How can e-retailers reduce the gap between online and offline conversion rates?

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Abstract

This paper introduces and investigates the gap between online and offline conversion rates. After reviewing a large body of literature on both physical retailing and e-retailing, the author designs a theoretical framework with nine factors that significantly influence conversion probabilities: customer characteristics, retailer characteristics, website characteristics, offering characteristics, session characteristics, competition, previous touch-points, post-purchase experience and exogenous factors. In order to validate this framework, qualitative and quantitative methods are applied. On one hand, the author conducted four focus groups and a few in-depth interviews to gather critical feedback from consumers and digital professionals. On the other hand, the author applied three statistical techniques (logistic, OLS and symbolic regressions) to a click-stream data set provided by a major click-and-mortar retailer in France. In addition to the theoretical framework and the statistical results, the author also outlines four major opportunities for e-retailers, and many ideas for further research. This effort should mainly be considered as a ground work for follow-up studies that the author wishes to pursue.

Keywords: E-retailing, Online purchasing, Conversion, Multichannel, Consumer behavior

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Part I

Introduction

Chapter 1

Conversion Gap

It is no secret that e-retailing maintains an impressive growth since the creation of amazon.com and ebay in 1995. Last year, global e-commerce sales almost exceeded one trillion US$ (Ben-Shabat et al., 2015) and with new levers such as mobile commerce (Criteo, 2016), this trend does not seem about to reverse. Thus, e-retailing might appear to be a complete success compared to the traditional brick-and-mortar model. However, the latter still beats its digital counterpart on one of, if not the most important key performance indicator in retailing: the conversion rate.

Online conversion rates are usually reported around 3,5% and below (Monetate, 2015), while in-store conversion rates often reach 25% (Perdikaki, 2011) and higher. We refer to this phenomenon as the *conversion gap*, and dedicate our study to the following question: how can e-retailers reduce it? Obviously, this issue is already well-known by e-retailers, who are constantly trying to optimize their conversion rates through extensive AB testing and whatnot. Nevertheless, we truly believe that the latest breakthroughs in digital marketing, namely Tag Management Systems (TMS) and Data Management Platforms (DMP) (McCormick, 2015) such as Ensighten, Tag Commander or Tealium can have a huge impact on the conversion gap. With those solutions, it is possible to collect, distribute and activate data in real-time across all digital environments, which means being able to deliver a customized, unique and unified experience for each customer on all its devices using personal and contextual data.

Those innovations are truly challenging the status quo of the conversion gap, and thus motivate this research. Our objective is twofold: we aim to build a theoretical framework of factors that influence conversion, and discover potential solutions that could reduce the conversion gap.

In order to study the conversion gap, we anchor this phenomena into existing literature in the next part, before introducing the theoretical framework in part three. Part four and five support our theoretical framework with qualitative and quantitative research. In the final part, we discuss the results, present our academic and managerial contributions as well as some limitations and possibilities for further research. But first, we detail the notion of conversion rates.

Chapter 2

Conversion Rates

Conversion rates indicate the percentage of users or visitors who take a desired action. Such metrics can be computed for different objectives, such as the percentage of visitors who subscribe to a newsletter or who create an account. However, conversion rates most often relate to the actual purchases that consumers make.

In a brick-and-mortar situation, converted visitors enter the store and buy at least one product. Non-converted visitors only come in, and leave without purchasing anything.

Online, we use the same logic, but it is worth noting that at least two reference points can be used. The most straightforward approach is to compute conversion rates per session, which means dividing the number of converted sessions by the total number of sessions. This indicator can be interpreted as the *likelihood of visits to end up with orders*. Yet, e-retailers are also able to compute conversion rates per visitor. This second type of conversion rate is computed differently: each visitor is identified by a unique browser cookie, and we consider them as converted visitors if they placed an order during at least one of their sessions. Then, the final ratio is the number of converted visitors divided by the total number of visitors, and one can interpret this value as the *likelihood to convert visitors to clients.*

Again, conversion rates are some of the biggest key performance indicators in retailing and especially e-retailing. Such metrics lead immediately to action (Peterson, 2006), and are economically relevant since a 1% increase in conversion rates has a drastic impact on sales, depending on your traffic size. In the industry, it is common practice to cross conversion rates with complex segmentations, in order to, for example, compare the performance of different traffic generation sources. Nevertheless, we were surprised to see that there is little empirical research on this output variable, even though it is of utmost importance for practitioners.

Please note that in the whole dissertation, we use the terms sessions and visits interchangeably.

Part II

Literature Review

Chapter 1

Comparing Channels

Why do we observe such a gap between on-line and offline conversion rates? When Salomon and Koppelman (1988) developed a framework for studying teleshopping versus store shopping in the late 1980s, it appeared that the system characteristics of those channels, such as the range of services or the user friendliness were fundamentally different. As a result, consumers would select their conversion channel. Likewise, e-retailing differs from store shopping on several levels, and as a result, conversion rates naturally diverge.

Many articles delve into those differences through multiple lenses. Hsiao (2009) presents five differentiating attributes (information gathering, shopping, purchase, transaction and delivery) that could influence the conversion likelihood of visitors. For example, customers in a store shopping situation (compared to e-retailing) face less information uncertainty but also need to recover from travel costs, which increases their propensity to convert. Lee and Tan (2003) identify two important factors that lead consumers to convert on-line or in-store: the retail context utility and consumers' perceived service risks. Their empirically-supported model suggests that consumers experience a higher retail context utility and lower perceived service risks in-store. Consequently, in-store conversion rates are expected to outperform on-line statistics. Avery et al. (2012) introduce a somewhat different perspective with the notion of capabilities, that is enabling characteristics of a channel that might differentiate it from another. Capabilities can be conspicuous, in other words, quickly apparent to consumers, or experiential, when they are discovered through shopping visits. Once again, retail stores seem to be the most appropriate channel for conversion according the capabilities framework, with minimal tangible and intangible transaction costs, a pleasurable shopping experience and a possible relationship with the retailer that makes shopping easier. Also, Grewal et al. (2004) detail eleven limiters of internet retailing, which seem very much like eleven weaknesses compared to store shopping. Among them, the absence of instant gratification when acquiring a product or service and the lower customer service certainly draw online conversion rates to the bottom.

Furthermore, the marketing literature offers many studies on unique advantages that only brick-and-mortar stores can benefit from. The effect of touch on perceived ownership and thus on product evaluation (Peck and Shu, 2009) undoubtedly increases the conversion probability, just as the ability to assess non-digital attributes (Lal and Sarvary, 1999) or being influenced by any sensory cues (Biswas et al., 2014). In a surprising article, Meyers-Levy et al. (2010) even support the notion that the texture of the flooring on which consumers stand in-store affect people's assessments of store products, and thus purchase intention or conversion probability. Also, customer-employees interactions play a major role in making or breaking the conversion and with the right abilities, retail employees show an above-average performance in converting customers. Kidwell et al. (2011) develop the concept of emotional intelligence, that is the ability to perceive, facilitate, understand and manage emotions, and investigate its impact on sales performance. Jasmand et al. (2012) demonstrate that ambidextrous behavior, the employee's ability to manage disparate task demands has a positive impact on sales performance and customer satisfaction. Finally, Gremler and Gwinner (2008) identify critical rapport-building behaviors that relate significantly to customer satisfaction and conversion, such as intense personal interest or unexpected honesty. Those interactions are key in provoking conversion, but they are almost impossible to reproduce online, even if retailers implement customer chats and other substitutes.

Altogether, those examples illustrate how the e-retailing environment, compared to physical stores, lacks critical levers and fails to convert customers. However, from the unique differences between the two channels emerge a particular behavior, referred to as *channel combinations*. We believe that this behavior plays an equal if not bigger role in explaining the conversion gap, and dedicate the following chapter to it.

Chapter 2

Combining Channels

Combining channels is not a new phenomenon, as Salomon and Koppelman (1988) already presented this behavior with their shopping-purchasing sequence in the late 1980s. After entering the market, individuals undertake a first shopping cycle where they select their shopping mode (in-home media alternatives or out-of-home shopping locations), gather information and evaluate the situation. At the end of this cycle, a decision has to be made: purchase the product or service, exit the shopping process or undertake another shopping cycle with a potentially different channel. Out of those three outcomes, only the first one leads to conversion. The other cycles, ending with a simple exit or with an additional cycle are non-converted visits or sessions in an online context.

Engaging in a shopping cycle without purchasing is well-known phenomenon, often referred to as *free-riding*. However, it is undoubtedly exacerbated with e-retailing (Huang et al., 2009). Engaging in additional shopping cycles online is only one click away, and visitors gather information from different websites before their final decision. Thus, many non-converted sessions occur before the actual conversion.

Nevertheless, the most comprehensive approach comes from the research-shopper phenomenon (Verhoef et al., 2007), defined as the tendency of customers to use one channel for search and another for purchase. Research-shopping is closely related to our conversion issue, because channels only used for search by customers are *de facto* non-conversion channels. In order to evaluate and compare store retailing against e-retailing, the authors provide three criteria: (1) search attributes, (2) search and purchase attributes and (3) purchase attributes. Those attributes influence the attractiveness to search in a channel and purchase in a channel. From this framework, they derive three mechanisms that encourage research shopping, and thus lead a visitor to adopt a non-conversion behavior: attribute-based decision-making, lack of channel lock-in and cross-channel synergy. Attribute-based decision-making leads to non-conversion if the e-commerce website is judged adequate for information search, but less adequate than another channel for actual purchase. Unfortunately, this is true for almost fifty percent of customers (Kelly, 2002). Lack of channel lock-in is directly related to conversion because it reflects the inability to conserve a customer from search to purchase, and finally, cross-channel synergy encourages non-conversion because non-converting in an online channel increases the utility of converting in another one. For example, one visitor could gather price information online, and use this knowledge for price negotiations in store.

If combining channels is a widespread phenomenon among customers, academicians and practicians alike also realized the importance of research-shopping and multichannel shopping. Major retailers such as Best Buy embrace the click and mortar business model while Google and Amazon recently opened their first physical stores (Sawers, 2015; Alter and Wingfield, 2016). At the same time, researchers clarify the complex interplays in multichannel shopping on different levels. Venkatesan et al. (2007) design a model predicting channel adoption duration, Dinner et al. (2014) reveal how advertising has cross-channel effects, when Kushwaha and Shankar (2013) investigate if multichannel customers are really more valuable, Anderl et al. (2016) evaluate the interactions between online channels and Li and Kannan (2014) look for the optimal method for attributing conversion in a multichannel environment.

As the two previous chapters illustrated, the conversion gap is the result of (1) unique differences between the e-retailing environment compared to physical stores and (2) the importance of the research shopping phenomenon. In the next part, we design a theoretical framework that aims to identify what increases or decreases the conversion likelihood of online customers.

On the next page, we present a figure that links together conversion rates, research shopping, and our theoretical framework.

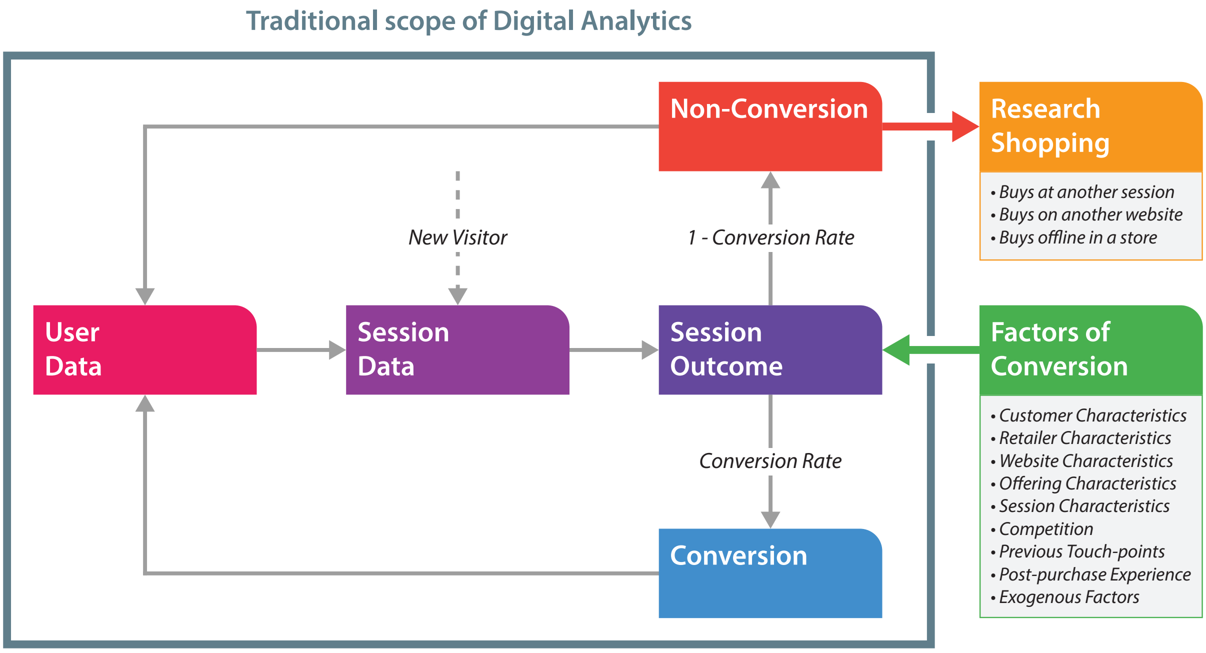

Figure 2.1: Conversion and Research Shopping

Part III

Theoretical Framework

Chapter 1

Overall Presentation

The theoretical framework set out below has one simple objective: offer a comprehensive overview of all the factors that affect conversion likelihood in a digital retailing environment. We designed this framework based on existing literature, but we admit that finding appropriate articles was a complex task, especially since conversion rate or conversion likelihood are rarely used as output variables. However, they are intimately related to more researched keywords such as unplanned purchase (Inman et al., 2009), purchase likelihood (Huang et al., 2009), e-impulse buying (Park et al., 2012) or purchase intention (Holzwarth et al., 2006).

Thus, we gathered articles that analyze what antecedents, mediators or moderators affect those proxy dependent variables in an online or offline situation. First, we conducted an issue-by-issue search for relevant articles in major journals, such as *Journal of Marketing*, *Journal of Marketing Research*, *MIS Quarterly*, *Marketing Science* or the *Journal of Retailing*. Second, we performed keyword searches in Google Scholar around "online conversion rates" and similar themes. Third, we carefully looked through the reference lists of our relevant articles and repeated this three-steps method when new factors were detected. Once new items completely overlapped with our existing body of literature, we stopped this research and started to synthesize all factors.

All in all, the framework consists of nine elements that influence conversion probability:

1. Customer Characteristics
2. Retailer Characteristics
3. Website Characteristics
4. Offering Characteristics
5. Session Characteristics
6. Competition Characteristics
7. Previous Touch-points
8. Post-purchase Experience
9. Exogenous Factors

The first eight factors were discovered during this phase, while the last item, *Exogenous Factors*, was highlighted later in the qualitative part of our research. Therefore, we now present the first eight factors and will introduce the last one later in part IV, page 37. A figure depicts the whole theoretical framework on page 17.

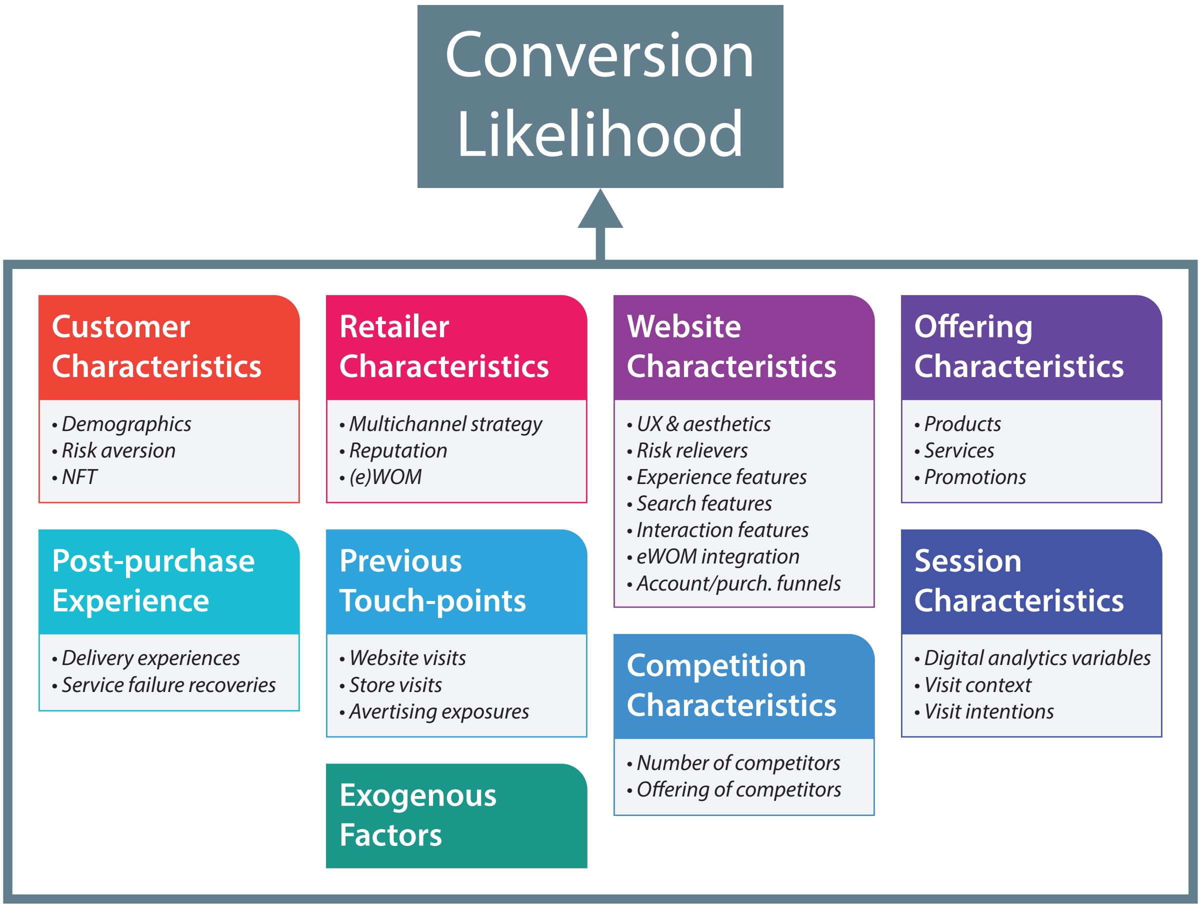

Figure 1.1: Theoretical Framework

Chapter 2

Factor Definitions

2.1 Customer Characteristics

Heterogeneity of customers has a notable impact on conversion likelihood. We concur with Forsythe and Shi (2003) and Lee (2002) that demographics, such as age, household income, gender and online experience have an influence on online shopping behavior and thus on conversion probabilities.

Among the many constructs used in marketing research to describe customers, we believe that two notions merit a special attention in our work: risk aversion, and the need for touch (NFT). Risk aversion relates to how customers perceive and tolerate risk. While risk-averse consumers avoid uncertain situations and need reliable information, risk-taking individuals have a higher tolerance against risk and are more likely to accept uncertain outcomes. Trust and risk are major themes in e-retailing (Rose et al., 2012; Gefen et al., 2003; Schlosser et al., 2006), and Lee and Tan (2003) empirically support that risk-averse customers are less likely to shop on-line. Thus, we predict that the conversion probability of risk-averse customers is lower that the conversion probability of risk-taking customers.

Our second construct, the need for touch (NFT) scale is a twelve items measure developed by Peck and Childers (2003). NFT is designed to assess individual differences in preference for haptic information, and the authors find that high NFT individuals only possess confidence in product judgment through direct physical experience. Citrin et al. (2003) present a similar construct with the need for tactile input, and investigate how it influences internet purchase with an ordinary least squares regression analysis. It appears that higher levels of the need for tactile input result in decreased levels of the use of the Internet for product purchase. Altogether, we hypothesize the following:

Proposition 1. *Customer characteristics, such as demographics, risk aversion or NFT influence the probability of conversion.*

2.2 Retailer Characteristics

Retailer characteristics have a major influence on conversion probability. First of all, the retailer strategy itself can hugely impact conversion rates: if the overall plan is to reach potential customers online and drive them to physical stores for conversion through cross-channel synergies (Verhoef et al., 2007), online conversion rates should be unsurprisingly low. In the opposite scenario, where stores are used as living billboards (Avery et al., 2012) to send customers online, e-retailing conversion rates should increase since customers only come to make the last click before purchase.

Also, retailer's reputation is expected to influence conversion. Reputable retailers should have better conversion rates than unknown retailers. Lee and Tan (2003) partially support an even more constraining hypothesis: consumers are more likely to shop on-line from reputable retailers for lesser-known brands than from lesser-known retailers for reputable brands.

Moreover, it is no secret that word-of-mouth and electronic word-of-mouth have higher elasticities on sales than any other marketing mix weapons such as advertising or promotions (You et al., 2015). Thus, we believe that retailers that benefit from positive word-of-mouth (fast delivery, excellent aftersales services...) will show better conversion rates than retailers that are victim of negative word-of-mouth. In brief, we assume that:

Proposition 2. *Retailer characteristics, such as its multichannel strategy, reputation and word-of-mouth influence the probability of conversion.*

2.3 Website Characteristics

Predictably, website characteristics have a central role in facilitating or preventing conversion. Providing a comprehensive and coherent overview of which website characteristics influence conversion appeared to be quite challenging. However, we managed to delineate seven elements that are particularly essential: user experience and aesthetics, risk relievers, experience features, search features, e-wom integration, interaction features and finally, account and purchase funnels.

2.3.1 User Experience & Aesthetics

When visitors arrive on a website, user experience and aesthetics are the first thing they assess. A quality user experience is a must-have for any e-retailer.

Lee (2002) insists on the importance of online purchase experience: users want ease of navigation, speedy access to all related web pages and he concludes that convenience is the motivating factor for purchase. Rose et al. (2012) suggest that online customer experience is made of a cognitive experiential state and an affective experiential state. Those two components have a major impact on purchase intention and among their antecedents, we notice telepresence, ease-of-use, aesthetics and perceived control. After all, perceived control and ease-of-use are building blocks of the Technology Acceptance Model (Gefen et al., 2003) and the Theory of Planned Behavior (Pavlou and Fygenson, 2006), both relevant in the context of e-retailing. An excellent user experience creates a state of *flow* (Rose et al., 2012), where consumers are completely absorbed by the shopping activity and show high levels of enjoyment. In such a state, consumers are more likely to convert.

Besides, Griffith (2005) investigates the importance of store layout in online retailing and how it influences different outputs, from perceived ease of use to purchase intentions.

Finally, as surprising as it may seems, aesthetics can deeply influence purchase behaviors. In auction and negotiation situations, Bagchi and Cheema (2013) find that a simple change in, for example, background colors leads to a higher willingness to pay. In the industry, retailers frequently modify the look of their call-to-action buttons, and analyze how new shapes, colors, or wordings influence their conversion rates. We conclude that a quality user experience and appropriate aesthetics are indispensable features for conversion.

2.3.2 Risk Relievers

As mentioned earlier in section 2.1, page 18, risk and trust are major themes in online retailing research. Kim et al. (2009) go as far as stating that trust is one of the two stepping stones for successful e-commerce relationships alongside customer satisfaction. In their research model, trust is the first of all antecedents, leading to perceived benefit, willingness to purchase, purchase behavior and in the long run, to satisfaction and e-loyalty. Forsythe and Shi (2003) indicate that consumers even face four different types of risks when ordering online related to product performance uncertainties, financial losses, psychological losses (user privacy) and time losses plus potential inconveniences.

In order to generate trust and reassure customers, "classic" risk relievers such as privacy and security statements, money-back guarantee, free trial and warranty have been proven effective (Lee and Tan, 2003). More surprisingly, the work of Schlosser et al. (2006) indicates that web site investments also generate trusting beliefs. Indeed, investments in the front-end of the website, resulting in better designs, more dynamic features or fancy animations generate ability beliefs: consumers, purely based on aesthetic judgments, become confident that the firm is able to and will provide a risk-free experience, from navigation to purchase and delivery.

Those risk relievers and trust building mechanisms are a must-have for any e-retailer, and in case of absence, many customers would leave the website before conversion.

2.3.3 Experience Features

As mentioned earlier in section II.1, page 10, online websites poorly perform against retail stores in terms of product assessment. However, e-retailers set up many substitutes that attempt to solve this problem. If customers are able to decide whether the products fit their needs online, they will be less likely to end up purchasing in a store, and more likely to purchase directly on the website.

The Need For Touch literature illustrate how haptic feedback influences purchase intentions, but also look at potential solutions when touch is not available (Peck and Wiggins, 2006; Peck and Childers, 2003; Peck and Shu, 2009; McCabe and Nowlis, 2003). Written descriptions, visual depictions, ownership imagery all serve as substitute for touch and are likely to increase conversion, especially for products with primarily material properties such as clothes. However, this discussion is not limited to touch: Krishna et al. (2014) argue that encouraging imagined scents and tastes using visual input and primed descriptions increases the desire to eat and the actual consumption.

According to Jiang et al. (2014), customers engage in self-imagery. In other words, they form mental images in order to create a story of the consumption experience or to acquire information about this experience. With four different studies, they stress the importance of offering the right visuals to facilitate mental images, who positively influence product evaluations and thus, purchase intentions. Elder and Krishna (2012) study a more detailed phenomenon by showing how product orientation (right orientation of the product for right-handed customers and vice-versa) facilitate mental simulations and increase purchase intentions.

Huang et al. (2009) study the effects of experience features in the context of e-retailing. Using website visitation and transaction data, they support an indirect effect of experience features on purchase likelihood, with time on site as a mediator. We conclude that the presence of experience features leads to higher conversion rates.

2.3.4 Search Features

Site search is not the only feature visitors use to find what they are looking for (Katz and Byrne, 2003). Still, it is proven to be essential in some cases. While some visitors only come for hedonic purposes, jump from one category to another, read editorial contents and look for a pleasurable experience, other visitors, like the *directed buyers*, know the exact product they want and are here to buy (Moe and Fader, 2004b). It is of utmost importance that we provide them with an efficient search engine, as well as similar product recommendations. If directed buyers are unable to find what they are looking for, they will surely quit the website and look if other retailers have what they need. On-site search optimization is a well-known problematic in the industry, since retailers' statistics always show that site search users have a higher conversion rate than the overall mean (Charlton, 2013; Killen, 2013; Sherice, 2013).

2.3.5 eWOM Integration

The importance of retailers' word-of-mouth was already highlighted in section 2.2, page 19. We now look at how product eWOM features are implemented in the website. It has been proven that word-of-mouth is important for customers' purchase decisions (Ludwig et al., 2013; Trusov et al., 2009; Gopinath et al., 2014; You et al., 2015), but these authors also argue that the effect size depends on how eWOM is integrated.

For example, You et al. (2015) show that platform characteristics, such as the expertise of the website (specialized vs. general review sites) and its trustworthiness (independent reviews, community-based systems) accentuate the effect of eWOM on sales. Thus, e-retailers could link reviews from indenpendent websites to increase the impact of eWOM on conversion.

Gopinath et al. (2014) argue that eWOM is made of three dimensions: attribute (evaluation of product performances and features), emotion (feelings associated with product usage) and recommendation (keywords that invite customers to buy the product). Among the three dimensions, recommendation has the biggest influence on purchase. E-retailers could encourage users to provide information on those three dimensions and especially recommendation to use eWOM as an efficient conversion lever. Finally, Ludwig et al. (2013) clarify the influence of affective content and linguistic style matches in online reviews on conversion rates. Their findings underline the importance of emotion keywords, and suggest that retailers could improve conversion rates by displaying reviews with strong affective content and aligned linguistic style first. The authors also discourage e-retailers to push forward extremely positive reviews that are viewed as biased or fake by visitors. In summary, eWOM influences conversion rates and e-retailers can derive an even greater benefit from it if eWOM features are well implemented.

2.3.6 Interaction Features

According to Song and Zinkhan (2008), interactivity is an important factor that influences purchase behavior. Interactivity comprises features such as e-mail links, live chats with employees or toll-free numbers. The authors find that personal messages and quick answers were the most important predictors of interactivity, and we suggest that retailers should follow those guidelines to maximize conversion probabilities.

Furthermore, Holzwarth et al. (2006) study the effects of avatars on online consumer shopping behaviors. With personified interaction features like virtual sales agents, customers declare greater purchase intentions. It is worth noting though that the level of product involvement moderates the effectiveness of avatar type. For high levels of product involvement, expert avatars are more appropriate than attractive avatars.

E-retailers are constantly implementing new interaction features. Offering live chat solutions like iAdvize is now common practice, but lately, vendors such as TokyWoky even allow for Customer-to-Customer live chat and crowd-sourced Q&A. Customers themselves are making other visitors convert by recommending products and reassuring risk-averse customers. Those companies claim that chat users are up to six times more likely to convert (TokyWoky, 2016). Thus, interaction features are an efficient lever for provoking conversion.

2.3.7 Account and Purchase Funnels

In his whitepaper, Baksa (2016) relates non-conversion to abandonment. In practice, visitors exit the website at different points before conversion. While some customers never enter the conversion funnel, other visitors add some products to cart but never go further. Surprisingly enough, a significant rate of customers even begin the checkout process, yet never convert. Those last customers indicate that the purchase funnel is truly permeable, and at each step of the checkout, customers are lost. According to Baksa (2016), there are three primary reasons for checkout abandonment: payment, shipping and promo code. *Payment abandonment* happens when customers experience trouble with the payment stage of the checkout, and the author suggests that retailers could provide a phone number with which customers could complete their orders. *Shipping abandonment* happens when customers experience issues with the shipping mode, are surprised by total shipping costs or cannot benefit from a free of charge shipment because their basket is just below the minimal value. Offering shipping discounts at that point could encourage those customers to pursue through the funnel. Finally, *promo code abandonment* happens when customers are unable to redeem their promo codes. Again, being able to detect those suspicious behaviors and offering additional promo codes would encourage customers to pursue in the conversion funnel. In short, a carefully designed purchase funnel with dynamic features that prevent customers from abandoning the conversion process are essential for conversion rate optimization.

However, before reaching the purchase funnel, account creation is often a mandatory step and once again, a significant amount of customers leave the account creation funnel before it ends. Since visitors commit to a relationship with the retailer when they create an account on the website, we believe that the framework of Noble and Phillips (2004) is perfectly applicable in this context. In total, they identify four themes explaining relationship hindrance: upkeep themes (too much efforts required), time themes (too much time required), benefit themes (members' advantages are unappealing) and personal loss themes (potential loss of private data). Consequently, retailers should make sure that the account creation process is effortless and quick, that the data is secure, and that they offer unique and interesting benefits to website members. On the whole, we posit that:

Proposition 3. *Websites characteristics, such as user experience and aesthetics, risk relievers, experience, search and interaction features, eWOM integration and account/purchase funnels influence the probability of conversion.*

2.4 Offering Characteristics

Offering characteristics consist of the products, services and promotions provided by the retailer.

2.4.1 Products

The first question to ask regarding products relates to the ability to assess product quality and make thoughtful decisions. Lal and Sarvary (1999) introduce the concept of digital and non-digital attributes. While digital attributes can be directly evaluated online through, for example, detailed product sheets, non-digital attributes (such as texture, smell or taste) can only be appreciated through physical inspection. Thus, when products are essentially defined by digital attributes, customers should be more likely to directly convert online, instead of engaging in research shopping and buying the product in-store after a first research online.

The search, experience and credence product classification framework validated by Girard and Dion (2010) goes in the same direction. Search products can be evaluated without experiencing the product, whereas experience products can only be evaluated through usage. Credence goods, for their part, are impossible to evaluate, whether it is before purchase, after purchase or during usage. In their study, the authors prove the influence of product classification on online-purchase intention. Customers appear more likely to convert with search products, and less likely to convert with credence products.

Regarding product characteristics, risk also seems to be of crucial importance. Forsythe and Shi (2003) argue that product perceived performance risks should influence the online shopping behavior, that is the amount spent online, the frequency of searching with intent to buy, and the frequency of purchasing online. Likewise, Lee and Tan (2003) consider in their theoretical model that consumers' perceived product and service risks is one of the two main factors impacting consumer choice between on-line and in-store shopping. Their findings indicate that customers are more likely to buy low risk products instead of high risk products. Hence, we hypothesize that perceived product and service risks influence conversion, such as higher risks prevent when lower risks encourage conversion.

2.4.2 Services

Offering products is not more than half of what e-retailers need to provide since each order is followed by a complex delivery system. Customers pay close attention to fast delivery, return policies and after-sales services (Lee, 2002; Srinivasan et al., 2002; Kim et al., 2009). We believe that without the adequate services, customers are not likely to convert, and this is why many retailers, like Asos, Zalendo or Sarenza go as far as offering free 24 hours deliveries and accept free returns with complete reimbursements for up to one hundred days after purchase. This point is discussed in details later in section 2.8, page 26.

2.4.3 Promotions

As one of the four components of the marketing mix, promotions are expected to favor conversion. Promotions can have many effects, such as provoke store switching, generate new users and accelerate purchase (Gedenk et al., 2006). Therefore, we believe that customers who can benefit from promotional activities are more likely to convert. For example, limited promotions could prevent a customer from engaging in research shopping and make him convert immediately instead. Zhang and Wedel (2009) develop a joint model of purchase incidence, choice, and quantity decisions with a comprehensive set of data on customized online promotions. As hypothesized, online promotions impact purchase incidence and increase conversion probabilities. All in all, we propose the following:

Proposition 4. *Offering characteristics, such as product class, perceived product risks, product price, delivery services and promotions influence conversion probability.*

2.5 Session Characteristics

Session characteristics obviously play a major role in conversion, because it is where it actually happens. Our definition of session characteristics includes what is traditionally measured by digital analytics, such as the entirety of page views, events, time on site, traffic sources, used device and whatnot (Google Analytics, 2016).

Using clickstream data, Montgomery et al. (2004) design a Markov model that predicts purchase conversion based on what types of pages are viewed during the session (home, account, category, product, information, shopping cart, order and exit). In the end, the model offers a 42% accuracy with as few as the first six pages, thus demonstrating the importance of the navigation path on conversion probability.

Likewise, time on site is supposed to have an important effect on conversion. In physical retailing, encouraging customers to stay as long as possible and to travel in-store as most as possible with a view to increasing unplanned spending is already well supported (Hui et al., 2013). Similarly, Huang et al. (2009) demonstrate how time on site is a major antecedent of purchase likelihood. Since visit duration appears to be a crucial variable, researchers even dedicate studies on how it can be increased (Danaher et al., 2006). Altogether, time on site is expected to have a major impact on conversion probability.

Also, we think that it is necessary to broaden our conception of session characteristics outside the scope of what digital analytics usually measure. For example, the visit time-stamp, easily retrieved with digital analytics might have an undeniable impact on conversion probability, but we believe that other contextual factors are more important. A visitor quickly checking the website on his smartphone when he takes the subway is less likely to convert compared to when he is at home, on his sofa with a laptop on his knees.

Among the many variables that digital analytics fail to retrieve, we believe that visit intentions are of utmost importance. Moe and Fader (2004b) indicate that visitors can be divided in four different groups: (1) directed buyers who come to order a particular product and have already made up their minds, (2) search/deliberation visitors who are unsure about which product they wish to buy but already acknowledged a need for a specific category, (3) hedonic browsers who have no purchase intention at first and only come in order to live a pleasurable experience and (4), knowledge-building visitors who are just entering the market and only looking for information. As a result, directed buyers and search/deliberation visitors should probably convert, whereas hedonic browsers could only do so because of self-control failures and impulsive purchasing (Baumeister, 2002). Unfortunately, knowledge-building browsers remain poor conversion candidates, at least in the short term. Kaltcheva and Weitz (2006) bring another contribution to this discussion by defining the concept of *motivational orientations*. According to the authors, store visits are either task-oriented or recreational, which means that customers engage in shopping because they need to buy something, or because they wish to spend a nice time. Naturally, task-oriented visits should be more likely to convert. On the whole, we suggest that:

Proposition 5. *Session characteristics, such as digital analytics variables (pages viewed, time on site, new or returning visitor), visit context and in-*

tentions influence the probability of conversion.

2.6 Competition

The whole concept of research shopping (Verhoef et al., 2007) is founded upon the presence of competitors, other retailers, and multiple channels. Thus, it is obvious that competition characteristics have a major influence on conversion rates.

If the e-retailer is operating in a highly competitive environment, such as well-known apparel brands or common consumer goods, it is likely that consumers systematically engage in research shopping. Also, comparing online offerings is effortless (Grewal et al., 2003). Therefore, if the retailer competes against perfectly designed websites, or is unable to offer the same prices and services than its competitors, its website is likely to be a simple transit point in the customers shopping journey, and should suffer from a low conversion rate.

On the contrary, if the e-retailer operates in a niche market or offers products and services that are not available elsewhere, consumers have no choice: it is impossible to engage in research shopping and if they plan to convert, they have to convert on the e-retailer's website. In conclusion:

Proposition 6. *Competition characteristics, such as the number and offerings of competitors influence the probability of conversion.*

2.7 Previous Touch-points

Since purchase decisions are often the culmination of many shopping cycles (Salomon and Koppelman, 1988) and long deliberations, previous touch-points play a major role in predicting conversion. We define previous touch-points as any way a consumer interacted with the retailer on the website, in its physical stores, through advertising messages or anything else before the conversion session occurred.

In their model of conversion behavior, Moe and Fader (2004b) predict customer's conversion probability based on previous website visits. Results indicate that each touch-point significantly increases the conversion probability of following sessions. Sometimes, customers even have the intention to convert before the last session actually starts: they already have all the information they need and know the exact product they wish to order (Moe and Fader, 2004b). In those situations, conversion is almost entirely explained by previous touch-points with the retailer and its competitors.

In a parallel study, the same authors (Moe and Fader, 2004a) design a non-stationary model referred to as the evolving visit (EV) model, based on disaggregate clickstream data with timing and frequency of online visits. Their findings confirm once more that frequent visitors are more likely to convert, but also bring to light a dynamic aspect: visitors who display an increasing visit frequency are significantly more likely to convert than others. Thus, we should emphasize in this section that both the frequency and velocity of touch-points play a major role in predicting conversion.

Regarding advertising, Manchanda et al. (2006) demonstrate that online banners impact purchase probabilities even if they suffer from low click-trough rates: with repetition, they increase brand awareness and constantly remind customers of their unfulfilled needs. Hence, customers that are exposed to banner advertising are more likely to convert than unknown customers. More recently, Liaukonyte et al. (2015) look into the effects of television advertising on online transactions. Their findings support our intuition: around the time of advertising broadcasts, the number of transactions increases even if the number of direct visits decreases, thus resulting in higher conversion rates.

Last but not least, Anderl et al. (2016) develop a comprehensive taxonomy of online channels or touch-points with two dimensions: the contact origin (firm or customer-initiated) and the brand usage (branded or generic). Using a proportional hazard model with time-varying covariates, they support the direct impact as well as the significant interactions between these different touch-points on the purchase outcome of a customer journey. All in all, the nature, number, frequency, velocity and combination of touch-points influence conversion probabilities. In other words, we propose the following:

Proposition 7. *Previous touch-points with the retailer, such as website visits, store visits and advertising exposures influence the probability of conversion.*

2.8 Post-purchase Experience

By post-purchase experience, we refer to everything that happens once a conversion is achieved, including but not limited to package tracking for customers, quality of delivery and potential service failure recoveries. Delivery services were already mentioned previously in section 2.4.2, page 23. However, we do not look at which services are offered and advertised on the website, but at how the actual experience of those services influence next conversions.

According to Lee (2002), satisfying after-purchase needs such as fast delivery, refunds, returns and after-sales services is one of the three key activities of online retailing, along building trust and confidence and providing a pleasurable online purchase experience. Srinivasan et al. (2002) also consider that the attention an e-retailer pays to the post-purchase experience is crucial in e-business. Finally, Kim et al. (2009) show in a longitudinal trust-satisfaction model how the perceived performance of post-purchase services influence satisfaction, and in the end, foster e-Loyalty. The latter construct, composed of repeated patronage, intention to repurchase and willingness to recommend the website to friends is likely to influence the conversion probability. If customers are delighted by their first post-purchase experience, they will convert more easily during following visits.

Also, the recovery paradox is a recurring theme in marketing research and has a role to play here. Tammo H.A. Bijmolt et al. (2014) study this phenomenon in the precise context of repurchase intentions on the internet, and their findings are no exception to the rule: highest repurchase intentions were not measured among consumers with positive experiences, but among consumers who faced negative experiences, complained and expressed satisfaction with how their complaints were handled. Regarding conversion, we believe that customers who experience the recovery paradox might display an additional positive effect on conversion probability. In short, we conclude that:

Proposition 8. *Post-purchase experience, such as delivery experiences or service failure recoveries influence the probability of conversion.*

Chapter 3

Factor Qualities

The previous chapter illustrated how each factors affect conversion probabilities. We now describe five qualities of conversion factors that we believe useful for practitioners and researchers alike. The five qualities are:

1. Content Nature
2. Interactions
3. Steerability
4. Measurability
5. Adaptability

3.1 Content Nature

By content nature, we refer to the on-line or off-line essence of what the nine factors include. As the name indicates, website characteristics only contain on-line features, whereas customer characteristics mainly involve off-line constructs.

However, most factors contain a mix of both. Session characteristics, for example, are made of purely digital measures, but also integrate the off-line context of the visit. Similarly, previous touch-points can be digital (online display, re-targeting advertising, website visits...) but also off-line with physical store visits or print advertising exposures. Specifically, it is important to note that post-purchase experience relates to what happens on the site after conversion, but most importantly and especially to how the product is delivered at the doorstep.

3.2 Interactions

If the nine factors should not overlap in terms of content, they do however interact between themselves. For instance, the presence of risk relievers (websites characteristics) should have an exacerbated impact for risk-averse visitors (customer characteristics), while experience features (website characteristics) should be more efficient for experience products (offering characteristics).

The marketing literature already offers extensive studies on interactions that can be applied here. Manchanda et al. (2006) find that responsiveness to advertising moderates the impact of advertising on customer's intentions, while Zhang and Wedel (2009) witness a significant heterogeneity across consumers regarding promotion sensitivity.

We introduced earlier in section 2.5, page 24 the work of Kaltcheva and Weitz (2006) on the importance of motivational orientations. In fact, motivational orientation (a session characteristic) is a key moderator between environmental (read website) characteristics and shopping behavior (conversion probability). If customers are here for a particular task, e-retailers should not display high-arousing features, since they result in lower levels of pleasantness and thus conversion probabilities. On the contrary, if customers have a recreational motivational orientation, e-retailers *should* display high-arousing features that are likely to spark unplanned conversions.

3.3 Steerability

By steerability, we refer to the the possible influence an e-retailer has on the nine factors. It did not go unnoticed that website characteristics were divided into seven subsections in the previous chapter. Many crucial and complex points were highlighted, but this is in fact good news for practitioners because e-retailers have complete ownership on website characteristics. A well-designed website that favors conversion is entirely up to e-retailers.

Retailers almost have complete ownership on retailer characteristics, offering characteristics and are directly responsible for the post-purchase experience. However, they can only influence previous touch-points with, for example, re-targeting advertising. Unfortunately, they have no power on competition characteristics and customer characteristics.

3.4 Measurability

Measurability indicates the possibility for e-retailers to gather data about the nine factors. Many tools allow e-retailers to do so, with site analytics for session characteristics, social media analytics for post-purchase experience and retailers' word-of-mouth (retailer characteristics), CRM systems for customer characteristics or competitive intelligence for competition characteristics.

Lately, the development of Tag Management Systems (TMS) and Data Management Platforms (DMP) multiplies measurability capabilities of e-retailers. In one database and for each customers, retailers can plug all the knowledge sources they have regarding customer characteristics, session characteristics or previous touch-points, notably for adaptability purposes.

3.5 Adaptability

As mentioned earlier, steerability can only go so far for some characteristics. But the latest breakthrough in measurability with TMS and DMP technologies take on its full meaning with adaptability.

Adaptability signifies the possibility for e-retailers to customize the experience they offer based on the nine factors. As we said before, it is impossible to influence customer characteristics such as risk aversion, but with the adequate measures, one could detect risk-averse behaviors and push forward risk relievers accordingly. This example is only one of the many applications that are induced from the steerability, measurability and adaptability qualities. Concrete applications will be discussed later, in section IV.3, page 38.

Part IV

Qualitative Axis

Chapter 1

Methodology

As mentioned in section III.1, page 16, there is little empirical research dedicated to the conversion gap, and to our knowledge, this is the first attempt in marketing research for a comprehensive conversion framework. Thus, we consider the conversion gap as a novel research idea, for which qualitative studies are particularly useful (Eisenhardt and Graebner, 2007). Also, qualitative data are key to solve "how" and "why" questions (Yin, 2009), which are at the heart of our research problem: why do visitors convert? How can we reduce the gap? Finally, the complex issues investigated in this paper require rich details and personal insights usually generated in qualitative settings (Engle, 1994).

The qualitative study of this research had two different purposes. First, we hoped to validate our theoretical framework by collecting critical feedback from practitioners and customers (Bloor et al., 2001). Second, we aimed to generate potential solutions in order to reduce the conversion gap. Our qualitative study mainly consisted of focus groups, but since the issues of interest required extensive probing, we deviated from the standard focus group procedure and carried out a mini-groups variation, with one moderator and only four or five respondents (Malhotra, 1999). We conducted four 90 minutes focus groups with different compositions in order to acquire and compare separate views (Bloor et al., 2001). The four groups were designed as follows:

1. One consumer group with four business school students in their early twenties.
2. One practitioner group with four professionals from different companies. Three persons were specialized in digital analytics and data management, and thus naturally familiar with TMS or DMP technologies, while the fourth member was a senior UX consultant.
3. One group with four marketers from a major fashion apparel click-and-mortar retailer in France. The group contained both specialists in digital marketing and traditional marketing.
4. One agency group composed of five professionals working in the same company with different expertise, such as UX design, strategic design, front-end development and project management.

We also gathered qualitative data from additional sources. 90 minutes in-depth interviews were conducted with two consultants from major TMS and DMP solution editors, mails were exchanged with data professionals and lastly, we consulted industry documents such as white papers, company reports and specialized blogs.

Overall, participants agreed with the proposed framework and brought many examples that match our propositions. However, the eight factors presented were not sufficient and an additional element, namely *exogenous factors* was detected. In chapter 2, we present the many comments regarding the theoretical framework and introduce the ninth and last proposition. In chapter 3, we present the creative solutions for the conversion gap highlighted during the qualitative study and link them to the existing literature.

Chapter 2

Findings

2.1 Customer Characteristics

The importance of customer characteristics was easily perceptible in the focus groups since participants frequently disagreed and expressed different views.

Some participants appeared to buy many different types of products and services online, while others showed higher levels of risk-aversion. In one group, participants had a heated debate on buying cars online. One respondent claimed that this was exactly the kind of products he would never buy on the internet when another participant declared that he recently bought his new car online without any test-drive at a local car dealership.

Participants were more or less risk-averse, but also differed on their willingness to share data about themselves with e-retailers:

> "I think there are different kinds of people. I always register my credit card online, because it makes transactions fast and easy. But I know that my mother hates to use her credit card information online and tries to disclose as less personal information as possible."

Participants reacted differently to certain website features. For example, the famous 1-click ordering of amazon.com was "fantastic" for some participants, while others disliked the feature and were afraid to order products by accident. Similarly, they all put forward different reasons for (not) buying online: some participants valued quick delivery above all, when others focused on price advantages or variety of product offerings.

2.2 Retailer Characteristics

As hypothesized, participants recognized the influence of retailer characteristics in their conversion behaviors. It appeared that many participants preferred to buy online from retailers that have both an online and offline presence:

> "Except for a few websites, it's usually hard to return products. That's why I particularly like retailers that have an e-commerce website and physical stores. When I'm buying clothes online, I know I can always return them at a store if they don't fit."

Moreover, digital professionals often pointed out during focus groups and in-depth interviews the importance of taking drive-to-store and drive-to-web strategies into account when looking at conversion rates. In high cross-channel synergies situations (Verhoef et al., 2007), conversions in-store might be due to online visits and vice-versa, making channel conversion rates unsuitable metrics without hindsight.

Finally, the importance of retailers' reputation and word-of-mouth was supported during the focus groups, above and beyond other characteristics such as risk relievers:

> "Of course, it's important for me to see guarantees on the website before I buy. But what matters more is simply the retailer's reputation, if I already know the brand, what my friends and family think of it if they already purchased something and so on."

2.3 Website Characteristics

In the previous chapter, website characteristics were divided in seven subsections in order to highlight the different key elements leading to conversion. During the qualitative research, participants spent a significant amount of time discussing those elements compared to other factors, and thus confirmed the large scope of website characteristics.

First of all, a pleasant user experience and effective aesthetics were an absolute must-have for most participants, who would otherwise quickly abandon the website (Baksa, 2016). Furthermore, risk relievers were particularly relevant for first visits, as one participant indicated:

> "The first time you visit the website, you don't know if you can trust the retailer regarding delivery or post-sales services. It is the first thing you check."

However, the discussion on perceived risks gravitated towards data privacy, and how visitors are most of the time uneducated about cookie usage and laws. One data professional explained:

> "There is a big debate around cookie consent. Today, the law requires us to force cookie consent before customers can continue their sessions. But it makes no sense for them, it doesn't mean anything to ordinary people."

Another participant bounced back on this and saw a real opportunity:

> "I think e-retailers often see the cookie consent as an obligation. But it can be a competitive advantage, it could create trust between customers and the website."

On another note, experience features were appreciated by our participants, and encouraged them to buy online:

> "There's a glasses website where you can use your laptop camera and see on your screen what each pair would look like on you. It's like you're wearing them for real, it's crazy!"

Interestingly, participants considered that simple product sheets are insufficient, even for search goods:

> "When I am buying a computer online, of course I can read that the processor is an i5k-something, but that is not really helping me. I think that giving information is a must-have, but e-retailers should also teach us what they mean so that we can decide. That's why I often end up buying electronic products in-store."

Regarding word-of-mouth, participants appeared sensitive to the format and its integration on the website. For example, one participant stressed the advantages of separated criteria:

> "When I'm looking for a hotel for example, I like it when there are grades for different things. Sometimes I don't care if the hotel is not well located and I only look for a correct price."

In another focus group, one participant highlighted a feature that greatly influenced is behavior. On some websites, he was able to connect his Facebook profile and reviews from his friends would appear first. Obviously, those reviews would have a strengthened effect on his decisions.

In addition, account and purchase funnels were discussed extensively and our participants showed an interesting choice of words:

> "Sometimes there are too many *barriers* between me and purchase. I often go online with the intention to buy something, but end up abandoning because I have to subscribe, to fill out many obligatory fields. There is a huge amount of steps and purchase funnels are, or at least seem too long."

> "Once, I had to create like ten accounts on ten different websites to buy presents for someone. And I can tell you that this is a *painful* experience, and it affects your evaluation of the retailer."

Finally, it appeared that providing many payment options was important for customers, as one practitioner testified:

> "When we introduced Paypal on our client's website, conversions went through the roof, even if they mostly used their credit cards in Paypal, which is something we already accepted on the website."

2.4 Offering Characteristics

Unsurprisingly, offering characteristics such as product type influenced conversion probabilities:

> "I have no trouble ordering something like a kitchen robot online, because product sheets and customer reviews *tell you everything there is to know.* However, I look for clothes online but always buy in-store, because I want to try them."

Participants also underlined the importance of services in their decision making:

> "Product offering is not the only thing that matters. I think the services around the product are crucial: having it delivered at your doorstep when you're at home, getting the product installed and set-up by the delivery guy, warranty... It doesn't cost a penny to e-retailers, but it's really important for customers.
>
> I'm willing to pay more for that. The first question I ask myself when ordering online is: what happens if it's not what I want and if I have to return it? Today, with most websites, you don't really know."

Finally, one participant had an interesting remark relating both search and experience products to previous purchases:

> "There are products that you have already bought many times. When I need a new pair of shoes or a new jeans, I just have to order the same size and model. I'll look online directly and choose where to buy purely based on price."

2.5 Session Characteristics

For session characteristics, participants were, once more, in line with the theoretical framework. However, they all insisted on the critical aspect of session context, beyond what is usually measured by digital analytics:

> "The context is super important. I can be an hardcore online shopper, but if I am abroad, I won't order anything. Same here, my online connection at home is the worst, so I always order things at work."

Another participant continued:

> "It depends on the weather, the hour, your situation, your mood... The pages I go through during my session are important, but my session in the subway will be completely different from a session at home even if I see the same pages."

In addition, one member echoed the notion of visit intentions, presented in the previous chapter:

> "We always have different motives for shopping. Sometimes, you want to spend an afternoon shopping in stores to relax, see products and spend time. Sometimes, you're in a rush and you're more likely to order quickly online."

2.6 Competition

As hypothesized, participants acknowledged the importance of competitors when buying something online. They all engaged in comparisons between the retailers, as one participant summarized:

> "That's the whole point of ordering online. You can compare the offer on all websites and then choose where to buy. You can't do this in stores.
>
> My girlfriend often creates big wish-lists, and we then compare everything before deciding on what and where to buy."

Comparisons were based on price, but also on other criteria such as delivery time:

> "Price is an important factor for me. When I look on different websites, I know that Amazon is often the cheapest, and that's why I buy on their website."

> "When I'm ordering food online for lunch, I choose based on delivery times. Most often, the fastest delivery wins."

Competition between offline and online channels was also mentioned by participants, and could take very simple forms:

> "If I have a physical store just outside my window, I will buy there. I will look for information online, but still buy in-store."

Finally, having the product in stock could make or break a conversion:

> "If something is not available on one website, like a vacuum cleaner, I'll order it on another website right after, even if it's 10 euros higher."

2.7 Previous Touch-points

In the second focus group, data professionals discussed the importance of previous touch-points in details. They agreed that the "one session conversion" is far from reality:

> "Today, visitors don't make one simple visit. And if you don't take this into account, if you only look at the last session characteristics, you're doing everything wrong."

They agreed that all touch-points matter, whether they are made on the website, in a physical store, or on any other media:

> "Maybe I'm converting a lot one month online because my stores did a major advertising operation the month before, and customers end up buying on the website."

We later elaborated on this with one participant via e-mail. He claimed that for some products, previous touch-points have a greater impact. For products such as flight tickets or holiday trips, customers convert after many exchanges: they do a first visit to look at prices and dates, discuss with other persons involved in the trip, come back later and eventually decide to convert before prices get too expensive.

Data professionals during the second focus group and during the two in-depth interviews illustrated the many opportunities created by TMS and DMP solutions with previous touch-points. These opportunities will be detailed later in chapter IV.3, page 38.

2.8 Post-purchase Experience

Post-purchase experience and especially poor delivery services were a recurrent theme. Loss of packages, lack of transparency and information, never-ending wait for delivery, impossibility to reach the retailer by mail or phone: the examples were numerous. This factor seemed particularly linked to best and worst experiences. One participant had an interesting example regarding service recovery, and illustrated how it impacts future conversions:

> "I once ordered a spa session for me and my boyfriend on a deal website. I later learned that only women were allowed to come with this deal, but there was no such mention on the website.
>
> Surprisingly, it was easy to cancel the reservation and I got my money back almost instantly. Now, I don't hesitate to buy anything there because I'm 100% sure that in case of trouble, everything is perfectly handled."

Another participant cited the following story as his best online purchase experience:

> "Something broke in my television, and I had to change a small thing inside. I didn't want to go in a store and pay 200 euros for the repair, so I ordered the 15 euros piece myself online on a marketplace from someone in China. I payed for the electronic part, he sent the product, I received the product and it turned out it was not working. I called him, he told me, don't worry, just send me back the product and he recommended me another product that worked perfectly.
>
> It's not a good experience per se, because I had the wrong product, but everything was handled smoothly. And when you compare this to the problem I once had with a French retailer, it's like night and day. You'd think a company close to you will have a better service, but with them, I received the wrong product and it was impossible to reach them by mail or phone. I had to send messages on Facebook and Twitter to get their attention."

That same participant concluded later:

> "The problem today with e-commerce is in commerce, it's not in "e" anymore. Offering a good experience online until conversion, it's easy, it's a must-have. But providing an excellent service, a good delivery, a real purchase ritual, that's what we need to work on."

Another respondent bounced on this and explained how his company, selling second-hand luxury goods online, applied extreme care in providing a brand-new product unboxing experience by cleaning and reconditioning goods before shipping.

In the last focus group, participants illustrated how post-purchase experience generates value beyond offering a quality delivery:

> "Sometimes I order something online just because I enjoy following the product delivery step by step. *Once it gets there, it's just a thing,* but before, you enjoy waiting for it."

In specific situations, post-purchase experience could even generate surprise and delight, as one participant indicated:

> "My best experience? When I ordered a very rare book online. The book was perfectly packaged, corners were well protected and the seller even included a hand-written card, especially made for me. That's a nice surprise!"

In the end, all participants agreed that it is worth distinguishing post-purchase experience from other factors as it can encourage or totally prevent customers to ever convert after the first purchase.

2.9 Exogenous Factors

In our literature review, we were unable to detect the importance of exogenous factors. However, during the second focus group with mostly data professionals, each participant gave precise examples of how external and unpredictable events affected conversion rates significantly:

> "If you're selling face masks during a H5n1 epidemic, your conversion rate will go through the roof. If you're selling the dress that Obama's daughter is wearing, you will definitely see a spike in performance."

One participant elaborated on this and described in details a professional example:

> "It happened once when I was working for a beer and alcohol retailer. One month, the conversion rate was low compared to the same month of the previous year. We spent days looking at every reports in our digital analytics system, and found nothing. Then, we realized that last summer, temperatures were three degrees higher."

One participant concluded:

> "You can't do anything about the exogenous factors, but you'd better take them into account when you analyze the performance of your website if you don't want to draw false conclusions."

Thus, we posit the ninth and last proposition:

Proposition 9. *Exogenous factors influence the probability of conversion.*

Chapter 3

Opportunities

Our theoretical framework already underlines the importance of many features and levers that e-retailers should focus on in order to encourage conversion. However, four particular opportunities were brought to light during the qualitative study. We believe that those potential solutions could have a significant impact on conversion, and thus present them in the following sections. The four opportunities are:

1. Real-time customization
2. Ego depletion
3. Feature usage
4. Instant gratification

3.1 Real-time customization

As described in section III.3, page 27, retailers can steer some of the nine factors for conversion. In regards to the remaining factors, retailers can still gather data and provide a customized experience thanks to TMS and DMP solutions. This customization varies in complexity, and can use many different sources of data, such as customer characteristics thanks to CRM systems or sessions characteristics with digital analytics. E-retailers can even gather data from external sources to develop an accurate picture of its visitors:

> "With a DMP system, you can retrieve third-party data, and know that your visitor is in-market for a new car insurance or something. With this information, you can push on the website what the visitor is looking for."

It is easy to see how customer journeys and conversion rates would benefit from such customized experiences. One could push forward experience features for visitors that tend to spend minutes zooming on product pictures, detail risk relievers for risk-averse consumers, offer a rebate for customers who reported a service failure or left a negative product review, display a particular homepage for customers who were exposed to a targeted advertising on their smart-phones or highlight the search engine for visitors who clearly intent to look for a particular product. This is also supported by the literature: when Kaltcheva and Weitz (2006) study the moderation effect of motivational orientation between arousal and pleasantness, they conclude that in order to optimize shopping behaviors, e-retailers should display high-arousing features for recreational visitors and simpler, low-arousal environments for task-oriented visitors.

It is worth noting that applications are not limited to real-time customization on the website, but can go deeper and use additional media:

> "There are considerably more levers and channels you can use: you can send SMS, in-app push, emails, display, re-targeting based on what you know on the customer."

3.2 Ego depletion

Measuring and activating ego depletion is somewhat related to real-time customization, but is based on a distinctive construct. As some participants indicated, last minute "bonuses" often convinced them to convert:

> "If I'm looking for a new television, and you offer me a nice bundle with an interesting price, I might convert. But if you offer a wall support at the last minute and free delivery because my basket size is big enough, you have me for sure."

Ego relates to an energy or strength customers deplete when resisting to temptation, making trade-offs or evaluating choices (Baumeister, 2002; Thomas et al., 2011; Wang et al., 2010; Loewenstein, 1996). Once ego is depleted enough, customers are more likely to convert and to stop resisting. E-retailers could easily use proxies to measure ego depletion by monitoring the number of product comparisons visitors do during their sessions, the amount of time spent examining product characteristics, the time of day or other variables. Highly depleted candidates could be encouraged to convert by offering additional discounts or advantages before they manage to leave the website: as the previous quote indicates, it only takes free delivery or one small complementary product to make the sale.

3.3 Feature usage

During the last focus group, one participant realized that visitors are often left alone when they arrive on an e-commerce website, even for their first session:

> "The first thing you hear when you enter a store is welcome. The first thing you see online is buy this, buy that... I don't know any e-retailer that welcomes its visitors."

In-store, new visitors are often welcomed by employees and accompanied during the first few minutes, whereas websites rarely introduce the features they offer to visitors. However, as one digital professional indicated, we could consider each website as a product, and guide visitors when they arrive for the first time:

> "With a product, you always have a user guide. Online, you could guide the visitor and show him the relevant features according to his objectives. In the software industry, it's common practice. Think of Evernote, or Dropbox. LinkedIn even uses gamification."

Two articles support those observations and the possible impact of feature usage on conversion. First, Song and Zinkhan (2008) notice during their research on the determinants of perceived web site interactivity that the mere presence of features has a marginal effect, when actually using those features significantly impacts perceived interactivity. Second, Gourville and Soman (2002) study the psychology of consumption, and show that consumption leads to sales and membership renewals. Thus, we believe that retailers would benefit from presenting the features they have and encouraging visitors to use those functionalities. As one participant said, retailers could adopt a gamification approach and offer rewards such as coupons when visitors create their account, use a new feature and so on. However, guided visits and contextual information should never hinder the overall user experience and stay optional. One respondent was quite vocal about a smartphone application example:

> "You need to do this carefully. For example, on some smartphone apps, those tutorials are mandatory, and that makes me crazy to click everywhere until it's done when I already know what I want and need to do."

3.4 Instant gratification

Instant gratification is identified as one limiter of internet retailing (Grewal et al., 2004), and our qualitative study supported this view. When consumers convert, the confirmation page they see right after is often unappealing and visitors are simply thanked for their purchase. Nothing generates instant gratification compared to in-store purchases and customers have to wait until the product is finally delivered. During the second focus group, participants used particular words and images to describe this:

> "For me, the last page often feels like an *abyss* where I left my private data and my credit card information. Would you leave your credit card at a store and get out without any shopping bags?"

Another participant continued:

> "That is exactly how it feels. You're in a dead end, it's as if the retailer told you: alright, thanks for your money, now please leave through the backdoor and the small alley behind the store."

Yet, e-retailers could implement many things to replace this "blank page" feeling and generate instant gratification. Most participants agreed that having a voucher at the end of the funnel, or some additional product were always good surprises, but cheaper solutions could also be effective:

> "When you book a flight, they tell you that you're leaving soon to Rio, and you're super happy. I don't even need a promo code or a voucher, the website could tell me that I'll be able to visit this and see that in Rio, or give me useful information about my trip."

We believe that the lack of instant gratification is one of the biggest disadvantages of online shopping. By increasing the attractiveness of buying online and rewarding online purchases, e-retailers would enhance the evaluation of websites as a conversion channel (Verhoef et al., 2007). These instant gratification features might not increase the likelihood of first conversions, but encourage current customers to convert more frequently online and less frequently in physical stores once they acknowledged the advantages of buying on the website.

Part V

Quantitative Axis

Chapter 1

Methodology

1.1 Introduction

As the reader may have noticed, the nine factors of our theoretical framework represent an equal number of fields for quantitative research, and the body of literature that allowed us to design such a framework already contains a certain number of quantitative analyses.

Although a comprehensive study accounting for all nine factors should yield interesting results, such as the relative weight of each factor or the sequence in which they matter, a project of this size is outside the scope of our paper. Some of the studies mentioned earlier do investigate two factors at once (see interactions, section 3.2, page 27), but as most references, we will mostly investigate the impact of session characteristics on conversion. That being said, our data set contains a few subtleties described in the next section that allow for deeper observations.

1.2 Data Set

The company we interviewed during the third focus group also provided us the data set for this study. As a reminder, this company is a major fashion apparel retailer in France, who has both physical stores and an e-commerce website. For this study, our data set only contains information about online visits and users.

Similar to digital analytics solutions such as Google Analytics or AT Internet, our retailer implemented a hand-made measurement system of users' navigation. Behaviors are monitored on a hit-base level (such as page views), and then unified by sessions (series of hits with less than thirty minutes of inactivity), client IDs (browser cookie) and user IDs (CRM account). Three days of data were provided: one day before the summer sales (June 19th 2016), the first day of summer sales (June 22nd 2016) and one day during the last discounts of summer sales (July 7th 2016).

In total, we dispose of 424 469 cases or sessions, of which 7 905 converted. Each session is described by the following variables:

- **Device Smartphone:** This variable is a binary coded value that indicates if our visitor is using a desktop or smartphone device during the session.

- **Support:** Those variables are a set of binary coded values that mostly correspond to the online channels described by Anderl et al. (2016). Our baseline is the SEO access, that is all visits initiated from a non-paid search result link. Support Direct signifies that a visit was initiated by a direct type-in of the website URL in the address box of the browser. Support

Mailing indicates that the visitor came from a mail link. Support Display refers to visual banners visitors see online. Retargeting is also a form of display, although customized based on viewed products. Referral and Affiliation both refer to visits coming from links on other sites, the latter being associated with paid partnerships. Shopbot indicates that the visitor came from a product comparison website, Chat from a partner chat website, and finally, SEA from paid search results.

- **Session Hour:** Session Hour is an integer variable that indicates when the session started, from 0 to 23.

- **Session Duration:** Session Duration is also an integer variable that contains the total session duration in seconds.

- **Number of Session:** Number of Session is an integer variable that indicates if our visitor is making his first, second, third... session of the day.

- **Pages:** Pages variables indicate how many pages are seen per page type in a session. Most types are self-explanatory, but to be clear, Account Pages are related to the personal account of the visitor (delivery addresses, payment data...), Brand Pages list all products of a specific brand, Cart Pages display all the products that were added to the cart, Editorial Pages are written contents about fashion news, Sales Pages list all the products of summer sales, Product Pages are detailed product sheets, Search Pages list the product results of a search query, and Navigation Pages are intermediate catalog pages that show all products from requested categories.

- Days: First Day Sales and After Sales Day are binary values that attach a session to its date. The day before sales is our baseline.

- Conversion: Conversion is our main output variable and is a simple binary value, with 1 for converted sessions and 0 for non-converted sessions.

- Order Size: Order size is an additional output variable, containing the total order value in euros for each converted session.

The table 1.1, page 45 offers a summary of all the variables in our the data set.

1.3 Models and Assumptions

As detailed earlier, we have two different output variables of interest. The conversion outcome is naturally our most important variable since it is the actual raison d'être of our study. Nevertheless, we also model the total order value with our input variables to allow for interesting comparisons. We present the logistic regression analysis conducted on conversion, the OLS regression conducted on total order value and a third technique used on both dependent variables in the following paragraphs.

1.3.1 Logistic Regression Analysis

Our dependent variable, Conversion, is binary. It is also coded accordingly to the logistic regression, with 1 being attributed to the desired outcome. Due to the nature of our data set, observations and error terms are both naturally independent. Non-multicolinearity was assessed using VIF scores (results in table 1.2, page 46) and our dataset is not subject to outliers (maximum Cook's distance below 0.05). Finally, our sample size is large enough for logistic regression, with considerably more than 30 cases for each parameter to be estimated. In order to reveal both meaningful and non-significant

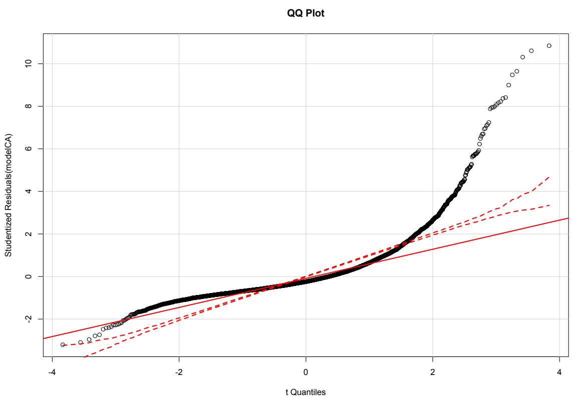

Figure 1.1: Order size model residuals

parameters, we present a complete model with all variables but one: Total Order Value.

1.3.2 OLS Regression Analysis

In this second regression analysis, our dependent variable, Total Order Value, is metric. We conduct a standard OLS regression of order value on all other variables for the converted sessions of our data set. Again, observations are naturally independent, non-multicolinearity was supported (table 1.2, page 46), an outlier detection test was computed and sample size is sufficient.

However, although we benefit from a comfortable sample size and are not using the regression estimates for prediction, we draw the attention of the reader towards a high non-normality in regression residuals. Skewness and Kurtosis are both outside acceptable values, and a QQ plot (figure 1.1, page 44) displays a heavy tailed and right skewed distribution. Thus, results should be carefully considered, even if OLS regression is somewhat robust in such situations, as some researchers challenge the assumption of normality (Thomas Lumley et al., 2002).

1.3.3 Symbolic Regression Analysis

There has been a recent and increasing interest in new data mining approaches for e-commerce and click-stream data (García et al., 2016; Shan et al., 2016; Lakshminarayan et al., 2016). We hope to contribute to this field of research by applying another technique to our dataset. Alongside the classic multiple linear and logistic regressions, we submit the conversion probability and the total order value to a symbolic regression approach using the software Eureqa (Nutonian, 2016). Eureqa has been applied in diverse industries and academic studies (Nutonian, 2016), including psychology and social sciences (Slater et al., 2013; Klug and Bagrow, 2016; Mitchell, 2015; Swain et al., 2015). In simple terms, the technique evolves equation families to maximize data fit (Klug and Bagrow, 2016).

To define its solution formulas, we allow Eureqa to use a basic set of mathematical operators, such as addition, subtraction, multiplication and division between all the input variables as well as real and integer constants. For Conversion and Total Order Value, the search are set as follows:

$$Conversion = logistic(f(...)) \tag{1.1}$$

$$TotalOrderValue = (f(...)) \tag{1.2}$$

We use absolute error (default) as the error metric for the linear equation search and area-under-the-curve (AUC) for the logistic formula.

Variables	Type	Description
Device Smartphone	Binary	1 if the session is made on a smartphone, 0 on a computer
Support Direct	Binary	1 if the session started from a direct access (base = SEO)
Support Mailing	Binary	1 if the session started from an e-mail (base = SEO)
Support Retargeting	Binary	1 if the session started from a retargeting ad (base = SEO)
Support Affiliation	Binary	1 if the session started from an affiliation link (base = SEO)
Support Shopbot	Binary	1 if the session started from a price comparator (base = SEO)
Support Referral	Binary	1 if the session started from a referral link (base = SEO)
Support SEA	Binary	1 if the session started from a paid search result (base = SEO)
Session Hour	Integer	Indicates the hour when the session started
Session Duration	Integer	Represents the total duration in seconds
Number of Session	Integer	Indicates the number of the session on a daily basis
Account Pages	Integer	Number of account pages viewed during the session
Brand Pages	Integer	Number of brand pages viewed during the session
Cart Pages	Integer	Number of cart pages viewed during the session
Editorial Pages	Integer	Number of editorial pages viewed during the session
Sales Pages	Integer	Number of sales pages viewed during the session
Product Pages	Integer	Number of product pages viewed during the session
Search Pages	Integer	Number of search pages viewed during the session
Navigation Pages	Integer	Number of navigation pages viewed during the session
First Day Sales	Binary	1 if first day of sales (base = day before)
After Sales Day	Binary	1 if last week of sales (base = day before)
Conversion	Binary	1 if an order was placed during the session
Order Size	Real	Total order value in euros for converted sessions

Table 1.1: Variables Summary

Variable	VIF - Conversion	VIF - Order Value
Device Smartphone	1.029693	1.025422
Support Direct	1.143241	1.153895
Support Mailing	1.10259	1.11045
Support Shopbot	1.03061	1.02667
Support Retargeting	1.044448	1.046936
Support Referral	1.026286	1.029879
Support Affiliation	1.025886	1.032571
Support SEA	1.014271	1.016063
Support Display	1	NULL
Support Chat	1	NULL
Session Hour	1.029649	1.065245
Session Duration	1.004014	2.732793
Number of Session	1.050936	1.086338
Account Pages	1.035165	1.105882
Brand Pages	1.168018	1.2077
Cart Pages	1.343558	1.531909
Editorial Pages	1.00201	1.007172
Sales Pages	1.707261	2.119976
Product Pages	2.795265	2.98654
Search Pages	1.125081	1.209483
Navigation Pages	1.739765	1.980281
First Day Sales	2.544566	2.807424
After Sales Day	2.52235	2.765617

Table 1.2: Multicolinearity Checks

Chapter 2

Findings

2.1 Conversion Models

2.1.1 Logistic Regression

The overall model displays a McFadden Pseudo R2 of 0.30, which represents an excellent fit (McFadden and others, 1977). A classification table showed that 98.1 percents of outcomes are correctly predicted. We report parameter estimates in table 2.1, page 51.

Among the 23 variables in the regression, 18 variables significantly impact conversion. First, visitors are more likely to convert when using a desktop computer. Second, some support dummy variables impact conversion probabilities: visitors coming from direct access, shopbot websites and affiliated links all show a higher propensity to convert compared to SEO. Surprisingly, visitors coming from e-mails are negatively impacted, although they are supposed to be known clients of the brand. The Session Hour variable has a negative and significant parameter, meaning that late visits are less likely to convert, while the Session Duration has a positive, although small, significant impact on Conversion. Number of Session shows an interesting negative and significant impact, indicating that visitors are more likely to convert during their first sessions. As one could predict, the type and number of pages viewed during each session have a significant impact on conversion. While Account, Cart, Product, Search and Navigation Pages all have a positive influence on conversion, both Brand and Editorial pages have a negative impact. Only Sales Pages prove to be insignificant. Finally, summer sales events have a significant impact on conversion, since both date dummies positively influence conversion compared to the baseline, which is a few days before the summer sales.

2.1.2 Eureqa Analysis

After 17 hours of computation, Eureqa returned the following solution:

$$\begin{split}Conversion = logistic(CartPages+\\ AccountPages * CartPages * ProductsPages+\\ ((-9 - 5.2 * CartPages * ProductsPages)\\ /SessionDuration) - 54)\end{split} \quad (2.1)$$

Eureqa reports a model fit of 0.460, an R squared value of 0.086, a correlation coefficient of 0.34 for a complexity score of 20. As the solution illustrates, Cart, Account and Product pages all have a positive impact on conversion probabilities, especially through three-way interactions. We note that Cart and Product Pages also have a negative impact that is limited by Session Duration.

2.1.3 Discussion

Both models yield interesting results that merit attention. The negative impact of using a Smartphone device found in the logistic regression is in line with our theoretical framework: mobile sessions are more likely to be realized in unfavorable visit contexts, or with a view to converting later. This user scenario was also identified as frequent by our focus group participants.

Regarding support variables, the negative parameter for mailing is particularly surprising. As we said, those visitors are supposed to be known clients of the retailer, who expressed a particular interest in receiving information and promotions. We see two possible reasons for this result: heterogeneity in e-mail contents and/or quality that we do not account for, and an overqualified SEO baseline that contains a significant amount of brand-related keywords (which is often considered in the industry as direct access).

Next, the negative impact of Session Hour certainly hides finer-grained phenomenons. After discussion with the retailer, it appears that most conversions happen in the morning, mid-day and early evening. Considering a simple linear effect for Session Hour is thus unsuitable. Also, following the ego depletion literature (Baumeister, 2002; Thomas et al., 2011; Wang et al., 2010; Loewenstein, 1996), we would expect a positive effect of late sessions on conversion that is not supported here.

The negative impact of Number of Session also raises a certain number of questions. Visitors that make several visits during the same day might not find what they are looking for, or come for non-conversion motives. As a reminder, we compute this value on one day only. Enlarging the data set to a whole week of visits could clarify the complex effects of this variable on conversion, since product consideration sets are not defined by customers in one day only.

The positive impact of session duration and most page views was predictable. After all, it even corresponds to offline behaviors, where customers are more likely to convert with time spent and number of alleys visited in physical stores (Bell et al., 2011). However, we notice that Brand Pages and Editorial Pages both reduce the probability of conversion. After close investigation of those pages, we stay unclear about the reasons behind Brand Pages, as they are only listing all products from a certain brand. However, the negative impact of editorial pages is understandable. If providing engaging contents is one of the latest trends in e-commerce supposed to generate conversions (Rogers, 2016), the articles of the website analyzed in this paper are somewhat disconnected from the catalog and they rarely push available products. Thus, visitors looking for the fashion news published on the website might represent a completely different audience compared to regular customers.

Last but not least, the impact of both date dummies hints towards the fourth and the last factors of our theoretical framework, namely offering characteristics and exogenous factors. Summer sales involve noticeable price reductions that heighten the offer attractiveness, and are considered as traditional shopping periods. According to our framework, higher conversion rates are to be expected in this situation, and the model actually supports our predictions.

Regarding the Eureqa solution, we are surprised by the low number of variables included in the final equation. Many reasons could explain this output: the size or nature of our data set may be inappropriate, we might have lacked of computation power or ended the process too soon (calculations were conducted on the desktop version of Eureqa instead of the cloud-powered service). We could have directed the software towards a defined target taking all variables into account, but such restrictions would have resulted in biased solutions. Still, the actual formula designed by Eureqa offers different insights on the impact of and the interactions between our variables. The model underlines the positive impact and powerful combination of Cart, Account, and Products page views. More interestingly, the formula shows that Session Duration conditions the effectiveness of page views, since it weakens a negative term generated by the latter in the formula. In other words, visitors who see a lot of pages and take their time are ideal candidates for conversion, while customers accumulating a lot of page views in a short time window are less promising than one could imagine.

2.2 Order Size Models

2.2.1 Linear Regression

To support the overall fit of the model, we conducted an F statistic who revealed to be significant, with a p-value below 0.001. The multiple R-squared is equal to 0.09639, while the adjusted R-squared has a value of 0.09399. We report parameter estimates in table 2.3, page 53.

Among the 21 variables of the model, 13 variables are significantly related to the Total Order Size. First of all, conversions made on smartphone devices significantly have lower order values. Second, three support variables significantly influence the order value compared to the SEO baseline: users coming from direct access and SEA have higher orders, while conversions started with retargeting advertising have lower order values. Also, Session Hour has a significant and negative estimate, meaning that late orders have lower total values, while Session Duration increases order values. The Session Number has a considerable and significant positive impact on order values, such that visitors making multiple visits in one day end up ordering bigger baskets. Regarding page views, Cart and Product Pages both significantly increase order value, while Editorial and Sales pages significantly decrease order values. Finally, summer sales significantly decrease order values since both date dummies have a negative parameter.

2.2.2 Eureqa Analysis

After 8 hours of computation, Eureqa returned the following solution:

$$\begin{gathered} TotalOrderValue = 57 + AccountPages + \\ CartPages + 3.1 * NumberSession \\ + 1.4 * ProductsPages - DeviceSmartphone \\ - 13.4 * AfterSalesDay - 0.006 * Products^2 \end{gathered} \tag{2.2}$$

Eureqa reports a model fit of 0.960, an R squared value of 0.012, a correlation coefficient of 0.29 for a complexity score of 25. The total order value model returns more variables than the conversion model, and fits with the linear regression results. Account, Cart and Products pages, as well as the Session Number all increase order values, while smartphone and After Sales Day conversions are impacted by negative terms. Finally, a squared Products Pages term reduces order values.

2.2.3 Discussion

Once more, both analyses merit discussion. We are not surprised by some results of the linear regression, such as the negative impact of smartphone devices on total order value: visitors on such systems are more likely to do quick sessions and small orders compared to customers who have plenty of time for shopping. Among support variables, the negative impact of retargeting advertising is quite interesting: as these display ads show the latest considered products of a visitor, they might encourage them to place an order with one or few products only, when they could spark conversions and propose additional products to increase basket sizes.

The negative impact of session hour is, again, not supporting our ego depletion theory. We would expect total order values during late conversions to be higher since customers are less able to resist, thus adding more considered products to cart. Nevertheless, the same limitations highlighted in the conversion model remain.

Comparing current results with the previous model, it appears that the number of sessions in a day negatively influence conversion probabilities, but positively influences total order values. Customers coming many times in a day may display this behavior because they expect to place a large order, and need time for decision. Also, the negative estimate for editorial pages confirms our observations made previously. It seems that articles are not pushing enough products, or not aiming to provoke conversions and enlarge cart sizes. Finally, the negative impact of both sales pages and date dummies reflect a natural collateral effect of summer sales: most price levels are reduced, and even if one could believe that price reductions are compensated by bigger carts, it doesn't seem to be as such.

Similarly to our previous study on conversion, the Eureqa solution offers additional insights. Most significant effects are detected by the symbolic regression, such as the positive impact of the session number, or the negative impact of the last day of our data set, where summer sales are at their maximum levels. We notice an interesting negative impact of the squared number of product pages viewed. This term might indicate that sessions looking at too many products might only be recreational, especially since a significant part of the catalog is dedicated to luxury goods.

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-4.5321	0.0580	-78.18	0.0000
Device Smartphone	-0.7757	0.0300	-25.86	0.0000
Support Direct	0.2001	0.0337	5.95	0.0000
Support Mailing	-0.4548	0.0475	-9.58	0.0000
Support Shopbot	0.4966	0.0859	5.78	0.0000
Support Retargeting	0.0329	0.0698	0.47	0.6380
Support Referral	-0.0036	0.0793	-0.05	0.9638
Support Affiliation	0.1844	0.0780	2.36	0.0180
Support SEA	-0.8177	0.7188	-1.14	0.2553
Support Display	-9.1606	119.8985	-0.08	0.9391
Support Chat	-8.5316	91.3240	-0.09	0.9256
Session Hour	-0.0255	0.0024	-10.62	0.0000
Session Duration	2.8e-06	0.0000	4.33	0.0000
Number of Session	-0.0311	0.0060	-5.16	0.0000
Account Pages	0.2657	0.0075	35.25	0.0000
Brand Pages	-0.0076	0.0029	-2.58	0.0099
Cart Pages	0.7329	0.0080	91.38	0.0000
Editorial Pages	-0.9385	0.2453	-3.83	0.0001
Sales Pages	-0.0019	0.0012	-1.52	0.1278
Product Pages	0.0265	0.0016	16.46	0.0000
Search Pages	0.0091	0.0037	2.45	0.0142
Navigation Pages	0.0064	0.0013	4.87	0.0000
First Day Sales	0.6325	0.0466	13.57	0.0000
After Sales Day	0.2154	0.0530	4.06	0.0000

Table 2.1: Conversion Model - Estimates

	Df	Deviance	Resid. Df	Resid. Dev
NULL			424468	78638.52
Device Smartphone	1	1080.26	424467	77558.26
Support Direct	1	447.82	424466	77110.44
Support Mailing	1	7.39	424465	77103.05
Support Shopbot	1	7.95	424464	77095.10
Support Retargeting	1	0.87	424463	77094.22
Support Referral	1	1.53	424462	77092.69
Support Affiliation	1	11.41	424461	77081.28
Support SEA	1	27.26	424460	77054.02
Support Display	1	0.72	424459	77053.29
Support Chat	1	0.65	424458	77052.64
Session Hour	1	13.90	424457	77038.75
Session Duration	1	143.20	424456	76895.54
Number of Session	1	23.81	424455	76871.73
Account Pages	1	2945.30	424454	73926.43
Brand Pages	1	762.39	424453	73164.05
Cart Pages	1	16928.21	424452	56235.84
Editorial Pages	1	16.86	424451	56218.97
Sales Pages	1	94.39	424450	56124.58
Product Pages	1	573.78	424449	55550.79
Search Pages	1	3.55	424448	55547.24
Navigation Pages	1	17.76	424447	55529.48
First Day Sales	1	288.98	424446	55240.50
After Sales Day	1	16.33	424445	55224.17

Table 2.2: Conversion Model - Analysis of deviance

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	100.8687	4.9151	20.52	0.0000
Device Smartphone	-9.6627	2.3423	-4.13	0.0000
Support Direct	7.6822	2.5261	3.04	0.0024
Support Mailing	2.8845	3.5256	0.82	0.4133
Support Retargeting	-15.2474	5.5270	-2.76	0.0058
Support Affiliation	0.8333	6.0785	0.14	0.8910
Support Shopbot	-10.8574	7.2397	-1.50	0.1337
Support Referral	7.1079	6.3861	1.11	0.2657
Support SEA	62.1387	29.2234	2.13	0.0335
Session Hour	-0.7704	0.1980	-3.89	0.0001
Session Duration	0.0044	0.0009	5.02	0.0000
Number of Session	4.2997	0.4813	8.93	0.0000
Account Pages	-0.5949	0.4271	-1.39	0.1638
Brand Pages	0.1915	0.1707	1.12	0.2618
Cart Pages	0.9213	0.3963	2.32	0.0201
Editorial Pages	-37.1406	12.5277	-2.96	0.0030
Sales Pages	-0.3183	0.0719	-4.42	0.0000
Product Pages	0.9749	0.0934	10.44	0.0000
Search Pages	0.0502	0.1768	0.28	0.7767
Navigation Pages	0.0762	0.0783	0.97	0.3308
First Day Sales	-13.3628	3.7507	-3.56	0.0004
After Sales Day	-30.4389	4.1640	-7.31	0.0000

Table 2.3: Order Size Model - Regression Estimates

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
DeviceSmartphone	1	121901.03	121901.03	14.52	0.0001
Support Direct	1	200555.93	200555.93	23.89	0.0000
Support Mailing	1	54268.85	54268.85	6.46	0.0110
Support Retargeting	1	110233.05	110233.05	13.13	0.0003
Support Affiliation	1	631.75	631.75	0.08	0.7838
Support Shopbot	1	62730.27	62730.27	7.47	0.0063
Support Referral	1	1182.69	1182.69	0.14	0.7074
Support SEA	1	67840.82	67840.82	8.08	0.0045
Session Hour	1	74108.99	74108.99	8.83	0.0030
Session Duration	1	3261324.60	3261324.60	388.51	0.0000
Number of Session	1	742013.27	742013.27	88.39	0.0000
Account Pages	1	19890.77	19890.77	2.37	0.1238
Brand Pages	1	139084.71	139084.71	16.57	0.0000
Cart Pages	1	113491.36	113491.36	13.52	0.0002
Editorial Pages	1	65289.18	65289.18	7.78	0.0053
Sales Pages	1	68785.57	68785.57	8.19	0.0042
Product Pages	1	1387733.12	1387733.12	165.32	0.0000
Search Pages	1	434.73	434.73	0.05	0.8200
Navigation Pages	1	10179.58	10179.58	1.21	0.2708
First Day Sales	1	108875.81	108875.81	12.97	0.0003
After Sales Day	1	448574.33	448574.33	53.44	0.0000
Residuals	7883	66173222.85	8394.42		

Table 2.4: Order Size Model - ANOVA

Part VI

Conclusion

Chapter 1

Overall Results

After a quite extensive review of the existing literature about online retailing, physical retailing, and a few precise themes, such as the Need-For-Touch (Peck and Childers, 2003) or other constructs, we designed a comprehensive theoretical framework around online conversion, with eight factors that can impact positively or negatively conversion probabilities.

Thanks to a qualitative research including a series of focus groups and interviews, we found global understanding and support of the framework from digital professionals, data experts, e-retailers, traditional marketers and customers. However, the need to include a ninth element, namely exogenous factors, appeared necessary to capture unpredictable events mentioned by interviewees.

Moreover, we combined this qualitative study with a quantitative research, applying OLS regression, logistic regression, and symbolic regression with the help of Eureqa. If this study was mostly centered on Session Characteristics due to the nature of our data set, we were still able to relate some variables to other factors. Date dummies, reflecting a temporary drop in prices are directly linked to offering characteristics, while the significant impact of the number of session and some support variables illustrate the importance of previous touch-points.

Considering the quantitative research as a solid support for our theoretical framework is however inappropriate, in view of the limitations of our models but above all because of the limited scope of the quantitative study itself. Thus, our research is affected by many limitations, and also calls for a certain number of additional studies.

We now detail our academic and managerial contributions before going into details with further research opportunities.

Chapter 2

Contributions

2.1 Academic Contributions

Although considerable research has been devoted to online retailing, a gap remains in our knowledge regarding online conversion. As a matter of fact, only a few articles use conversion as a dependent variable (Moe and Fader, 2004b; Ludwig et al., 2013), which is surprising since conversion rates are of utmost importance for practitioners. We believe that this paper is the first attempt in marketing research for a comprehensive conversion framework, and as such, we propose a new starting point for e-retailing studies and clarify the inter-dependencies between many articles and research streams.

In particular, we answer the call of Verhoef et al. (2007) and look at the issue of channel lock-in through the lenses of conversion. For the authors, the internet channel is unable to keep customers from the search phase to the purchase phase, and in our opinion, (low) online conversion rates perfectly reflect this phenomenon. Our nine factors affecting conversion all explain and clarify the lack of channel lock-in theorized by Verhoef et al. (2007).

Also, we add another building block to the bridge between academia and industry by dedicating this paper to and putting forward one of the most important key performance indicator for managers: conversion rates. Working in close collaboration with a major click-and-mortar e-retailer but also digital and data professionals, we combined their views, introduced their tools (TMS and DMP solutions) and used their data measures with the methods and the theoretical approach of academia.

Moreover, we propose an updated and complementary view on the traditional opposition between offline and online capabilities described by Avery et al. (2012). For example, we detailed recent examples throughout the theoretical framework development on how e-commerce websites minimize tangible and intangible transaction costs (free returns, door delivery in 24 hours...), offer better sales support, provide a pleasurable shopping experience or establish deeper customer relationships.

Finally, we do not consider the Eureqa exercise as a success since we hoped to obtain longer and more complex solutions, bus as mentioned before, many reasons could explain this modest output. We still encourage other researchers to try symbolic regression on click-stream data with or without Eureqa, and will personally submit other data sets to the exercise.

2.2 Managerial Contributions

Obviously, our research offers direct insights for the e-retailer that participated in the focus groups and shared his data for the study, especially with the quantitative results. However, the main findings are not brand-related and benefit to all practitioners.

First, we provide e-retailers with a coherent explanation of the conversion gap. According to the reasons exposed in section II.1, page 10, it is not, at least entirely, possible to close the gap between online and offline conversion rates. But it is not desirable either: retailers and researchers are not in a logic of confrontation anymore, and both acknowledge the importance and effectiveness of multi-channel strategies and click-and-mortar business models. Lately, the core issues investigated relate more to how we can provide a unified experience across channels and attribute conversions in a more clever way than the old "last click wins" rule (Sawers, 2015; Alter and Wingfield, 2016; Venkatesan et al., 2007; Dinner et al., 2014; Kushwaha and Shankar, 2013; Li and Kannan, 2014).

Second, we offer to e-retailers a holistic view of what encourages or holds back conversion. Practitioners traditionally focused on providing the best online experiences, but surprisingly enough, running a state of the art website is only one ninth of what truly matters in conversion analyses. With the use of our five factor qualities (content nature, interactions, steerability, measurability and adaptability) described in section III.3 page 27, we believe that e-retailers have the keys to reduce the gap and optimize their conversion rates. As steerability indicates, e-retailers are able to use website characteristics, offering characteristics and post-purchase experience to their advantage, and should thus start by focusing on them. For the other factors, they should gather data and adapt the customer experience online and on other media in order to maximize conversion probabilities.

Third, our quantitative analysis – although restricted to the data set of only one retailer – offers interesting observations for all practitioners. Our logistic regression does not support the promises made regarding editorial content and its ability to systematically provoke conversion. We draw the attention of practitioners towards the importance of integration and themes of these editorial contents: articles that are not closely linked to the catalog and do not push forward products may potentially have a non-significant or worse, negative impact on conversion as readers and customers progressively become two different groups of visitors. Moreover, the positive impact on conversion but negative effect on order value of retargeting indicates that such levers might encourage visitors to only consider the few products they already displayed interest for. By injecting additional product ideas in some way or another, retailers could maximize the effectiveness of retargeting, as a major weapon for conversion but also an opportunity to increase basket sizes. Finally, the number of sessions in one day appeared crucial in our models: when customers come many times in a day, they are less likely to convert, but when they do, they order bigger baskets. We advise retailers to detect those behaviors, and offer last minute advantages, such as reduced delivery fees to close the deal.

Last but not least, we detected four major opportunities during our qualitative research that seem particularly promising in the reduction of the conversion gap: set up real-time customization, use ego depletion for conversion, encourage feature usage and increase instant gratification. We strongly believe that today, real-time customization is the most promising lever retailers can use against the conversion gap. It will quickly become a unique point of differentiation between retailers before turning into an absolute must-have in a few years.

Chapter 3

Limitations and Further Research

As most scientific efforts, our research is affected by many limitations. Studying online conversion is already a challenge in itself, due to its novelty in academic research. We were not able to find a significant number of articles where conversion rates are used as dependent variables. Thus, we had to build our literature review and theoretical model on previous conversion works, but also on articles with different proxy variables, such as buying intention. We acknowledge the weaknesses caused by this situation, but still stand by the face validity of our framework. However, we agree that all nine factors of the framework call for extensive examination, since proxies often diverge from reality (Arts et al., 2011).

Also, our qualitative study calls for a larger scale series of in-depth interview. To truly support and enhance the theoretical framework, we believe that reaching a critical mass of interviews with digital professionals is necessary. Our first effort with a limited number of focus groups and interviews allowed to design a comprehensive view on conversion, but considering the complexity of the issue at hand, this is not enough.

The weakest link in this study is certainly the quantitative analysis in part 5. The non-normality of residuals for the OLS regression especially reduces the validity of our insights, but in the end, we stay unsatisfied with the four models, who all lack of explanatory power. However, theses conclusions encourage us to push forward the quantitative analysis in two directions: traditional methods such as OLS or logistic regression need to be replaced with more advanced model, and data sets have to contain more than the usual click-stream data. In the near future, we hope to retrieve more detailed data set from e-retailers' DMP, containing both data regarding session characteristics, but also offering characteristics, exogenous factors (weather, temperature...) and more.

Many questions emerged during the elaboration of this paper, and opportunities for further research are quite numerous. Researchers could of course investigate the actual impact of each factor using quantitative analyses or experimental settings and put to the test the four opportunities we detected. Also, two problems naturally arise from our theoretical framework: what are the relative weights of all nine factors? Is there a sequence in which they matter?

We really hope that academicians will challenge the theoretical proposition of this master thesis, and that marketing research will investigate deeper into the phenomenon of conversion and the exciting field of opportunities that digital analysis offers.

Chapter 4

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