS	3	32	12.50%	4

When moving to 3 touchpoints journeys, conversion rates vary greatly ranging from 4,76% to 18% with the highest CR sequence being “OS > PS > PS”. As mentioned prior, having a better understanding of OS composition would be greatly helpful to draw any significant conclusions.

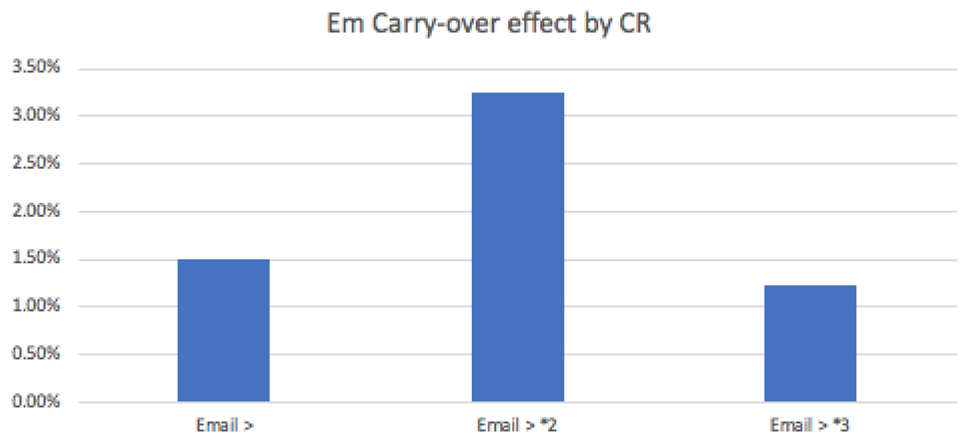
In short, the results found in the OS channel were inconclusive. Due to the murkiness of its composition, it was almost impossible to draw significant conclusions since the merits could not be awarded to a specific channel. Yet although its composition is unclear, this channel still showed that it could yield great CRs using the spillover effect in combination with affiliate marketing.

4.1.8. Email Marketing (Em)

Finally email marketing arrives in the last position when comparing the number of visitors brought from each individual channel. This can be surprising to some since email marketing is known to be a powerful and accessible tactic for most businesses due to its low costs and high response rates (Bostanshirin, 2014). However, low new visitors make sense since this channel is based on first-party data, meaning that consent has been given from clients to receive email. Thus this channel is not used for the acquisition of new clients, this would imply purchasing a third-party dataset of email and is not recommended. Overall, the email marketing channel yielded 3 410 visitors with a conversion rate of 1,50%.

4.1.8.1. The Carry-over Effect

21. How Email Marketing's conversion rate is affected by the Carry-over effect



From the first touchpoint to the second, the CR rate more than doubles, from 1,5% to 3,26%, and almost reaches the average CR of 3,53%. But when observing "Em > *3", there is an immediate diminishing return effect dropping from -2.04%. This appears to be the tipping point of this effect. This decline could potentially be associated with the frequency of emails sent monthly and could possibly be considered "spam" by the consumer. Overall, the average CR across all email carryover journeys is 1,99%.

4.1.8.2. The Spillover Effect

22. The Spillover effect on journeys starting with Email Marketing (with 2 touchpoints)

Journeys that include Em as a channel	Nbr of touchpoints	Nbr of Visitors	CR	Nbr Form filled
NS > Em	2	104	2.88%	3
PS > Em	2	33	9.09%	3
Dr > Em	2	31	3.23%	1
Af > Em	2	30	23.33%	7
Em > NS	2	96	1.04%	1

When observing the spillover effect in the dataset, a single example of journeys starting with email marketing can be observed. The sequence was “Em > NS” over 96 visitors achieving a CR of 1,04%. However, it is possible to observe spillover journeys that include Em as a channel. What is interesting to note is that the lower CR was obtained by the only journey that started with Em. Additionally, its greatest conversion rate was obtained when Em was combined with Af reaching 23,33% CR. Regardless, no concrete conclusions can be made in this section due to a lack of data including this channel in their journeys.

In short, the results found in email marketing were that this channel is barely utilized by this financial institution. Additionally, the carry-over effect did not react positively with this channel and the reason could potentially be associated with spam emails. Furthermore, the spillover effect didn’t have much data on journeys starting with Em thus no concrete conclusions could be made. However, this channel was still sometimes included in other journeys and displayed good CRs in combination with PS and Af. It would be interesting to see this channel more in action since it is considered a powerful advertising technique by most researchers.

4.1.9. Summary of the analysis made on Power BI

It was confirmed that every single channel has strengths and weaknesses, this analysis was primarily focused on the conversion rates of each for credit card applications of this specific financial institution.

In this section of the analysis, it was easier to compare single-channel journeys or journeys with multiple touchpoints in the same channel. Yet what is more interesting is seeing them interact and potentiate each other. It is possible to notice a trend in this case, that multiple touchpoints yield higher conversion rates, this can be explained by the fact that if a consumer is mildly interested in the service/product, (s)he will venture through the customer journey gathering additional information from different sources to make a more educated purchase.

First of all, every channel had relatively positive reactions to the carry-over effect with varying degrees of success. Some achieved diminishing returns and tipping points earlier than others, but overall, positive incremental increases up to that point were recorded for every channel. The latest tipping point appeared in the natural search channel at the 9th touchpoint and the soonest was in the email marketing channel at the 3rd. These tipping points show that this effect has its limits, but also that at a certain point, customers get tired of a journey composed of the same touchpoints. This is called the wear-out effect, it implies feelings of boredom and redundancy from the customer. This can be avoided by creating different and creative advertisements in the same channel or by diversifying advertising spending through multiple channels. It was established prior that the deeper a customer ventures in a journey, the higher its interest is in what the business is offering. This was confirmed by every channel showing a superior average with the carry-over effect compared to single touchpoint journeys.

The spillover effect demonstrated great results for conversion across every channel. When observing the overall CR averages of spillover journeys from 2-6 touchpoints, results from 2 touchpoints journeys are “skewed” due to the unbelievable conversion rate of journeys including affiliate marketing. The affiliate channel rarely made it to 3 touchpoint journeys and not even once in 4-6 touchpoint journeys. So to make an even comparison of averages of each different journey, affiliate marketing data were omitted for this specific section only. The average conversion rate of the journeys is as follows: 2 points (8,09%), 3 points (7,09%), 4 points (9,72%), 5 points (10,86%), and 6 points (11,33%). Though these results were “tampered with”, it can be observed that there is indeed a noticeable incremental increase with each additional touchpoint. It would have been optimal to have touchpoints of the affiliate channel in journeys of 4-6 points to have an even comparison, their CRs were so high that 2 touchpoints journeys averaged 17,42% on their own. This proves once and for all that this channel yields amazing conversion rates and should be invested in more than it currently is.

When comparing both effects, the average CR of carry-over journeys was around 6,21% compared to the spillover journeys averaging 14,96%. To assure that the conversion rate stays as high with the impending death of the cookies, new targeting techniques will need to be implemented as soon as possible.

4.2. Analysis from dataset made on Adobe Analytics

In this analysis section made on Adobe Analytics, the conversion metric will be the amounts of credit card forms launched. The forms analyzed are CCIA forms (Credit card instant approval) for easier data tracking, but there is something the financial institution refers to as “the gray zone”. This is either when the program that approves the credit card is uncertain about the approval (and a human need to double check) or when a customer starts a form online but then decides to finish on the phone or in person. This gray zone is small and is estimated at around 5% of cases, yet this is something to note when observing the results found in some cases.

4.2.1. What percentage of visits are actually new clients?

In Adobe Analytics, when looking at the total number of unique visitors coming from all the channels, a total of 546,842 is obtained in the 6-month time frame (Appendix 4a). From there, by adding an additional segment called “SBIP2 logged in (visitor)”, it will display the total number of visits coming from customers who logged in, in this case, 137 498. Then to verify this data, another column is added with the same segment but this time being excluded and 409 344 is obtained. Though this might not be 100% accurate, since some visitors could be clients that didn’t log in, it gives a great approximation.

The columns mentioned prior were then split into each individual marketing channel. But the three that stood out were natural search, paid search, and direct. In the natural search channel, a total of 253 541 visits were obtained, but 93 601 were already logged-in customers. This means that around 36,91% of all customers coming through the natural channel are already loyal customers who have accounts with this financial institution. When moving over to paid search, this channel had a total of 121 062 unique visitors, and out of that number, 35 501 (29,32%) were already logged in. The direct channel wasn't so surprising, since it is to be expected that a good portion of customers who have URLs memorized or bookmarked aren't new clients. Regardless it was found that 33,75% of clients in this channel were already clients of this institution. This table shows us that on average, considering all channels combined, 25,14% of all unique visitors are already clients. The caveat is that this table doesn't include app users since those aren't tracked in Adobe Analytics.

4.2.2. Credit card conversions by device type

23. Visits in the credit card section by device type by form submitted (conversion)

	Visits in credit card section	Credit-Card Form: Launch (e109)	% form launch	CCIA: Form Submit
Mobile Device Type Page: 1 / 2 › Rows: 5 1-5 of 8	Nov 1 715,865 out of 715,865	34,513 out of 34,513	Nov 1 4.82% out of 4.82%	Nov 1 22,535 out of 22,535
1. Mobile Phone	369,261 51.6%	22,580 65.4%	6.11%	12,708 56.4%
2. Other	302,157 42.2%	10,539 30.5%	3.49%	9,120 40.5%
3. Tablet	44,079 6.2%	1,377 4.0%	3.12%	697 3.1%

In this panel, the focus was to observe if there was a drastic difference in the number of forms completed on different devices, and if so, which one converts the most. The data was taken from the metric "visits in credit card section" and gives us a total of visits across all devices 715 865. Effectively, across all visits, 369 261 (meaning more than half, 51,6%) came from mobile devices. Afterward, with 42,2% (302 157 visits), the dimension called "other" was observed. This dimension is a combination of computers running with IOS or Windows. Finally, tablets had 44 079 or 6,2% of visits.

From there, the number of credit cards from launch was 34 513. Mobile phones had the highest number of launches with 65,4% of that number, followed by computers with 30,5% and tablets with 4%. This is surprising since filling up those forms is a commitment and not something that would typically be done on your phone. Regardless, the CRs were 6,11% for mobile users, 3,49% for computers, and 3,12% for tablets.

But by digging deeper and looking at the amounts of forms that were completed, it is possible to observe that out of the 22 580 forms started on mobile, only 12 708 were completed. This means that only 43,72% of those forms were abandoned. Contrary to the data found on computers where 86,53% of the forms launched were completed. Overall, the conversion rate of forms started is higher on mobile, but proportionally, the amount of forms completed and submitted is higher on computers. The reasoning behind that is clients start the forms on mobile and assume that it will be a quick procedure, then give up and delay the task for another time. Contrary to the ratio of forms submitted on a computer, where customers tend to finish the submission more often. But by looking at the forms submitted, the mobile user ratio resembles more 3,44% and computer users 3,01%. In general, mobile users convert more than the other category, but the difference is less significant when considering the proportion of forms abandoned midway by mobile users. It can be concluded that the device used for credit card forms have drastic differences when it comes to conversion.

4.2.3. What is the proportion of branded keywords vs generic keywords in paid search?

24. Branded keywords compared to generic keywords by visits and form submitted (conversion)

	Visits in credit card section	Credit-Card Form: Launch (e109)	CCIA: Form Submit
Marketing Channel Page: < 2 / 12 > Rows: 1 2-2 of 12	Nov 1 ↓ 715,865 out of 715,865	Nov 1 34,513 out of 34,513	Nov 1 22,535 out of 22,535
2. Paid Search	148,597 20.8%	11,344 32.9%	5,736 25.5%
Segments Page: 1 / 1 Rows: 5 1-2 of 2	Nov 1 Apr 30 ↓ 148,306	Nov 1 Apr 30 11,204	Nov 1 Apr 30 5,619
Paid Search 1. Branded only	93,916 63.3%	3,737 33.4%	2,476 44.1%
Paid Search 2. Generic only	54,390 36.7%	7,467 66.6%	3,143 55.9%

During this thesis, it was established that keywords could be categorized into two categories that yield different rates of engagement and can vary greatly in bid prices. This section of the analysis focuses on observing what proportion of visits in the credit card section is brought by each category of keywords. Branded keywords are less expensive, and have a significantly higher click-through rate, but bring visitors that are already aware of your business. This is reflected in the table above when observing that this type of keyword brought 63,3% of all visits in the credit card section, but only 3,97% of those visits started a form, with 66,25% of those forms being submitted.

Then when observing the total number of visits coming through the PS channel, a sum of 148 597, approximately a third of them, 36,7%, was generated by generic keywords. But conversion rates coming from generic queries bring way higher CRs, out of those 54 390 visits, 7 467 of them (or 13,7%) started a credit card form with 42,09% of them being submitted. Although these keywords are more expensive due to higher competition for the bidding process, and even though they brought just over half the traffic of branded keywords, they still achieved triple the amount of form started than their counterpart.

4.2.4. Comparing single-channel attribution & multi-touch attribution across marketing channels

4.2.4.1. Comparing LT & FT across marketing channels

In this section, the difference between first touch and last touch will be observed (Appendix 5a). This particular financial institution utilizes the last touch model to analyze its data and draw conclusions. This is to be expected since 83% of businesses use simple attribution methods. By breaking down the last touch attribution channels with the first touch dimension, it is possible to observe how these two channels offer different results based on the same conversions. This is an important thing to note because, in the long run, these results will reflect how the business will distribute its marketing budgets between each channel.

When observing the data, 32 513 credit card forms were launched. Both attribution methods rank PS as their first channel, but last touch (LT) attributes 11 344 forms to this channel compared to first touch (FT) 10 393, meaning a difference of 941 forms. Then, the next channel in both attributions is NS, with LT attributing 9 131 forms to this channel, compared to FT with 8 866. Affiliate marketing is in third for both methods with LT attributing 7 380 and FT 6 461. Then for LT the 4th channel is display with 1 815 while FT ranks the direct channel at this spot with 3 078. Afterward, LT's 5th is direct with 1 792, and NS's 5th is display with it 5th with 1 718. The differences continue to appear between both attribution methods since they both rank PSo and OS differently and so on.

In this comparison, it is clear that both methods attribute merits totally differently, even though they both give 100% of the credit to a single touchpoint. Though it has been established all along this research that each touchpoint represents a certain amount of weight toward the end conversion. This has confirmed that even if these attribution methods are similar, results change drastically, on a greater scale, these relatively small differences in each channel can drastically alter the investment choices the institution will make in the future.

4.2.4.2. Comparing LT, FT, linear, participation, U shape, J & inverse J across marketing channels

25. Comparison of attribution methods including: LT, FT, Linear, Participation, U-shape, J & inverse J across different marketing channels

Page: 1 / 2 > F	Credit-Card Form: Launch (e109) Last Touch | Visit out of 34,513		Credit-Card Form: Launch (e109) First Touch | Visit out of 34,513		Credit-Card Form: Launch (e109) Linear | Visit out of 34,513		Credit-Card Form: Launch (e109) Participation | Visit out of 34,513		Credit-Card Form: Launch (e109) U Shaped | Visit out of 34,513		Credit-Card Form: Launch (e109) J Curve | Visit out of 34,513		Credit-Card Form: Launch (e109) Inverse J | Visit out of 34,513	
1. Paid Search	11,072	34.1%	10,849	33.5%	10,980	33.9%	11,483	35.4%	10,970	33.8%	11,025	34.0%	10,916	33.7%
2. Natural S...	8,149	25.1%	8,117	25.0%	8,115	25.0%	8,652	26.7%	8,124	25.1%	8,135	25.1%	8,113	25.0%
3. Affiliates	7,229	22.3%	6,738	20.8%	6,990	21.6%	7,299	22.5%	6,987	21.5%	7,105	21.9%	6,869	21.2%
4. Display	1,736	5.4%	1,676	5.2%	1,705	5.3%	1,754	5.4%	1,706	5.3%	1,721	5.3%	1,691	5.2%
5. Direct	1,455	4.5%	1,733	5.3%	1,592	4.9%	1,733	5.3%	1,593	4.9%	1,524	4.7%	1,662	5.1%
6. Other so...	903	2.8%	1,387	4.3%	1,140	3.5%	1,387	4.3%	1,143	3.5%	1,023	3.2%	1,263	3.9%
7. Internal R...	831	2.6%	900	2.8%	864	2.7%	900	2.8%	865	2.7%	848	2.6%	882	2.7%
8. Paid Soci...	687	2.1%	663	2.0%	674	2.1%	693	2.1%	674	2.1%	680	2.1%	668	2.1%
9. Email	293	0.9%	274	0.8%	284	0.9%	306	0.9%	284	0.9%	288	0.9%	279	0.9%
10. Organic ...	70	0.2%	86	0.3%	80	0.2%	98	0.3%	79	0.2%	75	0.2%	83	0.3%

Due to Adobe Analytics' limitations, not every attribution method could be compared. This section of the analysis will not go over every single difference between every channel since it was proven with the comparison of LT & FT that there are some differences in attribution even with similar methods. Furthermore, every attribution method has its advantages and disadvantages and is utilized for different objectives and purposes.

This section will instead go over similarities between their current single-touch attribution method (LT), and different multi-touch methods. Doing so, it will allow for a recommendation of a multi-touch attribution method aligned with their current objectives. As established prior, single-touch attribution omits multiple crucial touchpoints during the customer journey, thus by finding a multi-touch attribution similar to their current one, more information will then be processed by their platforms during its analysis phase. Currently, the financial institution utilizes LT attribution because they attribute more value to search engine advertising and touchpoints happening toward the end of the conversion funnel. This can be assumed since otherwise, they would have used FT instead since this method also attributes 100% but prioritizes the beginning of the funnel and other methods of advertising.

By observing the table above, the multi-touch method with the most resemblance to the results found in LT is the J curve. When comparing the individual channels, almost the exact same attribution was given from both models through 8 channels. Out of these 8 channels, 5 had the same attribution, and the 3 other channels were PS, Ds, and Dr with differences between [0,01%-0,02%]. This makes sense since the J-shaped curve values points considered closers over finders and give most of its attribution to the last touch.

4.2.5. What is done in the credit card section before and during the form launch of credit cards?

In this part, metrics such as the number of visits, the average time per session, page views per visit, and credit card form launch will be observed through different dimensions. The following tables are made possible due to the addition of two custom segments called “e109 exists” (the nomenclature for this credit card form in Adobe) and another called “only before form launch” which only allows journeys that include a credit card form application to be analyzed just before the conversion. These additions will thus isolate the moment right before customers fill up credit card application forms. Then the tables will sometimes also be compared with the same dimensions and metrics, but without the “only before form launch” segment to be able to uncover CR.

4.2.5.1. Before and during the form launch per page types

26. Comparing the difference between before & during the form launch by page types

	DW - Site info - Credit card pages (hits)								
	Only before form launch								
	Visits		Avg. Time per Session	Avg. Time on Page	Page views per visit	Credit-Card Form: Launch (e109)	
Pages: Page Name T Page: 1 / 1 Rows: 10	27,991 out of 32,453		00:01:41 out of 00:01:42	00:01:11 out of 00:01:13	1.43 out of 1.41	0 out of 0	
1. Hub	12,143	43.4%	00:01:20	00:01:10	1.14	0	0.0%
2. Product	11,602	41.4%	00:01:30	00:01:04	1.40	0	0.0%
3. Promo	5,776	20.6%	00:01:32	00:01:24	1.09	0	0.0%
4. Category	2,158	7.7%	00:01:41	00:01:14	1.36	0	0.0%
5. Advantages	553	2.0%	00:02:22	00:01:48	1.31	0	0.0%

By looking at the pages in ascending order, Hub (the landing page) and Product are close with 37,41% and 35,75%% respectively for the total number of visits, followed by promo with 17,79%. Prior to filling up the form, customers stay on average 1:10 minutes on this page and visit around 1,14 additional pages. The number of additional pages is surprisingly low since it would be logical that from that page, the client would gather additional information. But there is a call to action “discover our cards” directed at the top of the Hub that brings you to the promotion page where you can pick a credit card, which is a good CTA placement on their part. Moreover, it was observed that the product page and the category page had the highest page views per visit at 1,40 and 1,36 respectively. This is explained by the customer navigating the different options available. Finally, the page with the highest average time on page was the advantage, since this page displays loads of different benefits with long descriptions. These low average time spent and page viewed rates are positive things because it signifies that customers fill up the forms rapidly due to CTA strategically placed on every page. CTAs range from “discover our cards”, “discover the offer” and “apply now”.

When taking out the segment “before launch”, it is then possible to observe how many credit card forms we launched on each different page (Appendix 6a). In this case, unsurprisingly, Product and Hub are at the top with 38,2%, and 37,8% of all visitors who went on credit card pages filled up a form! This is a great number since it shows that over a third of people interested in credit cards decide to trust and make a deal with this bank for credit cards.

4.2.5.2. Before and during the form launch per device types

In this section, three device types are being compared, mobile, other (computers running with IOS or Windows), and tablet (Appendix 7a). When comparing the number of visits, mobile is in first place with 67,1%, followed by other with 28,72%, and tablet with 4,11%. The device types were then broken down per pages visited, both mobile and tablet had the Hub first and product second and computers had the opposite.

Furthermore, computers had a greater average of page views per visit as well as a higher average time spent per session. This was explained previously by the ratio of forms launched compared to forms submitted on mobile. Customers using computers complete the whole journey more often than mobile users, thus equaling more time spent per session and more pages visited.

When removing the “only before launch” segment, each device had the highest conversion rates on its respective most visited pages (Appendix 8a). But what was surprising is how much more forms were filled out on mobile compared to computers. Mobile had a rate of 66,9% of forms launched as opposed to computers with 28,9% and tablets with 4,1%. Such high conversion rates on mobile just go to show how well-adapted their website is for mobiles. Yet when looking at the number of forms submitted mobile and tablet users had around 30% compared to 66,3% on computers. Thus mobile users must underestimate the task of filling up a form and over 70% of them give up.

4.2.5.3. Before and during form launch per channel

When dividing each channel individually, it is possible to get insight into which pages they primarily land on (Appendix 9a). PS and NS have hubs as their most visited, probably since those channels come from search engines, which can include all kinds of different search queries. However, every other channel has the product page as its most visited. Each channel had an average page viewed per visit ranging from 1,25 with the direct channel, all the way up to 1,60 with Natural search. When it came to time spent per session, results ranged from 1:23 min with affiliate marketing all the way to 2:03 for natural search.

27. Comparing the difference between before & during the form launch by channel types p.1

	DW - Site info - Credit card pages (hits)				
	Visits	Avg. Time per Session	Page views per visit	Credit-Card Form: Launch (e109)	CCIA: Form Submit
Last Touch Channel Page: 1 / 2 › Rows: 10 1-10 of 12	656,421 out of 656,421	00:01:49 out of 00:01:49	1.68 out of 1.68	32,844 out of 32,844	2,509 out of 2,509
1. Paid Search	145,848 22.2%	00:02:05	1.71	11,256 34.3%	698 27.8%
Paid Search — Pages: Page Name Type (v5) Page: ‹ 2 / 5 › Rows: 1 2-2 (	120,831 out of 145,848	00:02:09 out of 00:02:05	1.78 out of 1.71	9,377 out of 11,256	567 out of 698
2. Hub	50,681 41.9%	00:01:28	1.25	5,355 57.1%	237 41.8%
2. Natural Search	278,614 42.4%	00:02:14	1.86	8,075 24.6%	1,016 40.5%
Natural Sea... — Pages: Page Name Type (v5) Page: 1 / 7 › Rows: 1 1-1 of 7	278,614 out of 278,614	00:02:13 out of 00:02:14	1.86 out of 1.86	8,075 out of 8,075	1,016 out of 1,016
1. Product	110,615 39.7%	00:02:19	1.80	1,983 24.6%	407 40.1%

When observing the results without the “only before launch” segment, 32 844 forms were launched. From that number, PS had the most launches with 34,3% and 57,1% of those came from the landing page. Then 24,6% of the form launches were attributed to NS and out of those 48,7% came from the hub.

28. Comparing the difference between before & during the form launch by channel types p.2

	Visits	Avg. Time per Session	Page views per visit	Credit-Card Form: Launch (e109)	CCIA: Form Submit
3. Affiliates	31,348 4.8%	00:01:29	1.47	7,373 22.4%	509 20.3%
Affiliates — Pages: Page Name Type (v5) Page: 1 / 5 › Rows: 1 1-1 of 5	20,248 out of 31,348	00:01:36 out of 00:01:29	1.61 out of 1.47	5,557 out of 7,373	286 out of 509
1. Product	18,924 93.5%	00:01:22	1.43	5,206 93.7%	262 91.6%
Product — Campaign Source Page: 1 / 7 › Rows: 5 1-5	18,924 out of 18,924	00:01:21 out of 00:01:22	1.43 out of 1.43	5,206 out of 5,206	262 out of 262
1. Borrowell	10,575 55.9%	00:01:06	1.43	2,864 55.0%	127 48.5%
2. Ratehub.ca	3,034 16.0%	00:01:26	1.37	642 12.3%	34 13.0%
3. Mastercard	1,170 6.2%	00:01:34	1.36	426 8.2%	26 9.9%
4. Milesopedia	901 4.8%	00:02:11	1.45	160 3.1%	17 6.5%
5. Fintel	888 4.7%	00:02:02	1.57	212 4.1%	24 9.2%

Affiliate came closely in third with 22,4% and 93,7% came from the product page. This rate was surprisingly high so the product page was broken down by the campaign source. This is due to affiliate links all landing customers to the same page for easier tracking (for the payments due), and contrary to other channels where different ad formats can carry the customer to different pages. When breaking down the product page for customers coming through the affiliate channel by the campaign source, it was revealed that over 55% of those customers came from Borrowell-sponsored links. Borrowell is a company that gives free credit scores and reports. This showcases the power of targeting the right affiliate partners which have an audience curated to the right niche.

29. Comparing the difference between before & during the form launch by channel types p.3

	DW - Site info - Credit card pages (hits)				
	Visits	Avg. Time per Session	Page views per visit	Credit-Card Form: Launch (e109)	CCIA: Form Submit
3. Display	126,505 19.3%	00:00:38	1.18	1,808 5.5%	73 2.9%
Pages: Page Name Type (v5) Page: 1 / 5 › Rows: 1 1-1 of 5	102,689 out of 126,505	00:00:41 out of 00:00:38	1.20 out of 1.18	1,165 out of 1,808	No 43 out of 73
Display – 1. Product	67,083 65.3%	00:00:50	1.21	582 50.0%	25 58.1%
Device Type (v197) Page: 1 / 3 › Rows: 1 1-1	67,083 out of 67,083	00:00:50 out of 00:00:50	1.21 out of 1.21	582 out of 582	No 25 out of 25
Product – 1. Mobile/Tablet	49,549 73.9%	00:00:56	1.20	457 78.5%	8 32.0%
Campaign Source Page: 1 / 43 › Rows:	49,095 out of 49,549	00:00:56 out of 00:00:56	1.20 out of 1.20	345 out of 457	Nov 6 out of 8
Mobile/Tablet – 1. Youtube	19,470 39.7%	00:01:36	1.28	166 48.1%	0 0.0%
Creative Format Page: 1 / 1 Rows: 5	19,470 out of 19,470	00:01:36 out of 00:01:36	1.28 out of 1.28	166 out of 166	Nov 0 out of 0
Youtube – 1. Pre Roll 15 Sec	19,470 100.0%	00:01:36	1.28	166 100.0%	0 0.0%

When moving over to the display channel, half of the 5,5% contributed to the forms filled came from the product page. When digging deeper and breaking down the most visited page from display by mobile devices, 73,9% of those forms were filled on mobile, and tablets. Moreover, when breaking it down even further by campaign source, over 48,1% of the customers who took that path came from YouTube. Finally, when breaking down the campaign source by type of creative format, it was revealed that 100% of them were pre-roll 15 seconds videos. This isn't surprising since as established prior in this thesis when it comes to display ads, video formats are more effective since they are way harder to ignore.

Furthermore,15-20 seconds ads on YouTube are not skippable (Rose, 2022) and due to short attention spans, a 15-20 seconds video is the perfect amount of time to grab the attention of customers. Additionally, by targeting videos related to the topic of finance, the audience is already interested in the subject and thus is more likely to be interested in the products offered by this financial institution. When looking at the conversion rate of forms filled in this channel, 1,13% was obtained. This is a massive difference when compared to the Ds channel in the first section which was composed of banner ads and only yielded 0,34%, this is exactly 3 times higher.

This is the best example of conversion found in the data given by this financial institution for display advertising. This solidifies and proves prior concepts touched on in this research like the ineffectiveness of banners due to banner blindness and the power of short video content on social media platforms. It is a prime example of great display advertising placement on the right platforms, with the right format, targeted to an interested audience. This goes to show that, as mentioned prior, the main focus of display advertisements should be through short video formats. This format is harder to ignore and yields greater conversion rates. Furthermore, this can be adjusted to different social media platforms according to their respective age range depending on the audience targeted.

4.2.5.4. Before and during launch 1st or 2nd visit

When observing the number of visits, customers that only viewed one page made up 64,4% of total visits, followed by 2 page views with 18,1%, and 3 and over pages with 17,5% (Appendix 10a). Overall around 80% of visits are viewing the credit card section for the first time.

30. Comparing the difference between before & during the form launch by 1st or 2nd visit

	Visits	Avg. Time per Session	Page views per visit	Credit Card Launch Rate	Credit-Card Form: Launch (e109)	CCIA: Form Submit
Segments Page: 1 / 1 Rows: 400 1-4 of 4	656,421	00:01:49	1.68	5.00%	32,844	Nov 2,509
1. 1 page views in credit card section	444,157 67.7%	00:00:28	1.00	4.75%	21,105 64.3%	1,044 41.6%
1 page views in cr... **Segments** Page: 1 / 1 Rows: 5 1-2 of 2	444,157	00:00:57	2.00	8.80%	21,105	Nov 1,044
1. First visit in credit card secti...	348,606 78.5	00:00:28	1.00	5.02%	17,494 82.9%	841 80.6%
2. 2nd or more visit in credit c...	95,551 21.5%	00:00:28	1.00	3.78%	3,611 17.1%	203 19.4%
2. 2 page views in credit card sect...	90,810 13.8%	00:02:38	1.95	6.54%	5,943 18.1%	545 21.7%
2 page views in cr... **Segments** Page: 1 / 1 Rows: 5 1-2 of 2	90,810	00:05:24	3.91	12.60%	5,943	Nov 1 545
1. First visit in credit card secti...	68,972 76.0%	00:02:34	1.94	6.77%	4,671 78.6%	437 80.2%
2. 2nd or more visit in credit c...	21,838 24.0%	00:02:50	1.97	5.82%	1,272 21.4%	108 19.8%

Without the “only before launch” segment applied, it can be observed that 64,3% launched a form by viewing a single page. Out of that 64,3%, it was the first time visiting the credit card section for 82,9% of those customers. This is interesting since it demonstrates that clients in most cases go directly to the form application even if it’s their first time visiting the website and thus don’t spend much time looking for promotions and comparing offers. But by observing the ratio of the form submitted to the form launched by customers who visited a single page, first-time visitors gave a ratio of 4,8% compared to 2nd time or more with 5,62%. This gave an overall average of 4,94% for visits who clicked on a single credit card web page.

When comparing this result to customers who viewed 2 pages, the form submitted ratio was 9,17% composed of 9,35% for first-time viewers and 8,49% for 2nd time and above. By doing the same to 3 pages viewed and above, results show a form submitted ratio by first-time visitors of 13,29% and 2nd and above 14,43% for an overall rate of 13,54% (Appendix 11a). This is also interesting, this demonstrates that when customers take the time to get educated about different offers by visiting multiple pages, whether it's their first visit or not, the conversion rate is much higher. Overall, the more pages viewed by the customer prior to filling up the application form, the higher the odds of completion increase, from one page to 2 the rate increases by 4,23%, and from 2 pages to 3 and above the rate jumps by 4,37%. Thus inviting the viewer to educate themselves about the products offered yields great results.

4.2.6. Summary of the analysis made on Adobe Analytics

This section of the analysis touched multiple different subjects. Starting with what percentage of visits are actually new clients, it ranges from different channels, but the ones composed of the highest number of logged-in visitors (thus loyal customers) are NS, PS, and Dr.

Then the different device types and their impact on CR were observed. It was concluded that mobile users convert way more than computer users when it comes to starting the application form. However mobile users abandon the application form around 43,72% of the time, compared to 13,47% for computer users. Thus it can be assumed that mobile users underestimate the task associated with applying for a credit card, contrary to users using computers who usually follow through with their application forms.

Thenceforth, the differences, and proportions of how the paid search channel is divided between generic and branded keywords were observed. Overall, more traffic came from branded keywords, and generic ones offered better CRs.

Then attribution models were compared and analyzed. The overall conclusion was that FT and LT yielded vastly different results even though there similar methods of attribution. Additionally, every attribution method offered by the Adobe Analytic platform was compared with each other. The goal was to find an attribution multi-touch attribution method that had similar results and objectives as their current one, which is LT. The conclusion was that the J curve attribution was the best fit for their current goals.

Finally, multiple different metrics were observed before and during the credit card form launch. The product and the hub pages had the highest conversion rates. When comparing which page was the most visited per channel, both the PS and NS had the hub and the other channels had the product page as their first. The affiliate marketing was broken down to illustrate which affiliate brought the most visits and conversions, revealing Borrowell as the number one. Additionally, display advertising was deeply analyzed to reveal that 15 seconds of video ads displayed on YouTube yielded over 3 times the CR than the banner ads analyzed in the first section of the analysis. At last, 1st and 2nd or more visits were compared and broken down by the number of credit card pages visited. The results showed that clients who visited more pages during their visit converted more.

Chapter 5: Discussion

5.1. Summary of results

Overall, the results found in the analysis go as follows. First, the section on Power Bi revealed that the carry-over effect works on every channel with varying degrees of success, with affiliate marketing reaching the highest conversion rate and email marketing being barely affected by the effect. The varying wear-out tipping points associated with the repetition effect were discovered in every single channel, with natural search happening the latest and email marketing happening the quickest. Additionally, the spillover effect worked incredibly well with every single channel, but especially in combination with affiliate marketing. This confirms even further that omnichannel marketing techniques are very powerful and should be utilized as much as possible, especially when including the affiliate marketing channel in the customer journey. It was established prior during this thesis that customers tend to utilize the different channels that are at their disposition, thus it is to be expected that “many customers [will] visit company websites multiple times before concluding a purchase transaction” (Li & Kannan, 2014). Analyzing and understanding the carry-over and spillover effects will allow marketers to create more integrated online marketing strategies (Anderl et al., 2015).

Most importantly, the Adobe Analytics section helped uncover that the J curve multi-touch attribution model was the most appropriate for this financial institution since it focuses on similar objectives, but considers all touchpoints included in the journey. “Given the proliferation of online channels and the complexity of customer journeys, measuring the degree to which each channel actually contributes to a company's success is demanding” (Anderl et al., 2015). Yet, by simply changing a single-touch attribution model to a multi-touch attribution model, the results obtained will be based on more data points and thus will create a more accurate overview of the journeys. Consequently, by devoting particular attention to the “incremental value of a touchpoint and spillover effects across channels, attribution models can provide insights for allocating marketing investments across channels” (Kannan, 2016). Overall, a better understanding of; the customer journey, the strengths of individual channels at different moments in time, the individual impact of touchpoints, and their effects will result in more educated investment decisions into more impactful channels and advertising techniques.

Additionally, the results obtained in Adobe Analytics showed that the device type who started more credit card application forms were mobile users, yet in comparison, computer users submitted more forms in the end. This would imply that although initial motivation might be obtained more easily for mobile users, most of them will abandon the credit card application process due to its length, which is not the case for desktop users. When it comes to filling up forms, the overall bounce rate observed was much higher on mobile devices compared to desktops. It is to be assumed that mobile users might underestimate the time commitment and the intricacy of the forms and in most cases, don’t want to deal with complex application forms on their phones (Enge, 2021). A potential avenue could be that when mobile users are about to abandon the application form, a pop-up could appear that asks them if they want to save and transfer their progress. Then the started form could be sent by email to the customer for them to complete later on their desktop.

Smaller discoveries were made during the analysis as well, such as the fact that the display format that yields the highest CRs was confirmed to be video format. Additionally, while observing credit card application forms before and during the procedure, results showed that more pages viewed during the processes correlated with higher CRs. Moreover, it was discovered that around a third of visitors coming from NS or PS are loyal customers. This needs to be taken into consideration when observing the total number of visits brought by each channel since they can appear more impactful than they really are, which can skew investments in the long term.

Finally, when it comes to cookies, the financial institution still relies heavily on third-party data. Although their first-party data collection is impressive, changes will need to be implemented to collect data from different methods in the near future. This particular financial institution will need to experiment with up-and-coming tactics such as APIs and FloC or Google's PPIDs to find out what best fits its needs. Moreover, they will need to allocate additional resources to first-party data collection since this type of data will become highly valuable over time. This can be achieved by attributing more importance to email marketing and offline touchpoints being followed up by online touchpoints such as confirmation emails or satisfaction surveys.

5.2. Contributions to the literature

5.2.1. Findings on different advertising channels

5.2.1.1. The natural search channel

The natural search channel has a correlation with the notoriety of the brand in question. In fact, its main focus is aimed toward organic traction and relies heavily on the customer being aware of what the business is offering in the first place. As mentioned prior, this channel is not aimed towards conversion; thus rates weren't particularly high, in this case, it was even under the industry average of 4,17% (Bond, 2022). Yet this can be explained by the fact that the product analyzed (credit cards) has barriers to entry to be eligible, while the industry average accounts for products accessible to all. Regardless of the CR, this channel brings in the highest number of visitors by far, even when omitting the one that logs in. Although keywords can't be tracked since around 99% of them are hidden (Schmeh, 2018), insights can be obtained by looking at Google trends and SEO strategies can be implemented for optimal usage of this channel (Nash, 2020). Furthermore, during this thesis, hidden costs of SEO were revealed by digging in the institution's dataset and thus debunking the common knowledge that this channel is free, costs need to be accounted for in the marketing budget for SEO for quintessential results.

There is huge potential when it comes to retargeting since the customer has already shown interest in the business through NS. By using the tags manually implemented in search engines and by differentiating clients that have logged in from the ones that didn't, great customer journeys can be achieved leading to high CRs (Anja and Tucker, 2013). Furthermore, the more times the clients search for more information concerning your business or products, the higher their interest is, this is a focal point of retargeting since those clients are more likely to convert (Anderl et al., 2014). Overall this channel can be wielded to create great traction from online visits if the search engine optimization is done properly. To do so, the pyramid of Mozlow's hierarchy of SEO needs (appendix 1a) needs to be followed to the letter. To achieve optimal results in this channel, SEO consultants should be utilized to obtain the highest rankings possible in search engines like Google. Once optimized, the natural search channel will yield the best results when it comes to the number of visitors, at relatively low costs. This channel is powerful and should seriously be considered accordingly when distributing the marketing budget through the different channels.

5.2.1.2. The paid search channel

Overall, higher CRs can be expected in this channel since the method focuses on the intent of the customer (Blake 2014). Compared to the other channels, the paid search channel has the benefit of being able to only focus on interested customers looking for the business's particular product or service. Even though this channel yields great CRs overall, it comes at a steep cost depending on which niche is targeted. In this case, the financial institution is obliviously part of the finance niche; in this category keyword bids are ruthless, and the average CPC is 2,54$ CAD. Yet the CPC varies greatly, between [0,02$- 55,09$] CAD with expensive generic keywords such as “Low-interest MasterCard” or “Cheapest interest rate credit card” for example.

Although, as Blake mentioned (2015, p. 2), “in many cases, the consumers who choose to click on ads are loyal customers or otherwise already aware of the company’s product”. Two analyses made in Adobe Analytics proved this; the first one showed that around 30% of PS visitors were logged in (meaning that they already are customers of this institution). The second analysis was when comparing branded vs generic keywords, with branded showing far more visits than its counterpart, but with drastically lower CRs.

Additionally, branded keywords are less expensive than generic keywords, which is logical since there is far more competition for generic keywords because every competitor in that niche will want to bid on the same common keywords for their own purposes. Furthermore, it was found that branded keywords can easily be swapped with the natural search channel, which might be part of the reason why NS has that many visitors when compared to other channels. Overall this channel can be divided into two categories, the generic and the branded. Both types of keywords have their purpose and should be invested in accordingly, the split in the budget is up to the marketers and their needs. Branded keywords while cheaper need to be protected against the competition and will bring a higher number of visitors and some conversions as well. Compared to generic keywords, which will bring significantly fewer visitors but will yield greater conversion rates at almost triple the rate of their counterparts.

In short, this channel is very powerful since it can impact the customer at any point in their journey, but will usually take a great portion of the total marketing budget. Specific attention to detail needs to be ensured to maximize results. First, finding the appropriate way to divide the paid search budget into the two keyword categories needs to be considered seriously depending on the objectives. Additionally, the business needs to keep a close eye on keywords spending since CPC varies greatly and costs could potentially get out of hand rapidly. Overall, the paid search channel displayed great results across the board by being an amazing enabler for other channels when it comes to conversions.

5.2.1.3. The display channel

As Abhishek mentioned in his 2019 study, different ad formats influence customers differently (Abhishek, 2012). This statement combined with the data observed would imply that simply focusing on banner ads might not be the most efficient tactic when it comes to displaying advertising due to banner blindness, among other things. In fact, results found in the analysis support this statement by comparing CRs of banner ads to video display ads which showed over triple the CR. Display advertising has evolved over the years to be more intrusive (Goldfarb & tucker, 2011) and businesses need to take advantage of this. Diversifying display advertising investment is key to maximizing the channel's potential.

The strength of this channel lies in the awareness phase since it was established prior that mere exposure to display ads increases the intent of purchase from customers by around 7.1% (Ghose & Todri, 2015). Furthermore, this channel needs to work around obstacles such as banner blindness and ad blockers to be efficient. This can be done by utilizing video content for example. Creating a short enticing video and placing it at the beginning of a YouTube video aimed toward your particular niche can yield powerful results. Some specific display ad formats on YouTube don't allow the customer to skip the ad, forcing them to see it. Sadly for advertisers, not much can be done against ad blockers and businesses will need to utilize different channels to target them properly.

Overall this channel creates awareness which is the beginning of every customer journey and thus can't be omitted. Although this channel doesn't yield great conversion rates, it remains crucial since it impacts the first step of AIDA ("awareness-interest-desire-action") and educates the customers about the products/ services your business offers (Matoulek, 2018).

5.2.1.4. The affiliate channel

Affiliate marketing revealed amazing CRs during every step of the analysis. As mentioned by Jurišová (2013) this is a powerful technique for conversion since it creates trust from these third parties since the product is not directly connected with the business that is trying to sell it to you. A third party is usually more trustworthy and seems less biased from the client's point of view than the business itself trying to convince the buyer about themselves (Jurišová, 2013). This was clearly proven by the data observed during the analysis, with this channel being by far the best one when it came to conversion. The results of this analysis helped shine a light on the real potential of affiliate marketing by combining it with any channels in any sequence and obtaining amazing CRs regardless. As Duffy touched on in his research (2015), this channel probably will become the "go-to" for the majority of businesses, since affiliate marketing yields strong and constant results when it comes to conversion at low costs. The results obtained from this analysis couldn't agree more with this statement. Affiliate marketing's massive conversion rates combined with low upfront costs make this channel a "no-brainer" for future investments. Gaur & Bharti (2020) mentioned budget allocation depends on the results obtained in the channel; thus it would be optimal to allocate additional resources to this advertising method.

Evidently, affiliate marketing is not limited to aggregator websites currently utilized by the financial institution, it can be efficiently applied to influential individuals in a specific niche willing to do affiliate deals. Jurišová (2013) mentioned that it's like "personal selling to an online environment". Furthermore, as Gillin mentioned in his research, « the new influencers are beginning to tear at the fabric of marketing as it has existed for 100 years, giving rise to a new style of marketing that is characterized by conversation and community» (Gillin, 2008). For example, a potential customer watches YouTube videos to get financial advice and the financial institution made an affiliate deal with this Youtuber. With their massive audience, the power of influencers can't be undermined compared to traditional media, especially following the steps made by the financial institution to move to a younger audience.

Millennials grew up on the internet, digital marketing is the only way to get their attention efficiently, traditional media barely has an impact on them since they hardly consume any (Uzunoğlu & kip, 2014). Furthermore, customers build “parasocial relationships” (one-sided relationships) with “internet celebrities” and thus trust their opinions more than a faceless business (Jurišová, 2013). Customers are usually part of the influencers community and want to follow in their footsteps. In some cases, customers even want to encourage the influencer in some sort of way, and affiliate deals are usually one of them.

Overall, some contributions were made to the literature by further confirming points mentioned by renowned authors. Additionally, it has proven the impact of this channel on conversion. This analysis was limited to the type of affiliate marketing done by this financial institution, which was by partnering with third-party websites. Yet amazing results coming from this particular channel were observed across all types of customer journeys. This shows that this channel should receive additional marketing investments. Additional funds could be utilized to create an affiliate marketing branch that would dedicate its time to finding appropriately niched creators and creating affiliate deals with them. Affiliate marketing is slowly showing its powerful impact across the industry and will be adopted more universally with time. This is an “early adopter” opportunity for this financial institution to take advantage of this powerful advertising method.

5.2.2. The importance of the sequence of touchpoints during the customer journey

5.2.2.1. The natural search channel

Starting with the natural search channel, interesting sequences have been discovered. On average, journeys starting with the natural search channel and ranging from one to ten touchpoints had a conversion rate of 11.07%. This average may seem high for this channel, but it includes journeys with up to ten touchpoints (clearly depicting interest from the customers) and is also combined with different channels along the journeys. By itself, NS averaged a CR of 5.44%. Yet, this goes to show that NS can in fact be a good enabler and yield above-average CRs when combined with other channels through different sequences of touchpoints.

31. Some of the most interesting sequences of touchpoints of customer journeys starting with NS

Journeys starting with NS	Nbr of touchpoints	Nbr of Visitors	CR	Nbr Form filled
NS > Af	2	370	28.11%	104
NS > Af > PS	3	37	54.05%	20
NS > Af > Af	3	35	34.29%	12
NS > NS > PS > PS	4	127	16.54%	21
NS > NS > NS > PS > NS	5	75	14.67%	11
NS > NS > NS > PS > NS	5	75	14.67%	11

As seen from the table above, interesting sequences with higher than average conversion rates were observed. From the table above, 3 distinct channels can be observed in different sequences, NS, PS, and Af. In this case, results show that journeys ending with NS have on average lower CRs than journeys ending with Af or PS. Additionally, the sequence “NS > Af > PS” reached record highs of CR with 54,05%, being the 3rd highest CR obtained in the analysis. But the sequence of those touchpoints greatly matters. For example, similar sequences such as “NS > Af > NS” or even “NS > NS > PS” obtained CRs of 23.44% and 4.95% respectively. In those examples, only one touchpoint differed from the original sequence observed above of “NS > Af > PS”. Yet the difference in CR ranged from [30.61% - 49.1%] when a single touchpoint was changed.

As mentioned by Priest (2017), since a conversion can happen after the interaction of many touchpoints, advertising through different channels is key. Additionally, “different ad formats influence consumers in distinct ways" (Abhishek et al., 2012, p.1). Observing particular touchpoint sequences is filling a gap in the literature since it is almost impossible to pinpoint which sequences of touchpoints will have the greatest impacts on conversions universally. These examples of sequences are limited to this particular institution, but additional research on this subject could help discover powerful paths assuring higher-than-average conversion rates. Since it was established prior that some ad formats yield better results for different mental stages of the customer journey (AdRoll, 2016). It is thus possible to identify journey sequences that are more optimal than others. Meaning that the leverages obtained from different advertising channels can be maximized in specific orders. This further emphasizes the fact that the order of touchpoints can greatly matter and the results obtained in this thesis can help shine a light on some of the optimal sequences that are available and hidden in plain sight for future research.

5.2.2.2. The paid search channel

As established prior, search advertising is a powerful advertising technique since it affects the consumer profoundly across all different stages of the funnel/customer journey (Abhishek et al., 2012). This was confirmed with different sequences including PS in the journey. In fact, paid search was an amazing enabler and showed great CRs combined with almost any other channel at different moments in the sequence. PS might have been the most polyvalent touchpoint appearing in all sorts of different combinations and improving the overall CR.

32. Some of the most interesting sequences of touchpoints of customer journeys starting with PS

Journeys starting with PS	Nbr of touchpoints	Nbr of Visitors	CR	Nbr Form filled
PS > Af	2	258	24.03%	62
PS > PSo	2	66	18.18%	12
PS > PS > OS	3	55	27.27%	15
PS > NS > Af	3	37	56.76%	21
PS > OS > PS	3	53	16.98%	9

On average, PS yielded a conversion rate of 13.58% when considering journeys ranging from one to six touchpoints and including many different other channels. When observing the table above, interesting sequences are discovered. All those sequences are over the PS CR average, but one stands out in particular. When analyzing the sequence “PS > NS > Af” a CR of 56.76% is achieved, the second-highest conversion rate in the analysis. But when comparing it with a similar sequence, with the exact same touchpoints, but in a different sequence, in this case, “PS > Af > NS”, a CR of 18.18% is obtained. Although above average, a difference of 38.58% in CR can be observed. This is another example of the importance of the sequence of touchpoints to maximize the potential value of each individual channel at different points in the journey. Again, sequences ending with NS seem to have lower CR than journeys ending with other channels. This is only one example among others, but this goes to show that the sequence of touchpoints has an impact on the final conversion itself. This will hopefully help pave the path for further research by showing the versatility of this channel and how it can potentiate, amplify, and be matched with other channels in different sequences, while still yielding good CRs.

5.2.2.3. The display channel

When talking about the display channel, lower conversion rates are to be expected. Yet, display advertising remains important in the grand scheme of things. For instance, display advertising is considered to be more effective during the initial stages of the customer journey compared to other forms of advertisement (AdRoll, 2016). This was confirmed in the analysis since journeys that started with Ds advertising had better CRs compared to the ones that included this channel somewhere in the journey.

33. Some of the most interesting sequences of customer journeys including Ds as a touchpoint

Journeys including Ds	Nbr of touchpoints	Nbr of Visitors	CR	Nbr Form filled
Ds > NS	2	183	6.56%	12
Ds > PS	2	124	14.52%	18
Ds > OS	2	100	10.00%	10
Ds > Dr	2	89	5.62%	5
Ds > Af	2	51	23.53%	12
PS > Ds	2	137	6.57%	9
OS > Ds	2	105	7.62%	8

On average, when considering journeys from one to nine touchpoints and including different channels, display advertising average CR is 4.87%. Concrete examples that prove that display advertising yields greater results at the beginning of the journey is when observing either the sequence “Ds > PS” or “Ds > OS” with a CR of 14.52% and 10% respectively. Those numbers are far above average in this instance, but when looking at journeys including the same touchpoints but in a different order such as “PS > Ds” and “OS > Ds”, lower CR is obtained. The difference, in this case, is between [2.38% - 7.95%] lower than when Ds is the first touchpoint. This amplifies the fact that different channels have different potential impacts depending on when the customer interacts with them during their journeys and thus that some journeys can be optimized for maximum CR. This supports the points mentioned by Abhishek that display advertising has a greater impact at the beginning of the journey (2012) and is additional proof that the sequence order of touchpoints in a journey matters. Although examples of display advertising as a later touchpoint in a journey were scarce in this dataset, this analysis can still open the door for additional research when trying to compare the potential impact of different channels at different moments in time in the customer journey.

5.2.2.4. The affiliate channel

As mentioned multiple times in this research, the impact of the affiliate marketing channel on the final conversion is surprisingly powerful. In almost every customer journey that included affiliate marketing as a touchpoint, CRs higher than average were obtained. The conversion rate across all channels with journeys including one to four touchpoints was 15.73%. But if you omit the affiliate channel and take the same average without this advertising method, the average drops to 8.40%. This proves again the power and versatility of this channel. By itself, the affiliate channel has an average CR of 19.87%, but what is more interesting is observing how much this channel can potentiate the others when combined in a single journey.

34. Some of the most interesting sequences of customer journeys including Af as a touchpoint

Journeys including Af as a touchpoint	Nbr of touchpoints	Nbr of Visitors	CR	Nbr Form filled
Af > OS	2	169	68.64%	116
OS > Af	2	185	52.97%	98
Af > NS	2	420	25.48%	107
NS > Af	2	370	28.11%	104
Af > PS	2	253	22.92%	58
PS > Af	2	258	24.03%	62
Af > Dr	2	86	45.35%	39
Dr > Af	2	74	50%	37
NS > Af > NS	3	64	23.44%	15
NS > NS > Af	3	53	37.14%	20

As seen from the table above, all the CR are way above average. The highest conversion rate of the whole analysis was obtained by the sequence "Af > OS" with a 68.64% CR. But in a different sequence, "OS > Af" a drop of -15.67% in CR is obtained. A similar example is when taking the sequence "Dr > Af" with 50% CR and comparing it with the opposite sequence "Af > Dr". Although there is only a drop of 4.65% in CR, a difference can still be observed. The same types of examples can be observed when observing journeys such as "NS > Af" or "PS > Af". In those cases, their counterparts "Af > NS" or "Af > PS" have slightly lower CRs.

In short affiliate marketing is undeniably powerful when it comes to conversions as shown above. This channel will probably become a major part of marketing investments for businesses in the future since affiliate marketing yields strong and consistent results when it comes to conversion at a relatively low cost.

5.2.3. The tipping point of the carry-over effect in individual channels

Concerning the tipping points of the carry-over effect, multiple discoveries have been made concerning which channels react more to this effect than others. This analysis might now have found the "holy grail" of advertising efficiency, but it did shine a light on ad efficiency when repeated in the same channel constantly. Multiple examples were compared through different channels and yielded varying levels of success. For example, concerning the repetition effect, the negative feelings towards the ads were reflected through conversion rates quicker in channels like email marketing or display advertising than in the natural search channels. This means that the wear-out effect, meaning when the consumers start to have feelings of boredom or redundancy (Schmidt, 2015), is more rapidly reached in channels such as email marketing and display. A hypothesis could be that those channels are some of the ones that the consumer has less control over and thus could reach irritability quicker than through different ones.

The subject of tipping points of diminishing returns concerning ad repetition had a gap in the literature. This analysis opened a door with concrete examples of how many times an ad should be repeated in a channel for optimal results concerning this particular financial institution.

5.2.4. The spillover effect

When it came to the spillover effect, a handful of great examples of its potential were observed in the analysis. It accentuated the fact that “different ad formats influence consumers in distinct ways" (Abhishek et al., 2012, p.1) and that the sequence of touchpoints has an impact on CRs. For example, the spillover effect showed better results when it came to displaying ads being the first touchpoint. This further proves that this channel is used to plant a seed at the beginning of the conversion funnel to trigger the awareness stage, then reap the benefits of that seed though other channels later through online search activities (Xu et al., 2014).

The highest CRs were obtained by utilizing the spillover effect through the sequences "PS > NS > Af" and "Af > OS" with a CR of 56,76% and 68,64% respectively. The sequence of these ads through different channels definitely has an impact on CR since lower CRs (up to -38% in some cases) were obtained with the same channels in different orders.

Circling back to the repetition effect (Schmidt, 2015), combining different channels may have a positive influence on the wear-in effect and could help delay the wear-out effect and feelings of redundancy compared to single-channel journeys with the carry-over effect. The wear-in effect is positive feelings from the consumer's point of view up to a certain point (Schmidt, 2015). By showing different ads through different channels, the customer will get bored less quickly than by constantly seeing the same ad in the same channel. Thus the combination of channels could potentially help maintain the recall of the brand and keep a more positive attitude longer than single-channel journeys. Overall, the results found during this analysis on the spillover effect helped uncover additional knowledge on the difference between the single-channel repetition effect vs the multi-channel.

5.2.5. Attribution methods

Priest (2017) mentioned in his research that considering a single channel impedes organizations from isolating impactful marketing activities from ineffective ones, thus concluding that these models are flawed since they can't present a full picture of the journey. This was supported by other researchers who said that companies should utilize omnichannel marketing to maximize the spillover, carry-over, and interaction effects (Dhar, 2016). Through extensive research and with the results obtained, it is clear that the LT attribution method used by this institution is far from optimal. As mentioned by Romero (2020, p.19) "attribution models are a key tool to define digital marketing strategies and investment plans". It was thus a priority in this research to be able to find a multi-touch attribution method that fitted the needs of this financial institution. The contribution to literature from these results is simple, single-channel attribution methods can be changed to omnichannel attribution by focusing on the goal and objective of the previous method utilized. For example, a switch from FT which values touchpoints considered "finders" could easily switch to an Inverse J model which has similar objectives but includes multiple touchpoints (Adobe Analytics tool center, 2022). These simple changes will help businesses paint clearer pictures of their customers journeys and thus will be able to distribute their marketing budgets more efficiently. The results help shine a light on how outdated single-touch models were and how similar multi-touch models, oriented on the same objectives, could be implemented instead at almost no cost.

5.3. Managerial implications

Multiple different results we obtained during the analysis will help guide this financial institution by using more efficient advertising techniques and having more knowledge about their advertising spending.

5.3.1. Advertising channels

5.3.1.1. Display advertising

Starting with display advertising, the research findings combined with the results obtained show that banner advertising yields are affected by banner blindness. Thus this format yields lower results when compared with video display advertising, which is more intrusive. By relocating spending in this channel accordingly, higher reach, click-through rates, and conversion rates could be obtained. Furthermore, native advertising format showed great results in the analysis when considering click rates. Although this method has the trade-off of sacrificing some brand recognition (Aribarg, 2020), results in natural search, paid search and the direct channel explicitly showed the high level of notoriety the institution currently has. Thus it could be interesting to consider this trade-off.

5.3.1.2. Affiliate marketing

Researchers such as Duffy and others, consider this channel the future of advertising, and results found in the analysis agree with that statement. Astonishing conversion rates were obtained no matter where the affiliate touchpoint was in the customer journey. Although the results are limited to aggregator platforms like Borrowell, influencer programs should highly be considered.

Influencer marketing “is characterized by conversation and community” (Gillin, 2008). Creating an influencer affiliate marketing branch in the financial institution could yield amazing results. Using platforms such as YouTube, TikTok or Instagram Reels could easily target younger audiences. Additionally, the creators on those platforms create deep connections with their audiences and thus have great influence over them (Jurišováa, 2013). This new affiliate marketing opportunity could bring quality traffic when it comes to people in the shopping process for credit cards. This form of marketing is also considered a cheap channel since the payment is synonymous with new clients, meaning you pay the affiliate at the conversion stage. Thus most of the costs would come from creating that new branch and the salaries associated with it. Considering the power of affiliate marketing, this relocation in the advertising budget should be highly profitable. Additionally, proof of concept has been seen utilized by competitors. Either way, spending in this channel should be increased accordingly, since the mere presence of this channel in the journey increases CRs drastically. This advertising technique yields the highest CRs of all channels by far.

Investments in platforms like RateHub and Milesopedia showed amazing results and need to have a constant flow of investments. But it would also be recommended a greater focus on influencer marketing, especially the ones that are in the niche of finance in Quebec, Toronto, and Vancouver. They can easily be found on their respective platforms and contacted with offers. Examples of finance influencers in Quebec: @ohdearbudget, @ree2mz, and @modestmillionaires to name a few on Instagram. The following accounts are in the financial niche, thus targeting directly their audience would guarantee interested viewers.

5.3.1.3. Email marketing

Throughout the research, the importance of this channel was emphasized multiple times. Results from the analysis depict the underutilization of this channel and could be considered a missed opportunity. A hypothesis that could be tested at low cost, could be to implement promotions directly into the emails that are already being automatically sent recurrently to the customers. For example, at the bottom of electronic bank statements, specifically targeted promotions could be added. This method could lead to cross-selling and up-selling loyal customers and suggesting products/services they don’t already have. This would avoid the customer from considering additional emails as spam and ensure that the email will be open since the client needs to look at the information in it.

However, since great changes in targeting are expected with the death of the cookie era approaching, the value of first-party data like emails is rising and will need to be capitalized on further. Thus offering more advantages to customers through this channel might become a necessary investment in the long run and can’t be neglected.

5.3.1.4. Paid social

The recommendation for this channel is to diversify spending through different platforms. Since different platforms have different age ranges, it will be helpful to try the different options out there and compare the results. Additionally, for video-focused platforms such as Instagram Reels or TikTok, videos received from affiliates could be re-purposed and boosted accordingly for easy ad creation.

5.3.1.5. Offline touchpoints

Concerning offline touchpoints, it would be interesting to consider email confirmation after a client call or a visit in person. Satisfaction surveys on the quality of the service and additional questions such as “did you complete the order?” could be added. Such surveys would also increase first-party data collection, which will become crucial in the near future. Then these data points could be transferred to the dataset and analyzed for a more complete customer journey.

5.3.2. Attribution models

It was established by research and results that single-touch attribution paints an inaccurate picture of the customer journey compared to multi-touch models. On paper, the best attribution models to implement would be data-driven models. Since they are powered by AIs, they rely on “statistical techniques such as predictive analytics” (Swan, 2020) and thus can offer more accurate attribution. But costs related to this method are considerable and require time and knowledge for the implementation process. Additionally, this type of attribution model heavily relies on cookies to accurately identify the customer combined with their login data. Thus this attribution method will need to adapt the way it operates in the future to properly function due to the incoming death of cookies. The way this attribution will adapt to those changes is still unclear.

Thus an inexpensive change would be to switch to a multi-touch attribution model, which would yield more accurate results by considering additional touchpoints. Additionally, the model proposed is still aimed at the same objectives as the currently used model (Last touch), which is prioritizing points considered closers. Thus, the implementation of the J curve attribution model would be recommended, instead of the one used currently. This model offers a more balanced approach by attributing some merits (20%) to the initial touchpoint, while still prioritizing the last one (60%). The remaining 20% is distributed between the remaining touchpoints. It was established during this research that every touchpoint carries some contribution to the final conversion. By considering more than a single point, a more realistic image of the customer journey will be obtained. Moreover, Berman (2018), also says that institutions will spend less on digital marketing overall when more advanced attribution techniques will be utilized due to better allocation of resources. In short, the purpose of attribution is to better understand the results obtained from previous investments and to better assign future ones. Switching to a multi-touch attribution method can be a simple adjustment that will offer a more optimized view of future budget allocations. The main hurdle in implementing this new method will be to convince and inform current employees of this institution of the major benefits of this change.

5.3.3. Third-party data changes and new options for data collection

As mentioned in this thesis, cookies will soon be a thing of the past. Thus the institution should brace itself accordingly. To prepare for this new era, recommendations imply gathering as much clean first-party data as possible. Additionally, the institution will need to put measures in place by choosing which alternative fits their needs more specifically. The recommendation, in this case, would be to start by utilizing the FLoC API offered by Google as soon as possible. Furthermore, prioritizing first-party data collection in any way possible will be crucial. As mentioned in the offline touchpoint recommendation, the addition of surveys following offline interaction will also help gather additional data on the customers. The financial institution will also need to ensure the safety of the collected data.

5.4. Limits and potential research avenues

Although the results obtained during this project were interesting, multiple limits need to be taken into consideration. First, the results found only apply to the datasets of these specific institutions. Additionally, missing data entries and cloudy classifications like “Other source” or “unclassified” sometimes hindered the capacity of drawing meaningful conclusions. Furthermore, due to the fact that offline touchpoints in the journeys were not tracked, some of the journeys will inevitably have gaps in knowledge and needed to be abandoned.

Furthermore, in the Power BI analysis section, journey sequences rarely implicated more than 2 different channels past the 4th touchpoint. Also, not all attribution methods could be observed due to the limitations of Adobe Analytics. Moreover, only a period of 6 months was considered due to the massive size of the data set that needed to be limited. Finally, the only product that was analyzed was credit card forms and in most cases, specifically CCIA forms.

Regardless of those limits, the results found in this thesis will contribute to some subjects to the overall knowledge in literature and help fill some gaps. Future researchers will need to explore if the spillover effect has a link with the educational process of the customer done through the journey, by providing different sources of information instead of the same source being repeated multiple times. Additionally, owing to the non-linear paths taken by customers today before converting, it is essential for studies in the future to examine ways in which firms can adapt their marketing practices and approaches to provide personalized experiences to customers even after the death of cookies. Finally, future researchers could examine the various ways in which firms can use AI-based attribution models to create and deliver an effective Omni-channel approach using data, touchpoint optimization, and eliminating silos to identify real use cases.

Chapter 6: Conclusion

In conclusion, this descriptive quantitative study on the subject of exploring which combinations of touchpoints optimize online conversion when it comes to acquiring new clients for financial products showed the importance of touchpoint sequence within a customer journey. In fact, multiple combinations depicted the range of different conversion rates that can be obtained solely by changing the sequence, since different ad formats can affect customers differently depending on which stage of the journey they currently reside.

The first objective of the study was to categorize and observed which touchpoints, in which channel, had the greatest impact towards conversion, results clearly showed that the affiliate advertising method was by far the most powerful and probably will become the go-to advertising method in the future. The second objective was to find the sequence of a combination of touchpoints that brought the highest conversion rate, it was revealed that paid search, followed by natural search and then affiliate marketing converted over half of the consumers. The final objective was to find the most efficient investment and which ones were lackluster. By finding the most efficient channels, like affiliate marketing and paid search, additional funds could then be reoriented toward them for maximum efficiency. Additionally, by pinpointing the channels considered weaker, techniques and changes were recommended to amplify their investments.

Finally, recommendations for a more advanced multi-touch attribution method were made to the financial institution for them to save money by more adequately distributing and investing their marketing budgets in the future.

By leaning on the research’s findings, this research tries to steer this institution toward better budget allocation, new techniques to maximize their investments in individual channels and increase their overall conversion rate of credit cards.

Bibliography

Abhishek, V., Fader, P., & Hosanagar, K. (2012). Media exposure through the funnel: A model of multi-stage attribution. *SSRN Electronic Journal.* https://doi.org/10.2139/ssrn.2158421

Abishek, S., King, A. J. C., Mead-Hunter, R., Golkarfard, V., Heikamp, W., & Mullins, B. J. (2017). Generation and validation of virtual nonwoven, foam and knitted filter (separator/coalescer) geometries for CFD simulations. *Separation and Purification Technology*, *188*, 493-507. https://doi.org/10.1016/j.seppur.2017.07.052

Adobe analytics tools guide. (2022). *Attribution models and lookback windows.* Experience League. https://experienceleague.adobe.com/docs/analytics/analyze/analysis-workspace/attribution/models.html?lang=en

AdRoll. (2016). *The state of marketing attribution*. AdRoll. https://www.adroll.com/assets/pdf/guides-and-reports/AdRoll-State-of-Marketing-Attribution-2017.pdf

Amazon Web Services. (2022). *What is an API?*, https://aws.amazon.com/what-is/api/?nc1=h_ls

Anderl, E., Becker, I., Wangenheim, F. V., & Schumann, J. H. (2015). Mapping the Customer Journey: Lessons Learned from Graph-Based Online Attribution Modeling. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2685167

Anderl, E., Becker, I., Wangenheim, F. V., & Schumann, J. H. (2014, October 18). Mapping the Customer Journey: A Graph-Based Framework for Online Attribution Modeling. Papers.ssrn.com. http://ssrn.com/abstract=2343077

Andrews, M., Luo, X., Fang, Z., & Ghose, A. (2016). Mobile ad effectiveness: Hyper-contextual targeting with crowdedness. Marketing Science, 35(2), 218-233.

Aribarg, A., & Schwartz, E. M. (2020). Native advertising in online news: Trade-offs among clicks, brand recognition, and website trustworthiness. Journal of Marketing Research, 57(1), 20-34.

Balzter, H. (2000). Markov chain models for vegetation dynamics. *Ecological Modelling*, *126*(2-3), 139–154. https://doi.org/10.1016/s0304-3800(00)00262-3

Barry, T. E., & Howard, D. J. (1990). A Review and Critique of the Hierarchy of Effects in Advertising. *International Journal of Advertising*, *9*(2), 121–135. https://doi.org/10.1080/02650487.1990.11107138

Bergen, M. (2021, April 26). *Apple and Google Are killing the (Ad) cookie. here's why.* Bloomberg.com. https://www.bloomberg.com/news/articles/2021-04-26/how-apple-google-are-killing-the-advertising-cookie-quicktake

Berman, R. (2018). Beyond the last touch: Attribution in online advertising. *Marketing Science*, *37*(5), 771-792. https://doi.org/10.1287/mksc.2018.1104

Berman, R., & Katona, Z. (2013). The role of search engine optimization in search marketing. *Marketing Science*, *32*(4), 644-651. https://doi.org/10.1287/mksc.2013.0783

Bernhart, B. (2022). *Social media demographics to inform your brand's strategy in 2022.* Sproutsocial. https://sproutsocial.com/insights/new-social-media-demographics/

Blake, T., Nosko, C., & Tadelis, S. (2015). Consumer heterogeneity and paid search effectiveness: A large‐scale field experiment. *Econometrica*, *83*(1), 155-174. https://doi.org/10.3982/ECTA12423

Bond, C. (2022). *Conversion rate benchmarks: Find out how your conversion rate compares, reporting & analysis.* WordStream. https://www.wordstream.com/blog/ws/2019/08/19/conversion-rate-benchmarks.

Bostanshirin, S. (2014, September). Online marketing: challenges and opportunities. In *Proceedings of SOCIOINT14-International Conference on Social Sciences and Humanities, Istanbul, September* (pp. 8-10). https://www.academia.edu/8512383/ONLINE_MARKETING_CHALLENGES_AND_OPPORTUNITIES

Buttle, F. A. (1998). Word of mouth: understanding and managing referral marketing. Journal of strategic marketing, 6(3), 241-254.

Campaign Monitor. (2017). *What's considered email spam and how to avoid it.* https://www.campaignmonitor.com/blog/email-marketing/whats-considered-email-spam-avoid/

Carrabis, J., Cass, J., Gillin, P., Nacht, & R., Peverill-Conti, G. (2008). New media, new influencers and implications for public relations. Issue Lab. https://search.issuelab.org/resource/new-media-new-influencers-and-implications-for-public-relations.html

Cinar, N., & Ateş, S. (2022). Data Privacy in Digital Advertising: Towards a Post Third-Party Cookie Era. In Filimowicz, M.(Ed.) *Privacy: Algorithms and Society*. Routledge. https://dx.doi.org/10.2139/ssrn.4041963

Colicev, A., Kumar, A., & O'Connor, P. (2019). Modeling the relationship between firm and user generated content and the stages of the marketing funnel. International Journal of Research in Marketing, 36(1), 100-116.

Comber, N. analytics & Google marketing platform trainer. (2020). *Understanding google analytics channels.* JellyfishTraining. https://www.jellyfish.com/en-us/training/blog/google-analytics-channels-explained.

Cooper, B. (2013). *Google hides keywords from marketers: The complete guide to using alternatives from the experts.* Buffer. https://buffer.com/resources/google-hides-keywords-from-marketers-industry-responses-and-suggested-alternatives/

Cordeiro, A. C. M. (2018). *The attribution problem: an analysis for a focal company* [MAs Dissertation]. https://run.unl.pt/bitstream/10362/38614/1/Cordeiro_2018.pdf

Cortiñas, M., Chocarro, R., & Elorz, M. (2019). Omni-channel users and omni-channel customers: a segmentation analysis using distribution services. *Spanish Journal of Marketing - ESIC*, *23*(3), 415–436. https://doi.org/10.1108/sjme-06-2019-0031

Crawford, F. (2019). *Now live for your SEO learning pleasure: The NEW beginner's guide to SEO.* Moz. https://moz.com/blog/new-beginners-guide-to-seo.

Crête, D. (2016). *Qualité de la publicité en ligne: développement d'une nouvelle échelle de mesure*. HEC Montreal (Canada).

De Bruyn, A., & Lilien, G. L. (2008). A multi-stage model of word-of-mouth influence through viral marketing. International journal of research in marketing, 25(3), 151-163.

De Veirman, M., Cauberghe, V., & Hudders, L. (2017). Marketing through Instagram influencers: the impact of number of followers and product divergence on brand attitude. International journal of advertising, 36(5), 798-828.

Dhar, T., & Weinberg, C. B. (2016). Measurement of interactions in non-linear marketing models: The effect of critics' ratings and consumer sentiment on movie demand. *International Journal of Research in Marketing*, *33*(2), 392–408. https://doi.org/10.1016/j.ijresmar.2015.10.003

Di Fatta, D., Patton, D., & Viglia, G. (2018). The determinants of conversion rates in SME e-commerce websites. *Journal of Retailing and Consumer Services*, *41*, 161–168. https://doi.org/10.1016/j.jretconser.2017.12.008

Duffy, D. L. (2005). *Affiliate marketing and its impact on e‐commerce. Journal of Consumer Marketing*, 22(3), 161-163. https://doi.org/10.1108/07363760510595986

Dutton, S. (2022). *What is FLoC?* Web.dev. https://web.dev/floc/

Enge, E. (2021). Mobile vs desktop usage in 2020. Perficient. https://www.perficient.com/insights/research-hub/mobile-vs-desktop-usage

Ertemel, A. V., & Ammoura, A. (2016). The role of social media advertising in consumer buying behavior. *International Journal of Commerce and Finance*, *2*(1), 81-89.

Fazio, R. H., Zanna, M. P., & Cooper, J. (1978). Direct experience and attitude-behavior consistency: An information processing analysis. *Personality and Social Psychology Bulletin*, *4*(1), 48–51. https://doi.org/10.1177/014616727800400109

Ford, J. B. (2018). What do we know about digital attribution? *Journal of Advertising Research*, *58*(4), 383–384. https://doi.org/10.2501/jar-2018-044

Forrester Consulting. (2012). *Digital attribution comes of age*. Www.sas.com. https://www.sas.com/no_no/whitepapers/forrester-consulting-digital-attribution-comes-age-106095.html

Gaur, J., & Bharti, K. (2020). Attribution modelling in marketing: literature review and research agenda. *Academy of Marketing Studies Journal*, *24*(4).

Ghose, A., & Todri, V. (2015). Towards a digital attribution model: Measuring the impact of display advertising on online consumer behavior. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2638741

Gillin, P. (2008). New media, new influencers and implications for the public relations profession. *Journal of New Communications Research*, *2*(2), 1-10. https://www.issuelab.org/resources/928/928.pdf

Goldfarb, A., & Tucker, C. (2011). Online display advertising: Targeting and obtrusiveness. *Marketing Science*, *30*(3), 389-404. https://doi.org/10.1287/mksc.1100.0583

Goldschmidt, S., Junghagen, S., & Harris, U. (2003). *Strategic affiliate marketing.* Edward Elgar Publishing.

Google Ads Help Center. (2022). *conversion rate definition*. Google Support. https://support.google.com/google-ads/answer/2684489?hl=en#

Google Ad Manager (2021). New ways for publishers to activate first-party data.https://blog.google/products/admanager/new-ways-publishers-activate-first-party-data/

Google Analytics Help Center. (2022). *About the default MCF attribution models.* Google Support. https://support.google.com/analytics/answer/1665189

Google Analytics Help Center. (2022). *Default channel definitions*. Google Support. https://support.google.com/analytics/answer/3297892?hl=en

Google Analytics Help Center. (2022). *Overview of Attribution modeling in MCF.* Google Support. https://support.google.com/analytics/answer/1662518?hl=en

Google Analytics Help Center. (2022). *Use and interpret MCF Data-Driven Attribution.* Google Support. https://support.google.com/analytics/answer/3070279?hl=en&ref_topic=3180362

Guo, Z. (2012). Optimal decision making for online referral marketing. *Decision Support Systems, 52*(2), 373-383. https://doi.org/10.1016/j.dss.2011.09.004

Harris, I. (2018, May 2). *Marketing attribution comes of age*. CEO Review. https://www.ceo-review.com/2018-marketing-attribution-comes-of-age/

Hassani, M., & Habets, S. (2021, June). Predicting Next Touch Point In A Customer Journey: A Use Case In Telecommunication. In ECMS (pp. 48-54).

Hollis, N. (2005). Ten years of learning on how online advertising builds brands. *Journal of Advertising Research*, *45*(2), 255-268. https://doi.org/10.1017/S0021849905050270

Iftikhar, F., & Khan, I. (2017). The impact of email marketing, mobile marketing and re-targeting on online consumer buying behavior. *Haaga-Helia University of Applied Sciences*, 66. https://core.ac.uk/download/pdf/161418166.pdf

Indeed Editorial Team. (2021). *Indeed career development, 10 types of display ads for online marketing (with benefits)*. Indeed. https://www.indeed.com/career-advice/career-development/types-of-display-ads

Jenkins, S. (2008). The truth about email marketing. FT Press.

Jeziorski, P., & Segal, I. (2015). What makes them click: Empirical analysis of consumer demand for search advertising. *American Economic Journal: Microeconomics*, *7*(3), 24-53. http://ssrn.com/abstract=1417625

Ji, W., & Wang, X. (2017). Additional multi-touch attribution for online advertising. In *Proceedings of the AAAI Conference on Artificial Intelligence*, *31*(1). https://ojs.aaai.org/index.php/AAAI/article/view/10737

Ji, W., Wang, X., & Zhang, D. (2016). A probabilistic multi-touch attribution model for online advertising. *Proceedings of the 25th ACM International on Conference on Information and Knowledge Management - CIKM '16*. https://doi.org/10.1145/2983323.2983787

Jílková, P. (2019). Online Marketing Campaign in Context of Influencer Marketing. In Scientific Conference of Business Economics Management and Marketing 2019 (p. 57).

Jurišová, V. (2013). Affiliate marketing in the context of online marketing. *Review of Applied Socio-Economic Research, 5*(1), 106-111.

Kakalejčík, L., Ferencova, M., Angelo, P., & Bucko, J. (2018). Multichannel Marketing Attribution Using Markov Chains. *Journal of Applied Management and Investments*. http://www.jami.org.ua/Papers/JAMI_7_1_2018_49-60.pdf

Kannan, P. K., Reinartz, W., & Verhoef, P. C. (2016). The path to purchase and attribution modeling: Introduction to special section. *International Journal of Research in Marketing*, *33*(3), 449–456. https://doi.org/10.1016/j.ijresmar.2016.07.001

Kaushik, A. (2015). See, think, do, care winning combo: Content +marketing +measurement!. https://www.kaushik.net/avinash/see-think-do-care-win-contentmarketing-measurement.

Kearl, M. (2021). *Single-channel vs cross-channel customer engagement : A closer look*. Braze. https://www.braze.com/resources/articles/single-channel-vs-cross-channel-customer-engagement-a-closer-look

Kuan, H.-H., Bock, G.-W., & Vathanophas, V. (2008). Comparing the effects of website quality on customer initial purchase and continued purchase at e-commerce websites. *Behaviour & Information Technology*, *27*(1), 3–16. https://doi.org/10.1080/01449290600801959

Kubiak, B. F. (1970). Cross and up-selling techniques in e-commerce activities. *The Journal of Internet Banking and Commerce, 15*(3), 1-7. https://www.icommercecentral.com/open-access/cross-and-upselling-techniques-in-ecommerce-activities-1-7.php?aid=38427&view=mobile

Lee, G. (2010). Death of “last click wins”: Media attribution and the expanding use of media data. *Journal of Direct, Data and Digital Marketing Practice*, *12*(1), 16–26. https://doi.org/10.1057/dddmp.2010.14

Leguina, J. R., Rumín, Á. C., & Rumín, R. C. (2020). Digital marketing attribution: Understanding the user path. *Electronics*, *9*(11), 1822. https://doi.org/10.3390/electronics9111822

Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. *Journal of Marketing*, *80*(6), 69–96. https://doi.org/10.1509/jm.15.0420

Lynch, K. (2021). *How often should you send email marketing campaigns.* https://keap.com/business-success-blog/marketing/email-marketing/how-often-should-you-email-your-list

Matoulek, M. (2018). *Data analytical way to identify an appropriate attribution model for digital marketing* [Diploma Thesis]. https://dspace.cvut.cz/bitstream/handle/10467/76768/F3-DP-2018-Matoulek-Matej-dp-kos.pdf?sequence=-1&isAllowed=y

McDowell, W. C., Wilson, R. C., & Kile, C. O. (2016). An examination of retail website design and conversion rate. *Journal of Business Research*, *69*(11), 4837–4842. https://doi.org/10.1016/j.jbusres.2016.04.040

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An Integrative Typology. *Information Systems Research*, *13*(3), 334–359. https://doi.org/10.1287/isre.13.3.334.81

Moe, W. W., & Fader, P. S. (2000). *Which visits lead to purchases? Dynamic Conversion Behavior at e-Commerce Sites*. http://lcm.csa.iisc.ernet.in/scm/webmetrics.pdf

Moorthy, S., & Hawkins, S. A. (2005). Advertising repetition and quality perception. Journal of business research, 58(3), 354-360.

Nash, K. (2020). *A best practices guide for the web designer utilizing Search Engine Optimization and Social Media Optimization*. https://digitalcommons.lindenwood.edu/cgi/viewcontent.cgi?article=1020&context=theses

Notebaert, J.-F., & Attuel-Mendès, L. (2014). La place du client dans les stratégies multicanaux des banques françaises sur Internet. *Gestion*, *39*(2), 37. https://doi.org/10.3917/riges.392.0037

Office of the Privacy Commissioner of Canada. (2020). *Guidance for businesses doing e-marketing.* https://www.priv.gc.ca/en/privacy-topics/privacy-laws-in-canada/the-personal-information-protection-and-electronic-documents-act-pipeda/r_o_p/canadas-anti-spam-legislation/casl-compliance-help-for-businesses/casl_guide/

Perrin, N. (2020). Search Marketing 2020, Pandemic promises short-term pain but long-term gain. Insider Intelligence E-Marketer. https://www.insiderintelligence.com/content/search-marketing-2020

Perse, E. M., & Rubin, R. B. (1989). Attribution in social and parasocial relationships. *Communication Research*, *16*(1), 59-77. https://doi.org/10.1177/009365089016001003

Priest, C. (2017). *Multichannel marketing attribution with DataRobot EXECUTIVE BRIEFING*. https://datateam.mx/downloads/datarobot/DataRobot_Marketing_Attribution_Executive_Briefing.pdf

Rathod, A. (2011). AIDA model of Advertising Strategy. *Indian Journal of Applied Research*, *1*(10), 122–125. https://doi.org/10.15373/2249555x/jul2012/39

Rentola, O. (2014). *Analyses of Online Advertising Performance Using Attribution Modeling*. https://aaltodoc.aalto.fi/bitstream/handle/123456789/13898/master_Rentola_Olli_2014.pdf?sequence=1

Rojalin, K. (2020). *Search Engine Optimization for an international business to business company in the beauty industry: Measuring the results with web analytics*. https://www.theseus.fi/bitstream/handle/10024/353383/Thesis_%20Rojalin_Kati.pdf;jsessionid=792C7BE688200610C3AEAD01E4EADE09?sequence=2

Rose, E. (2022). *Make the best youtube video ads with this ultimate guide.* Idea Rocket. https://idearocketanimation.com/25519-youtube-video-ads-guide/

Rutz, O. J., & Bucklin, R. E. (2011). From generic to branded: A model of spillover in paid search advertising. Journal of Marketing Research, 48(1), 87-102.

Rycroft, B. (2022). *9 Best alternatives to third party cookies (2022) definitive guide.* Snigel. https://snigel.com/blog/best-third-party-cookie-alternatives

Sapp, S., & Vaver, J. (2016). Toward improving digital attribution model accuracy. Google Inc.

Saravanakumar, M., & SuganthaLakshmi, T. (2012). Social media marketing. *Life Science Journal, 9* (4). https://www.academia.edu/36229626/Social_Media_Marketing

Schmeh, D. (2018). *4 fastest ways to view Google organic search not provided.* Keyword Hero. https://keyword-hero.com/blog/4-methods-find-not-provided

Schmidt, S., & Eisend, M. (2015). Advertising repetition: A meta-analysis on effective frequency in advertising. Journal of Advertising, 44(4), 415-428.

Shao, X., & Li, L. (2011). Data-driven multi-touch attribution models. *Proceedings of the 17th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining - KDD '11*. https://doi.org/10.1145/2020408.2020453

Sharma, H. (2022). *What is direct traffic in Google Analytics & why is it so high?* Optimize Smart https://www.optimizesmart.com/what-is-direct-traffic-in-google-analytics-why-it-is-so-high/#2-how-google-analytics-attributes-conversions-to-direct-traffic

Sirrah, A. (2019). A Guide to Native Advertising.

Skyword Staff. (2020). *How the marketing funnel works from top to bottom.* Skyword. https://www.skyword.com/contentstandard/how-the-marketing-funnel-works-from-top-to-bottom/

Subramanian, K. R. (2018). Myth and mystery of shrinking attention span. *International Journal of Trend in Research and Development*, *5*(1). http://www.ijtrd.com/papers/IJTRD16531.pdf

Swan, G. (2020). *Custom data attribution models: which is best for your business?* Tinuiti. https://tinuiti.com/blog/analytics/custom-data-attribution-models/

Szabo, P., & Genge, B. (2020). Efficient conversion prediction in e-commerce applications with unsupervised learning. *2020 International Conference on*

Software, Telecommunications and Computer Networks (SoftCOM). https://doi.org/10.23919/softcom50211.2020.9238344

Tamble, M. (2022), social media cross-promotion strategies for corporate communication, Neal Schaffer, https://nealschaffer.com/social-media-cross-promotion-strategies-corporate-communication/

Taylor, G. (2013). *Advertising in a digital age: Best practices & tips for paid search and social media advertising. Global & Digital*. https://www.goodreads.com/en/book/show/18309754-advertising-in-a-digital-age

Temkin, D. (2021). *Charting a course towards a more privacy-first web.* Google ads & commerce blog. https://blog.google/products/ads-commerce/a-more-privacy-first-web/

Think with Google, (2013). Future of Marketing, Google Display Network. https://www.thinkwithgoogle.com/intl/en-145/future-of-marketing/digital-transformation/google-display-network/#:~:text=The%20Google%20Display%20Network%20is,1%20billion%20users%20every%20month.

Transformation. (2019). *Touchpoint definition, part of the journey is mapping glossary of definitions*. https://transformation.ai/touchpoint-definition/index.html

Tunuguntla, V., Rakshit, K., & Basu, P. (2022). Bidding for an optimal portfolio of keywords in sponsored search advertising: From generic to branded keywords. European Journal of Operational Research.

Uzunoğlu, E., & Kip, S. M. (2014). Brand communication through digital influencers: Leveraging blogger engagement. *International journal of information management*, *34*(5), 592-602. https://doi.org/10.1016/j.ijinfomgt.2014.04.007

Vakratsas, D., & Ambler, T. (1999). How advertising works: What do we really know? *Journal of Marketing*, *63*(1), 26. https://doi.org/10.2307/1251999

Vizu. (2013). *Paid social media advertising. Industry update & best practices.* New York: Nielsen Company. https://www.slideshare.net/wiseknow/nielsen-paid-social-mediaadvreport2013

Waters, M. (2022), *social media conversion rate benchmarks (and how to beat them), Chatdesk*, https://www.chatdesk.com/blog/how-to-increase-social-media-conversion-rate-benchmarks

Wei, A.-P., Chen, M.-L., & Peng, C.-L. (Edward). (2011, January 10). *The advertising spillover effect: Implications for mutual fund families*. Papers.ssrn.com. https://ssrn.com/abstract=1779584

Weilbacher, W. M. (2001). Point of view: Does advertising cause a "Hierarchy of Effects"?. *Journal of Advertising Research*, *41*(6), 19–26. https://doi.org/10.2501/jar-41-6-19-26

Wu, T. (2017). The attention merchants: The epic scramble to get inside our heads. Vintage.

Xu, L., Duan, J. A., & Whinston, A. (2014). Path to purchase: A mutually exciting point process model for online advertising and conversion. *Management Science*, *60*(6), 1392–1412. https://doi.org/10.1287/mnsc.2014.1952

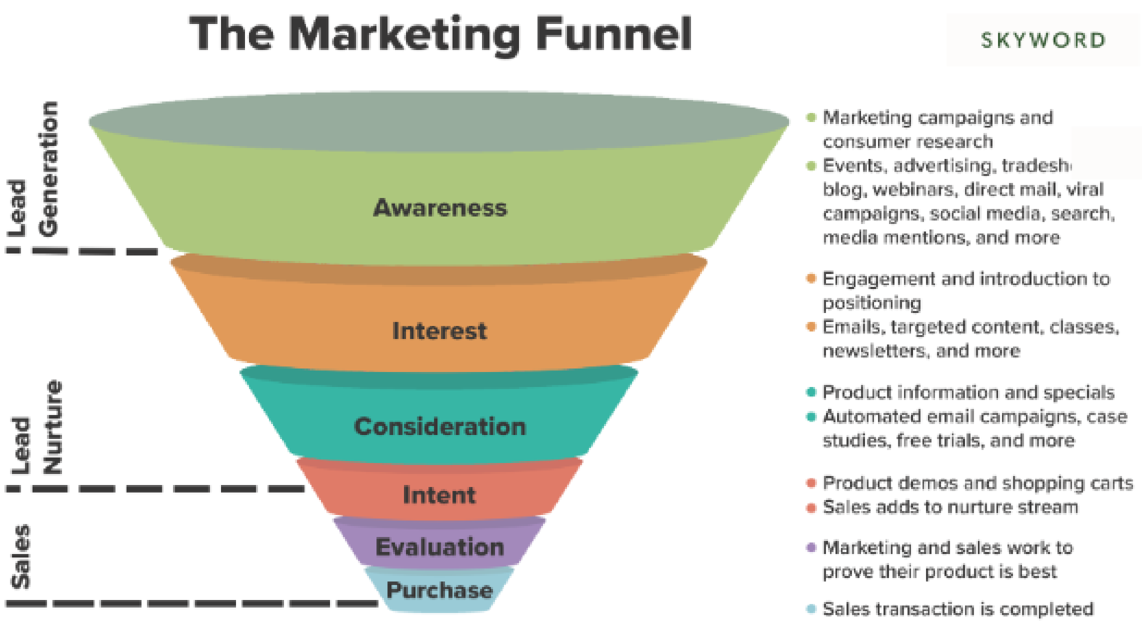
Yang, S., & Ghose, A. (2010). Analyzing the relationship between organic and sponsored search advertising: Positive, negative, or zero interdependence?. Marketing science, 29(4), 602-623.

Appendices

1a. Mozlow's hierarchy of SEO needs

Crawford, F. (2019)

2a. The Marketing funnel



(Skyword, 2020)

3a. Screenshots of examples of types of display ads from Beezwax's database

Filter by Campaign:

mxxxx_CREDIT-CARDS_Always-On_FY2023 (26)

+ New | Bulk Actions | Edit Mode | 50 rows | Download as

	Line Item ID	Line Item Name	Line Item Type	Line Item Budget	Line Item Spend	Start Date	End Date
	407	Audiences_High-Value_Quebec_EN	banner	14,611.87	0.00	11/07/22	10/31/23
	406	Audiences_High-Value_Quebec_FR	banner	34,094.37	0.00	11/07/22	10/31/23
	404	Audiences_Prospecting_Quebec_FR	banner	14,611.87	0.00	11/07/22	10/31/23
	405	Audiences_Prospecting_Quebec_EN	banner	6,262.23	0.00	11/07/22	10/31/23

Filter by Campaign:

M225002C_CREDIT-CARDS_Always-On_FY2022 (23)

+ New | Bulk Actions | Edit Mode | 50 rows | Download as

	391	High Value_Bid-Model_In-Market_Non-Clients_QC_FR	banner	30,006.52	29,405.26	03/10/22	09/21/22	0
	388	Prospecting_Bid-Model_In-Market_Non-Clients_QC_EN	banner	2,501.00	2,497.40	03/10/22	08/21/22	5
	389	Prospecting_Bid-Model_In-Market_Non-	banner	10,002.00	9,900.62	03/10/22	08/21/22	5

4a. New clients vs Loyal customers in each channel

- New clients vs loyal customers in each channels

Marketing Channel Page: 1 / 1 Rows: 400 1-12 of 1	Exclude SBIP2 logged in (visitor) Unique Visitors		SBIP2 logged in (visitor) Unique Visitors		Unique Visitors	
	Nov 1 409,344 out of 409,344		Nov 1 137,498 out of 137,498		Nov 1 546,842 out of 546,842	
1. Natural Search	159,940	39.1%	93,601	68.1%	253,541	46.4%
2. Display	98,972	24.2%	3,008	2.2%	101,980	18.6%
3. Paid Search	85,561	20.9%	35,501	25.8%	121,062	22.1%
4. Direct	25,107	6.1%	12,796	9.3%	37,903	6.9%
5. Affiliates	23,558	5.8%	3,043	2.2%	26,601	4.9%
6. Paid Social Media	22,999	5.6%	605	0.4%	23,604	4.3%
7. Internal Referrer	6,954	1.7%	3,196	2.3%	10,150	1.9%
8. Other sources	6,508	1.6%	3,412	2.5%	9,920	1.8%
9. Email	2,714	0.7%	2,169	1.6%	4,883	0.9%

5a. FT compared with LT across marketing channels

Last Touch Channel Page: 1 / 2 › Rows: 10 1-10 c	Credit-Card Form: Launch (e109) 34,513 out of 34,513	
1. Paid Search	11,344	32.9%
2. Natural Search	9,131	26.5%
3. Affiliates	7,380	21.4%
4. Display	1,815	5.3%
5. Direct	1,792	5.2%
6. Other sources	990	2.9%
7. Internal Referrer	940	2.7%
8. Paid Social Media	711	2.1%
9. Email	317	0.9%
10. Organic Social Networks	75	0.2%

First Touch Channel Page: 1 / 2 › Rows: 10 1-10 c	Credit-Card Form: Launch (e109) 34,513 out of 34,513	
1. Paid Search	10,393	30.1%
2. Natural Search	8,866	25.7%
3. Affiliates	6,461	18.7%
4. Direct	3,078	8.9%
5. Display	1,718	5.0%
6. Internal Referrer	1,513	4.4%
7. Other sources	1,356	3.9%
8. Paid Social Media	737	2.1%
9. Email	265	0.8%
10. Organic Social Networks	87	0.3%

6a. During form launch per page types

	DW - Site info - Credit card pages (hits)					
	Visits	Avg. Time per Session	Avg. Time on Page	Page views per visit	Credit-Card Form: Launch (e109)	
Pages: Page Name T Page: 1 / 1 Rows: 10	588,191 out of 656,421	00:01:53 out of 00:01:49	00:01:06 out of 00:01:04	1.72 out of 1.68	28,095 out of 32,844	
1. Product	283,422	00:01:47	00:01:06	1.61	10,726	38.2%
2. Hub	202,453	00:01:24	00:01:08	1.24	10,626	37.8%
3. Promo	69,040	00:01:14	00:01:05	1.13	5,010	17.8%
4. Category	109,248	00:01:18	00:00:55	1.41	1,590	5.7%
5. Advantages	56,896	00:01:39	00:01:14	1.34	143	0.5%
6. FAQ	5	00:00:06	00:00:06	1.00	0	0.0%

7a. before the form launch by device types

	DW - Site info - Credit card pages (hits)			
	Only before form launch			
	Visits	Avg. Time per Session	Avg. Time on Page	Page views per visit
Mobile Device Type Page: 1 / 1 Rows: 10 1-6 of 6	32,453 out of 32,453	00:01:42 out of 00:01:42	00:01:13 out of 00:01:13	1.41 out of 1.41
1. Mobile Phone	21,779	00:01:26	00:01:03	1.37
Pages: Page Name Type Page: 1 / 1 Rows: 5 1-5 o	18,986 out of 21,779	00:01:25 out of 00:01:26	00:01:01 out of 00:01:03	1.39 out of 1.37
1. Hub	8,300	00:01:12	00:01:03	1.13
2. Product	7,408	00:01:12	00:00:52	1.39
3. Promo	4,204	00:01:22	00:01:14	1.10
4. Category	1,299	00:01:26	00:01:03	1.36
5. Advantages	298	00:02:05	00:01:36	1.30

Mobile Phone

	DW - Site info - Credit card pages (hits)			
	Only before form launch			
	Visits	Avg. Time per Session	Avg. Time on Page	Page views per visit
2. Other	9,322	00:02:17	00:01:31	1.50
Pages: Page Name Type Page: 1 / 1 Rows: 5 1-5 o	7,870 out of 9,322	00:02:17 out of 00:02:17	00:01:29 out of 00:01:31	1.54 out of 1.50
1. Product	3,804	00:02:02	00:01:25	1.43
2. Hub	3,329	00:01:38	00:01:23	1.18
3. Promo	1,311	00:02:01	00:01:54	1.06
4. Category	785	00:02:02	00:01:28	1.37
5. Advantages	229	00:02:47	00:02:07	1.31

Other

	DW - Site info - Credit card pages (hits)			
	Only before form launch			
	Visits	Avg. Time per Session	Avg. Time on Page	Page views per visit
3. Tablet	1,335	00:02:02	00:01:33	1.32
Pages: Page Name Type Page: 1 / 1 Rows: 5 1-5 o	1,123 out of 1,335	00:02:01 out of 00:02:02	00:01:31 out of 00:01:33	1.33 out of 1.32
1. Hub	505	00:01:34	00:01:25	1.11
2. Product	387	00:02:01	00:01:28	1.37
3. Promo	258	00:01:47	00:01:41	1.07
4. Category	74	00:02:26	00:02:00	1.22
5. Advantages	26	00:01:54	00:01:14	1.54

Tablet

8a. During Form launch per device types

	DW - Site info - Credit card pages (hits)					
	Visits	Avg. Time per Session	Avg. Time on Page	Page views per visit	Credit-Card Form: Launch (e109)	CCIA: Form Submit
1. Mobile Phone	22,116	00:02:13	00:01:20	1.66	21,973 66.9%	30.0%
Mobile Phone — Pages: Page Nam Page: 1 / 5 › Ro	19,446 out of 22,116	00:02:13 out of 00:02:13	00:01:19 out of 00:01:20	1.67 out of 1.66	19,082 out of 21,973	Nov 1
1. Hub	8,691	00:01:50	00:01:23	1.32	7,359 38.6%	38.2%
2. Other	9,738	00:03:54	00:02:06	1.85	9,503 28.9%	66.3%
Other — Pages: Page Nam Page: 1 / 5 › Ro	8,413 out of 9,738	00:03:52 out of 00:03:54	00:02:03 out of 00:02:06	1.88 out of 1.85	7,872 out of 9,503	Nov 1
1. Product	4,329	00:03:18	00:02:01	1.63	3,406 43.3%	43.7%
3. Tablet	1,362	00:03:10	00:01:55	1.65	1,351 4.1%	3.7%
Tablet — Pages: Page Nam Page: 1 / 5 › Ro	1,162 out of 1,362	00:03:05 out of 00:03:10	00:01:51 out of 00:01:55	1.65 out of 1.65	1,129 out of 1,351	Nov 1
1. Hub	536	00:02:38	00:02:00	1.31	477 42.2%	30.6%

9a. Before the form launch by channels

	DW - Site info - Credit card pages (hits)			
	Only before form launch			
	Visits	Avg. Time per Session	Page views per visit	Credit-Card Form: Launch (e109)
Last Touch Channel Page: 1 / 2 › Rows: 10 1-10	32,453 out of 32,453	00:01:42 out of 00:01:42	1.41 out of 1.41	0 out of 0
1. Paid Search	11,499 35.4%	00:01:38	1.29	0 0.0%
Paid Search — Pages: Page Name Type Page: 1 / 5 › Rows: 1 1-	9,587 out of 11,499	00:01:37 out of 00:01:38	1.31 out of 1.29	0 out of 0
1. Hub	5,811 60.6%	00:01:16	1.12	0 0.0%
2. Natural Search	8,232 25.4%	00:02:03	1.60	0 0.0%
Natural Sea... — Pages: Page Name Type Page: 1 / 6 › Rows: 1 1	8,232 out of 8,232	00:02:03 out of 00:02:03	1.60 out of 1.60	0 out of 0
1. Hub	4,710 57.2%	00:01:24	1.15	0 0.0%

	DW - Site info - Credit card pages (hits)			
	Only before form launch			
	Visits	Avg. Time per Session	Page views per visit	Credit-Card Form: Launch (e109)
3. Affiliates	7,385 22.8%	00:01:23	1.34	0 0.0%
Affiliates — Pages: Page Name Type Page: 1 / 5 › Rows: 1 1-	5,602 out of 7,385	00:01:16 out of 00:01:23	1.39 out of 1.34	0 out of 0
1. Product	5,365 95.8%	00:01:08	1.31	0 0.0%
4. Display	1,820 5.6%	00:01:36	1.28	0 0.0%
Display — Pages: Page Name Type Page: 1 / 5 › Rows: 1 1-	1,176 out of 1,820	00:01:32 out of 00:01:36	1.37 out of 1.28	0 out of 0
1. Product	611 52.0%	00:01:23	1.35	0 0.0%
5. Direct	1,761 5.4%	00:01:28	1.25	0 0.0%
Direct — Pages: Page Name Type Page: 1 / 6 › Rows: 1 1	1,761 out of 1,761	00:01:24 out of 00:01:28	1.25 out of 1.25	0 out of 0
1. Product	829 47.1%	00:01:10	1.07	0 0.0%

10a. Before form launch 1st or 2nd visit

	DW - Site info - Credit card pages (hits)			
	Only before form launch			
	Visits	Avg. Time per Session	Page views per visit	Credit-Card Form: Launch (e109)
Segments Page: 1 / 1 Rows: 400 1-5 of 5	32,453	00:01:42	1.41	0
1. 1 page views in credit card section	20,912 64.4%	00:00:54	0.98	0 0.0%
1 page views in cr... — **Segments** Page: 1 / 1 Rows: 5 Retrieving data...	20,912	00:01:43	1.96	0
1. First visit in credit card section (exclude ...	17,333 82.9%	00:00:55	0.98	0 0.0%
2. 2nd or more visit in credit card section	3,579 17.1%	00:00:47	0.97	0 0.0%
2. 2 page views in credit card section	5,887 18.1%	00:02:04	1.55	0 0.0%
2 page views in cr... — **Segments** Page: 1 / 1 Rows: 5 Retrieving data...	5,887	00:04:06	3.05	0
1. First visit in credit card section (exclude ...	4,630 78.6%	00:02:06	1.56	0 0.0%
2. 2nd or more visit in credit card section	1,257 21.4%	00:02:00	1.49	0 0.0%

11a. During form launch 3rd and above page views

		Visits	Avg. Time per Session	Page views per visit	Credit Card Launch Rate	Credit-Card Form: Launch (e109)	CCIA: Form Submit
	3. 3 page views in credit card sect...	43,257 6.6%	00:04:35	2.81	5.44%	2,355 7.2%	294 11.7%
3 page views in cr...	**Segments** Page: 1 / 1 Rows: 5 1-2 of 2	↓ **43,257**	**00:09:49**	**5.66**	**10.63%**	**2,355**	Nov 1 **294**
	1. First visit in credit card secti...	33,672 77.8%	00:04:20	2.79	5.55%	1,868 79.3%	234 79.6%
	2. 2nd or more visit in credit c...	9,585 22.2%	00:05:29	2.87	5.08%	487 20.7%	60 20.4%
	4. 4 page views in credit card sect...	27,248 4.2%	00:05:24	3.72	4.28%	1,167 3.6%	183 7.3%
4 page views in cr...	**Segments** Page: 1 / 1 Rows: 5 1-2 of 2	↓ **27,248**	**00:11:36**	**7.47**	**9.11%**	**1,167**	Nov 1 **183**
	1. First visit in credit card secti...	21,622 79.4%	00:05:08	3.70	4.09%	885 75.8%	132 72.1%
	2. 2nd or more visit in credit c...	5,626 20.6%	00:06:27	3.77	5.01%	282 24.2%	51 27.9%