Automated web personalization in the automotive sector: the SEAT case

PhD Thesis

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ABSTRACT

Context: Over the last decades, the interest in personalization and, namely, web personalization has grown exponentially, both in industry and in academia. But still, while web personalization is already a standard practice in big digital corporations, its implementation in other companies is proving to be more challenging than anticipated. Despite many years of transformations, investments and massive efforts, a growing number of companies feel unsatisfied with their ability to implement web personalization and see positive effects on their business. Because of this, some authors predict that in the coming years, many of these companies will abandon their efforts to implement personalization in their websites. Consequently, this research is framed in the context of a company of the automotive sector that is currently interested in implementing website personalization in their website.

Objectives: The research presented in this thesis aims to study how to implement web personalization using an automotive sector company as a reference, as this type of company exemplifies a business with long industrial tradition before the era of digitalization. With this objective we aim to understand which are the main difficulties that are holding back the expansion of web personalization in these sectors, as well as to propose some considerations to take into account during its implementation. In order to obtain a global vision, this research thesis is divided into four main sections, each of them representing a fundamental component in the implementation of web personalization in the organizations.

Method: This research includes different methodologies such as an extensive literature review, an applied analysis, an assessment of the current situation based on surveys and interviews and a case study

Conclusions/Implications: This research sheds light on the current situation of website personalization as its automatic implementation in companies other than digital organization. The main conclusion of this thesis is that the most important impediment for those companies to implement effective website personalization is the lack of understanding of the fundamental bases of personalization.

Author's declaration

I declare that the work in this PhD thesis was carried out in accordance with the regulations of the Universitat Politècnica de Catalunya - BarcelonaTech and the requirements of the Ph.D. program in Business Administration and Management in the Department of Management. Except where indicated by specific reference in the text, the work is the candidate's own work. Work done in collaboration with, or with the assistance of, others, is indicated as such. Any views expressed in the dissertation are those of the author.

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CHAPTER 1

INTRODUCTION

How would you feel if you arrived one morning at your go-to café and your favorite coffee was already waiting for you? Personalization is not a new concept, it has been used since antiquity, when business owners gave individual attention to the frequent customers (Tuzhilin, 2009). But it was not until the 1870s that it started gaining research attention (Vesanen, 2007).

Today, more than a century later, the use of websites to attract potential buyers to someone's specific product or service has become a reality, while website marketing is considered key to improve the customer's engagement to any brand (Chen et al., 2002; Cockburn and Wilson, 1996; Demangeot and Broderick, 2016; Ng et al., 1998). Because of it, for the last decades, applying personalization tools in websites has been gaining academic and industrial interest (Harvard Business Review Analytic Services, 2018; Gregg et al., 2016; SmartFocust, 2014; Tam et al., 2006).

Nowadays, personalization and especially website personalization is a completely integrated practice in some big technology companies, specially those born in the digital era (Kardan and Roshanzamir, 2012). As a consequence, website personalization has expanded to an extent in which customers no longer perceive it as an advantage but as an expected commodity, and failing to personalize is considered a risk of losing revenue for companies (Boudet, Julien; Gregg, Brian; Rathje, Kathryn; Stein, Eli, Vollhardt, 2019; Harvard Business Review Analytic Services, 2018; Goldenberg et al., 2021; Fenech, Céline; Perkins, 2015; SmartFocust, 2014). Therefore, in the last few years, personalization interest has spread to companies from almost any sector, which are now increasingly trying to adopt personalization initiatives (Accenture Interactive, 2018; Christian Thomson, 2019; Gregg et al., 2016). Consequently, in the last years abundant research has addressed the technical part of implementing automatic website personalization (Wu et al., 2003). Moreover, given the industrial interest, some commercial platforms have been created, therefore, it is technically possible for any organization to implement automatic personalization in their websites (Gartner, 2021). However, website personalization is conceptually and organizationally complex and its expansion to these other sectors has become more challenging than anticipated (Kardan and Roshanzamir, 2012; Tuzhilin, 2009). Because of this, and despite the efforts made, most of these companies are still not confident enough in their ability to effectively personalize their websites (Boudet, Julien; Gregg, Brian; Rathje, Kathryn; Stein, Eli, Vollhardt, 2019; Evergage, 2019; Harvard Business Review Analytic Services, 2018; Qualifio, 2019). In consequence, some authors predict that, in the coming years, and resulting from the frustration derived from not being able to accurately implement website personalization, these efforts will be massively abandoned by most companies (Gartner, 2019; Kaneko et al., 2018b).

In summary, website personalization has been extensively studied from different fields (i.e. marketing, computer sciences, psychology and economics) for decades (Fan and Poole, 2006; Soui et al., 2013). Moreover, it has been widely applied in digital industries (Goldenberg et al., 2021; Kardan and Roshanzamir, 2012). However, its successful expansion to companies from other sectors, such as industrial companies, remains an elusive goal (Boudet, Julien; Gregg, Brian; Rathje, Kathryn; Stein, Eli, Vollhardt, 2019; Kardan and Roshanzamir, 2012). In conclusion, there is a research gap in the understanding of how companies from other sectors, as it is the case of industrial companies, can also implement website personalization.

In order to help fill this gap, we present a research which aims at studying how to implement website personalization in a company of the automotive industry, as this type of company exemplifies a business with long industrial tradition previous to the era of digitalization. Namely, this research is conducted within the Spanish automotive company SEAT, S.A, and more specifically, in the 'digital platforms data and analytics' team.

SEAT (which in Spanish stands for Sociedad Española de Automóviles de Turismo, S.A.) was founded in the 50s and incorporated into the Volkswagen group in 1986. Today SEAT is a brand established in the city of Barcelona and with presence in more than 60 markets. With the opening of new facilities such as 'Casa SEAT' or 'SEAT:CODE', the creation of the new brand CUPRA and the average consumer almost 10 years younger than the average car buyer in Europe, this company aims to establish its brand as customer-centered, digital, urban and fresh. As for their websites, SEAT manages more than 40 brand official websites across different markets. Their websites are mainly divided in informative sections (detailed description of these sections can be found in chapter 4.1) and a car configurator. The car configurator is an interactive website section dedicated to car customization. In this section the user is interactively guided through the car-building process and allowed to select different car options (such as car model, trim, engine, transmission type, color, interior design or accessories) while a visual representation of the generated results is presented in real time. Because of the wide range of combinations, the car configurator can adapt its content (i.e. visual representation of the car) to more than 1 million possible resulting cars. Regarding the websites' traffic, and depending on the presence in each market, the websites volumes can be divided into three main groups:

1. Websites of the main markets: Includes markets in which the brand has a strong presence and it is well known, such as the Spanish market. The volume of visits on their website ranges from 1 to 1.5 millions per month.

2. Websites of markets with solid brand presence: the brand has a solid presence in the market, such as the French market. The volume of visits in their website is approximately 0.5 millions per month.

3. Websites of smaller markets: Includes markets that are small, where the brand is still unknown or new. The volume of visits in these websites is highly variable.

The management of these websites is distributed between the SEAT central team and SEAT market teams (i.e. local teams or each market). Moreover, a network of collaborating agencies (e.g. communication agencies, technical agencies or creative agencies) also contribute to the daily performance and improvement of the website.

Therefore, with the collaboration of SEAT, this thesis aims to study how to implement website personalization in the automotive sector and, in turn, to understand which are the main difficulties that are holding back the expansion of website personalization in companies from traditionally industrial sectors. Based on this aim, the research question is:

RQ: Which considerations should be taken into account when designing an automatically personalized website in the automotive sector?

In order to obtain a global vision of the problem which will be needed to answer the aforementioned question, we have divided our research into four main studies, each of which represents a fundamental component in the adoption of website personalization in the organization.

First, and to accurately assess the objectives of this thesis, it is essential to understand what personalization is. To achieve this goal, our research starts with the evaluation of the meaning of this concept. For that, we develop and present a novel conceptual framework for the definition of personalization which is applicable to different industry sectors and research fields.

Second, to apply personalization, it is important to know what customers want. Therefore, our research continues with an extensive analysis on the possibility of acquiring knowledge about the preferences of the web users through segmentation criteria. We also consider whether these criteria can be used to personalize websites. With this, we create a variable that can be applied for segmentation based on the premises of other segmentation criteria presented in the literature, and we further assess its potential to be used in web personalization.

Third, before implementing any real change in the website, it is essential to evaluate the effects these changes might have. In consequence, in the following section of this thesis we have examined different approaches to evaluate web performance, presented a guideline to implement testing on the website and finally we have also pointed out some of the most common misconceptions regarding its implementation. Additionally, we have also assessed whether these mistakes are recurrent in the automotive or other sectors.

Finally, even if website personalization can be unequivocally defined, implemented and evaluated accurately, in reality traditionally industrial companies are facing substantial problems to effectively include personalization actions, given that these actions require significant changes in the way these organisations work. For this reason, the last study presented in this thesis evaluates how a company from the automotive sector is able to face the organizational transformation needed to implement web personalization based on a case study.

Accordingly, specific research sub-questions for each of these sections have been defined:

RQ1: What is personalization?

RQ2: Which users' segmentation criteria can we use that are informative enough in the implementation of website personalization?

RQ3: How can we evaluate website personalization?

RQ4: Which are the potential factors that may affect the success of an organizational change in a company from the automotive sector?

In accordance with the previous described studies included in this research, the rest of this thesis has been structured in six chapters. First, Chapter 2 (*Literature review*) presents an exhaustive literature review including the research context of this thesis. Second, Chapters 3 to 6 (namely *A broader concept of personalization*, *Finding persons: audience segmentations*, *Dos and don'ts in the evaluation of personalization* and *Organization readiness for personalization strategies*) present each of the four aforedescribed studies included in the thesis. Finally, Chapter 7 (*Final discussion and conclusions*) highlights the main conclusions issued from the research, including the limitations of the study and future lines of research.

CHAPTER 2

LITERATURE REVIEW

The research context of this study is framed around three main topics: website personalization, personalization automation and websites of the automotive sector. The first involves the study of the impact of personalization in the company-customers' communications based on the web channel (Murthi and Sarkar, 2003; Kwon and Kim, 2012). The second topic consists in a broad concept with several valid meanings, one of the most extended reflects the idea of self-acting web adaptation (without user action) (Kramer et al., 2000) based on some predefined aspects or rules (Soui et al., 2013). The third main topic framing this research deals with the consideration of web pages of the automotive sector. In this chapter a literature review is performed including the three of them.

2.1 Website personalization

Personalization of any kind (products, services, communications, price, etc.) has gained much attention in the last years (Kwon and Kim, 2012). In addition to marketing and information systems, personalization has also drawn increasing research importance in various other fields, such as computer science, management and economics (Soui et al., 2013). With it, a variety of definitions, discussions and dissimilar methodologies and results have thrived in in the literature over the last decades. This makes personalization a broad and complex topic that needs to be mapped out before attempting to work on it. Specifically, personalization of websites is the area which receives the most attention, both in the literature and in the industry (Salonen and Karjaluoto, 2016).

As previously commented, web personalization is a core topic in this thesis, therefore it is necessary to start with a wide-ranging literature review aiming to include important aspects of the concept. With this goal, and based on an adaptation of the outline used in Adolphs and

Winkelmann (2010) and Salonen and Karjaluoto (2016), the following website personalization literature review will include the topics:

- Theoretical foundations
- Business results
- User-specific aspects
- Technical and implementation aspects

2.1.1 Theoretical foundations

Web personalization and, more generally, personalization, has been a widely discussed topic in the last few years. In the early web personalization research, most part of it addressed implementation systems rather than the theoretical foundations of web personalization (Wu et al., 2003; Tam et al., 2006). After several years, some authors identified the lack of a clear conceptualization of terms as a possible slow down in the development of the field (Sunikka and Bragge, 2012). In this section we are going to discuss the meaning of website personalization, different website personalization classifications and the website personalization process.

Personalization as a term

The first topic to be addressed, and certainly one of the most mentioned topics by personalization scholars in their research papers, is the personalization term itself (Blom, 2000; Kim, 2002; Sunikka and Bragge, 2012; Vesanen and Raulas, 2006).

The personal treatment from business owners to customers by remembering or knowing them is not a new concept, as it was already used in the antiquity (Tuzhilin, 2009). However, the first attempts to study it and its effects draw back to the 1870s used in marketing letters (Al-Khanjari, 2013; Vesanen, 2007). About a century later, the personalization research flourished with special attention on two different topics. On the one side, authors focused on the potential benefits of including human models, mainly representative of the target customer of the products, in advertising (Kanungo and Pang, 1973; Klapp, 1941). On the other side, authors focused on the influence of personalizing the communication regarding mail questionnaires (e.g. on response rates, quality and time) (Dillman and Frey, 1974; Horowitz and Sedlacek, 1974; Kerin and Peterson, 1977; Landy and Bates, 1973). Even if somewhat effective, all of these approaches proved to be very costly in terms of time and effort, as all of them were performed manually (e.g. creation of different images, handwritten letters or personal signatures) (Tuzhilin, 2009). It wasn't until the late 1960s when the first attempts to use computers to generate different contents emerged (Tuzhilin, 2009). Finally, the areas of personalization which experienced major advances in the late 1980s were user modeling, web mining and targeted marketing (Krishnaraju and Mathew, 2013). With the combination of all three, increased the interest in studding and using website personalization to attract users (Mulvenna et al., 2000; Vesanen, 2007).

As a term, personalization has its first known use in 1741 in its verbal form "personalize" (Merriam-Webster, 2020). Moreover, according to Cambridge Business English Dictionary, it means © "The process of making something suitable for the needs of a particular person" (CambridgeDictionary, 2020). However, the meaning of the term has been widely discussed in the literature and a consensus has not yet been reached (Sunikka and Bragge, 2012; Vesanen and Raulas, 2006), since it seems to have a different meaning for each author (Riecken, 2000). In the case of website personalization, it is used as a sub-topic of personalization research, since it has traditionally been considered as the personalization of the website (Tuzhilin, 2009). However, given that some authors consider personalization to mostly concern Internet-related and digital environments, nowadays, personalization is also used to refer to website personalization, both terms often being used interchangeably (Salonen and Karjaluoto, 2016).

As can be seen, the conceptualization of website personalization diverges in the research literature and makes it difficult to get a clear understanding by its definition (Sunikka and Bragge, 2012). Therefore, a possible solution is to identify the attributes that have been most frequently given to it throughout time (Adomavicius and Tuzhilin, 2005a; Vesanen and Raulas, 2006). To do so we have reviewed the literature in website personalization from 2000 to 2020 and extracted the explicit definitions given to website personalization (considering only the definitions used in each article as correct and excluding all the definitions given as "examples of other authors' definitions"). Moreover the descriptions of personalization not formulated as explicit definitions have not been included in the sample. The result is a set of 105 explicit definitions of website personalization. Based on this, we extracted the most used attributes by the authors. Figure 2.1 shows the eight most frequently used attributes found in the reviewed set of articles and the percentage of occurrence that each definition represents.

As can be seen in Figure 2.1, website personalization is frequently understood as, firstly, "Based on interests/needs" (appearing in 50,5% of the definitions). This includes all the definitions where authors see website personalization as being based on the interests, desires, needs or preferences of the user or customer (e.g. Kalaignanam et al. (2018); Lin et al. (2010); Riecken (2000)). Secondly, it is understood as "Based on navigational patterns" (25,7%), which includes all the references to data gathering or observation from the users' navigational patterns, past browsing behavior, website tracking or, in general, past online interactions (e.g. Adomavicius and Tuzhilin (2001); Pandey et al. (2019); Thirumalai and Sinha (2011)). Overall, 27,6% of the definitions understood personalization to be related to the "User" (e.g. Mulvenna et al. (2000); Salonen and Karjaluoto (2019); Sia et al. (2010)). Whereas, 26,7% of the authors explicitly define website personalization as being a "Process" (e.g. Balan U and Mathew (2020); Ho et al. (2011); Tam et al. (2006)) and, in a similar proportion (27,6%) as being related to "Tailoring" the website (e.g. Karat et al. (2003); Kim and Sundar (2012); Xiao and Benbasat (2018)). Moreover, almost half of the authors (47,6%) see website personalization as one-to-one, focusing on "Individual", particular or unique users (e.g. Gao et al. (2010); Murthi and Sarkar (2003); Zanker et al.

(2019)). Finally, the most commented objects of the personalization process have been the website "Content" and the "Structure or Layout" (including the format, presentation and interaction) appearing respectively in 32,4% and 18,1% of the definitions (e.g Blom (2000); Fan et al. (2015); Manjula and Chilambuchelvan (2019); Mothersbaugh et al. (2012)).

Some other less frequently given definitions to website personalization are related to website "Adaptation or Modification" (13,3%) (e.g. Goyal et al. (2010); Pandey et al. (2019)), to "Groups of users" (as opposed to focusing on individual users) (9,5%) (e.g. Anand and Mobasher (2007); Cobaleda et al. (2016)) or to the adaptation of the website "Information" (7,6%) or "Experience" (6,7%) (e.g. Chellappa and Sin (2005); Gao et al. (2010); Weinmann et al. (2013)).

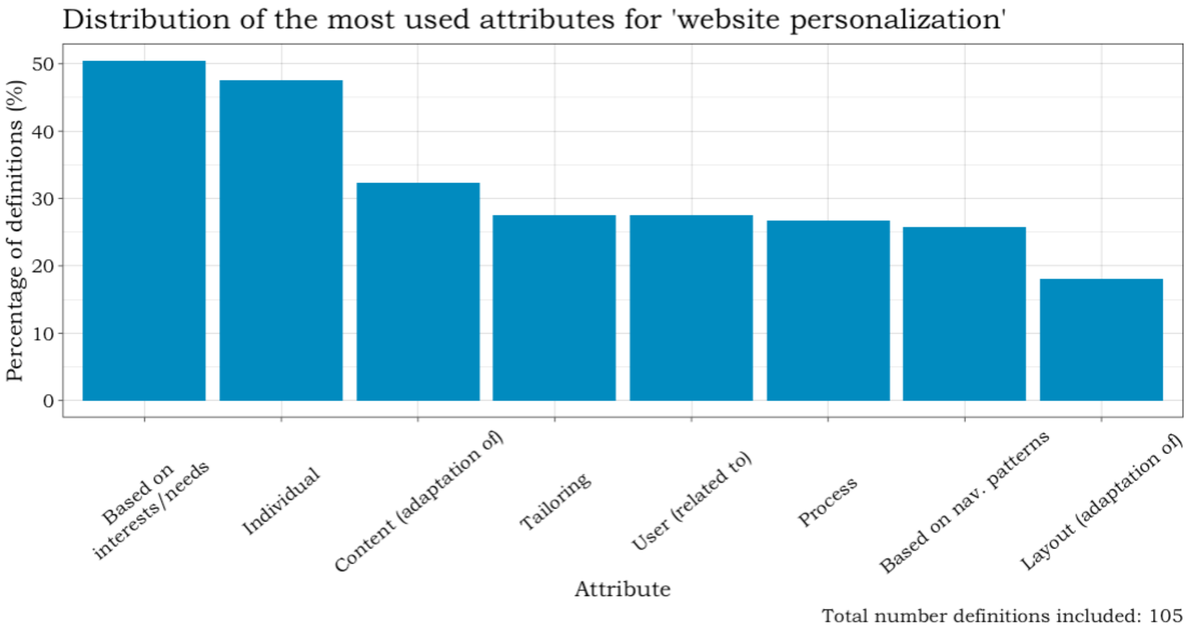

FIGURE 2.1. Most frequently used attributes for "website personalization". Different research publications where "personalization" is described using each attribute. Colors represent the chronology.

Website personalization vs. website customization

The lack of agreement in the meaning of website personalization does not only affect the term personalization itself, but also other closely related terms such as individualization, segmentation or targeting (Sunikka and Bragge, 2012). Above all, the most closely related term to personalization is customization (Salonen and Karjaluoto, 2016). This close connection between the terms personalization and customization has created some inconsistencies surrounding their use in the literature (Arora et al., 2008; Fan and Poole, 2006; Salonen and Karjaluoto, 2016).

For a large number of authors (e.g. Bodoff and Ho (2015); Ho et al. (2011); López-Pelayo et al. (2019); Miceli et al. (2007); Sia et al. (2010); Wu et al. (2003)), the term "Personalization" is synonym of "Customization", and both can be used interchangeably. Although there is also a great number of authors that agree that the terms "Personalization" and "Customization" are different (e.g. Arora et al. (2008); Ho et al. (2014)), there is still not a consensus regarding their distinction or their meaning (Salonen and Karjaluoto, 2016). For some authors (e.g. Krishnaraju et al. (2016); Kumar (2007); Mothersbaugh et al. (2012); Ramnarayan (2005)), web "Personalization" is a specific and extreme case of web "Customization", the later meaning one-to-N marketing and "Personalization" its limiting case, one-to-one marketing. For other authors (Arora et al., 2008; Sunikka and Bragge, 2012), the term "Personalization" can be used as a synonym of one-to-N marketing (being one-to-one just an extreme case) but also as a synonym of "Segmentation". There is even another group of authors (Fan and Poole, 2006; Instone, 2000; Kramer et al., 2000; Lu et al., 2013; Malcorps, 2019) who consider web "Customization" a specific case of web "Personalization" in which users explicitly indicate how the website needs to be tailored for them (or they can even do it by themselves). But still, for some authors, the latter is not considered to be web "Personalization" as they state that, although both terms are one-to-one marketing forms, "Personalization" must specifically be system-driven (i.e. carried out by the company without any user action) (Arora et al., 2008; Salonen and Karjaluoto, 2016). Additionally, some authors define the differences between web "Personalization" and "Customization" in terms of what is being tailored (i.e. structure and coloring vs. content tailoring) (Bouras and Poulopoulos, 2012; Eirinaki and Vazirgiannis, 2003) or if the tailoring is required by the user or directly provided by the system (Montgomery and Smith, 2009).

The Figure 2.2 shows this disparity of opinions and conceptualization by displaying a timeline of various research papers regarding personalization. Only explicit definitions explicit definitions of personalization have been included in the figure (i.e. if personalization and customization are interchangeable used within a paper but it is not explicitly stated that both terms are synonyms, the reference has not been included in the timeline). In the plot, different colors represent the different meanings given to the term web "Personalization" in each paper. It can be seen that there is no general trend on the definition of the concept over time, although some conclusions can be drawn. For example, use of both terms (i.e. personalization and customization) has been a stable practice during the timeline. However, the during the last decade more authors included explicitly stated personalization to be nonequivalent to customization.

Web personalization as a process

As previously discussed, website personalization is commonly described as a process (e.g. Cobaleda et al. (2016); Huang and Zhou (2018)). Although there are previous website personalization definitions that mention this process (e.g. Blom (2000); Peppers and Rogers (1997)), one of the first actual descriptions of the stages of the personalization process is the one presented in Adomavicius and Tuzhilin (2001) (Tuzhilin, 2009). In this publication, its authors argue that website personalization consists in an iterative process of five stages: (1) collecting customer data, (2) building customer profiles, (3) matchmaking, (4) delivery and presentation of personalized

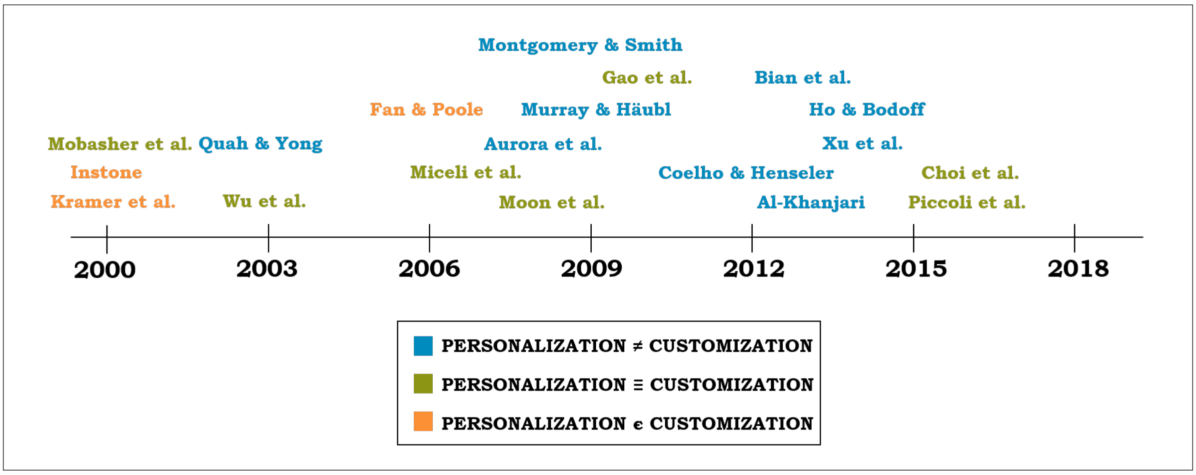

FIGURE 2.2. Time evolution of the personalization conceptualization. Colors represent different concepts

information, and (5) measuring customer response (using the results of the measurements as feedback for the previous four stages) (Adomavicius and Tuzhilin, 2001). This process was further developed by Murthi and Sarkar (2003), who conceived the personalization process in only three phases: (1) Learning (which comprises everything from the collection of the user's data to learning about their preferences), (2) Matching (which is to develop offerings that satisfy the learnt users' preferences) and (3) Evaluation of the effectiveness of the two previous phases. Based on this, Adomavicius and Tuzhilin (2005a) presented a refined personalization process proposing the Understand-Deliver-Measure cycle. This is, as shown in Figure 2.3, a process of three phases including two sub-phases in each.

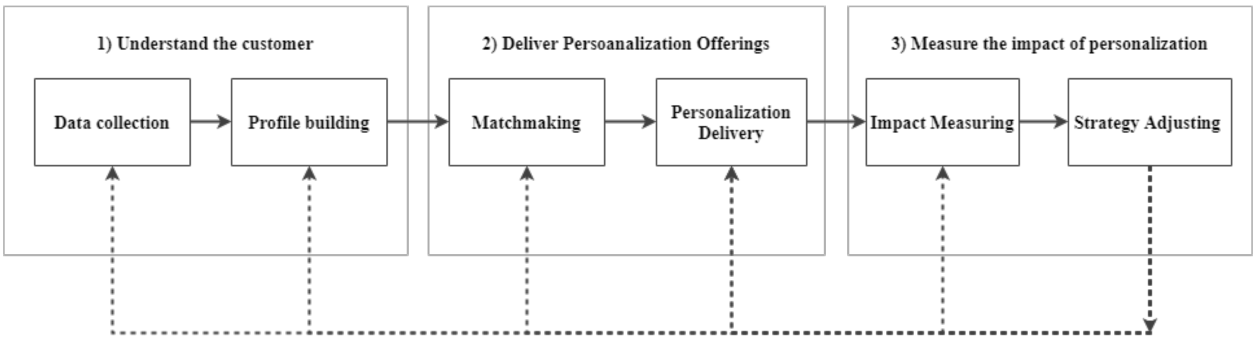

FIGURE 2.3. Personalization process described in Adomavicius and Tuzhilin (2005a)

Both processes presented in Murthi and Sarkar (2003) and Adomavicius and Tuzhilin (2005a) have been widely accepted in the literature (e.g. Lin et al. (2010); Thirumalai and Sinha (2011);

Zanker et al. (2019)). Alternative processes have also been presented (e.g. Albanese et al. (2004); Greer and Murtaza (2003); Jayanthi and Rathi (2014); Kabassi (2010); Kardaras et al. (2013); Verma and Kesswani (2017)). In particular, special emphasis should be given to the personalization process presented in Vesanen and Raulas (2006) (which is not limited to website personalization), that was later adapted to website personalization in Weinmann et al. (2013). This last process consists in four stages: (1) Interaction with the users to gather user's data, (2) Processing of the data to generate user models, (3) Adaptation of the website based on the user models, and (4) Delivery of the adapted website to each user.

Later authors support the above mentioned processes but focus their research on the implementation of one of the stages (e.g. Bouras and Tsogkas (2017); Hawalah and Fasli (2015); Velasquez et al. (2011); Verma and Kesswani (2017)).

2.1.2 Business Results

As previously seen, website personalization is a very commented topic in the scientific literature, however, part of this hype lies in the interest shown by the industry (Harvard Business Review Analytic Services, 2018; Gregg et al., 2016; SmartFocust, 2014; Tam et al., 2006). Even though companies have been increasingly trying to adopt personalization initiatives in the last few years (Christian Thomson, 2019; Gregg et al., 2016; Accenture Interactive, 2018), most of them are still not confident in their ability to personalize (Qualifio, 2019; Evergage, 2019; Boudet, Julien; Gregg, Brian; Rathje, Kathryn; Stein, Eli, Vollhardt, 2019). Moreover, there is an increasing concern regarding the lack of ability to determine whether these initiatives are having any positive results on their revenue (Harvard Business Review Analytic Services, 2018) compounded by the contradicting results on whether or not users value website personalization (Adobe, 2013; Acquia, 2019; SmartFocust, 2014). All this, combined with the lack of understanding of the core personalization concepts might lead to the decline of personalization efforts (Gartner, 2019; Jolly, A., Skiles, B., Cousins, L., Grobbel, W., Sandoz, A., Williams, 2020; Boag, 2018).

Accordingly, over a decade ago, authors started warning about the lack of real understanding regarding the direct effects of personalization for business results (Adomavicius and Tuzhilin, 2005a; Arora et al., 2008; Choi et al., 2017a; Fan and Poole, 2006; Li and Liu, 2017; Noar et al., 2009; Sunikka and Bragge, 2008; Tam et al., 2005; Thirumalai and Sinha, 2011) and its possible role as an impediment to the general adoption of personalization (Vesanen and Raulas, 2006; Vesanen, 2007).

What is clear is that the overall economic benefits and the cost of personalization have to be considered beforehand, as it does not always make sense to start personalization initiatives (Tuzhilin, 2009). Therefore, in order for personalization to continue prospering, it needs to be evaluated based on business goals and to ensure positive results (Kaptein and Parvinen, 2015; Mulvenna et al., 2000). Some companies have already created models to evaluate the value of their personalized features (e.g. *Personalization Value Model* (Karat et al., 2003)). However, once again, there is not a consensus between the authors on this issue. There is some research that affirms the beneficial effects of web personalization (Benlian, 2015; Cobaleda et al., 2016; Li and Unger, 2012; Liang et al., 2012). Most of there research focus on user-related business effects, such as user satisfaction, user persuasion, brand image, vendor perception, user attitude, perceived usefulness or loyalty (Blasco-Arcas et al., 2016; Choi et al., 2011; Jiang et al., 2015; Kim and Gambino, 2016; Liang et al., 2012; Mahesh Balan et al., 2019; Pappas et al., 2016, 2017; Thirumalai and Sinha, 2013; Zhang et al., 2014b). Whereas some others focus on the potential business effects such as revisit intention, purchase intention or willingness to pay for website personalization services (Kim and Gambino, 2016; Li and Unger, 2012; Pappas, 2018; Thongpapanl and Ashraf, 2011). There are also authors that are supportive of the positive economical business results of website personalization in terms of business performance, reduction of cash flow volatility or sales performance (Kalaignanam et al., 2018; Krishnaraju and Mathew, 2013; Thongpapanl and Ashraf, 2011).

By contrast, some authors have found no benefit from website personalization (Coelho and Henseler, 2012; Lee et al., 2015; Oertzen and Odekerken-Schroder, 2019) or even a negative effect in terms of intention of usage continuation, increased price sensitivity or decrease of the non-recommended products selection (Bodoff and Ho, 2015; Jiang et al., 2015; Oertzen and Odekerken-Schroder, 2019).

Finally, there is a third group of authors that report different effects of website personalization depending on the context (Ho et al., 2011; Li, 2019; Thirumalai and Sinha, 2013), the affected user segment (Lee et al., 2015; Li and Liu, 2017; Moon et al., 2008), the personalization strategy used (Mahesh Balan et al., 2019; Noar et al., 2009; Tam et al., 2005; Thirumalai and Sinha, 2013; Vesanen and Raulas, 2006), the user's trust on the company (Aguirre et al., 2015) or how personalization is defined (Chen et al., 2002). Overall, authors have not reached consistent results to achieve a general conclusion (Choi et al., 2011; Kalaignanam et al., 2018; Li and Liu, 2017).

Additionally, some authors have studied the negative effects of excessively personal or malfunctioning website personalization in particular (Chau et al., 2013; Shanahan et al., 2019; Xiao and Benbasat, 2018) . All this makes website personalization evaluation a non trivial matter from the perspective of business results (Salonen and Karjaluoto, 2016).

2.1.3 User Specific Aspects

Cultivating a personalized relationship with the user makes future transactions smother and more efficient which, in the long term, will benefit both parties (Fan and Poole, 2006). Accordingly, the main focus of personalization should be providing value to the end user (Kramer et al., 2000). Therefore, once we have a general overview of what personalization represents, it is time to start paying attention to the end user. The user-centric aspects focus on the behavioral responses of the user and are central to personalization research efforts (Adolphs and Winkelmann, 2010; Arora et al., 2008; Krishnaraju et al., 2016; Salonen and Karjaluoto, 2016). Some of the user-specific topics that have received more attention in the personalization research area are users satisfaction (Edvardsson et al., 2000; Lee and Lin, 2005), users loyalty (Hong et al., 2009; Kwon and Kim, 2012; Piccoli et al., 2017), users privacy concerns (Pitkow et al., 2002; Chellappa and Sin, 2005; Ho, 2006), trust (Kimery and McCord, 2002; Miceli et al., 2007; Sharma and Ray, 2016), users feelings (Venkatesh et al., 2012; Xu et al., 2014a; Maruping et al., 2017), users context (Ha et al., 2010; Li and Liu, 2017) and users perception (Coelho and Henseler, 2012; Demangeot and Broderick, 2016; Choi et al., 2017b).

Satisfaction and Loyalty

Due to being considered essential drivers of business performance (Kwon and Kim, 2012; Choi et al., 2017b) and due to their interplay with personalization (Miceli et al., 2007), satisfaction and loyalty are key concepts in web personalization. According to Edvardsson et al. (2000), customer satisfaction is defined as the overall evaluation of a customer's own experience in the purchase and consumption.Customer loyalty, however, is defined as the customer's predisposition (or intention) to repurchase from the same firm, which makes it strongly related to the concept of customer retention (Kwon and Kim, 2012). As stated in Fornell (1992), they are highly interrelated, since satisfied customers tend to be loyal, however, it is not a two-way relation, as loyal customer do not necessarily have to be satisfied.

Measuring user satisfaction in a fair manner has been an issue of concern for academics and practitioners for some time (Lee and Lin, 2005). To the extent that, in 1992, Fornell presented the Swedish Customer Satisfaction Index, based on the Swedish Customer Satisfaction Barometer. After that, governmental organizations and researchers started developing their local customer satisfaction indexes (CSI) (Eklöf and Westlund, 2002), some examples are the European (ECSI) and the American (ASCI) indexes (Coelho and Henseler, 2012). However, for more than 20 years, satisfaction has widely been used as a tool to measure effectiveness and the user's perception of service quality more than as a valuable measure itself (Watson et al., 1993).

Regarding the effects of web personalization on user satisfaction, despite a minority of authors reporting no significant effect (Surprenant and Solomon, 1987; Lee and Lin, 2005), there is a generalized agreement on its positive effect (Arora et al., 2008; Flory and Thomas, 2017; Liang et al., 2012; Oberoi et al., 2017; Piccoli et al., 2017; Thirumalai and Sinha, 2011; Thongpapanl and Ashraf, 2011; Verma and Kesswani, 2017). The reasoning given for that positive effect is that tailored offers are likely to satisfy a customer more than standardized ones, since they facilitate a real match between customer and the product of service (Coelho and Henseler, 2012). However, it is important to remark that an inadequate web personalization presenting irrelevant content to personal needs or tastes, can cause dissatisfaction (Miceli et al., 2007; Flory and Thomas, 2017), and it mostly depends on the choice of the personalization strategy suited to for each company (Kwon and Kim, 2012).

The effect on user loyalty has not been as extensively commented in the literature- Nevertheless, according to Pierrakos et al. (2003), one of the main goals of a website is to create loyal users and this can be achieved by website personalization. Similarly to case the of satisfaction, there is an almost general agreement on the positive effect of web personalization on user loyalty (Al-Shamri, 2014; Bazdarevic and Cristea, 2015; Dzulfikar et al., 2018; López-Pelayo et al., 2019; Oberoi et al., 2017; Thirumalai and Sinha, 2013; Zhang et al., 2018).

Trust and Privacy Concerns

Users' concern regarding threats to their privacy and how online merchants use their data is constantly increasing (Pitkow et al., 2002). These concerns for privacy have an effect on web usage (Chellappa and Sin, 2005), such as heightening online distrust, which has a great impact on in the relationship between the user and the company (Lee and Lin, 2005). Consequently, privacy issues have been considered in the literature as one of the most important factors affecting users' attitude towards web personalization (Lee et al., 2015; Tuzhilin, 2009).

On the one side, the relationship between the users' privacy concerns and their willingness to benefit from web personalization has been widely studied in the literature as it is considered a paradox (Aguirre et al., 2015; Awad and Krishnan, 2006; Garcia-Rivadulla, 2016; Mothersbaugh et al., 2012; Pappas, 2018; Zhao and Zhao, 2016). Whilst, an important proportion of online users are concerned about how companies are using their personal data (Kalaignanam et al., 2018; Mulvenna et al., 2000; Zhao and Zhao, 2016), they seem to be willing to share their data for convenience when the perceived benefits from personalization overweight the drawbacks of information disclosure (Chellappa and Shivendu, 2010; Garcia-Rivadulla, 2016; Mothersbaugh et al., 2012). However, this willingness seems not to be unlimited (Chellappa and Shivendu, 2010) and has been found to be affected by different factors such as the trust in the website owner organization (Li and Unger, 2012; Zhao and Zhao, 2016), the sensitiveness of the information (Mac Aonghusa and Leith, 2018; Mothersbaugh et al., 2012), the awareness and feeling of control over the information (Kobsa, 2007) or the personalization strategy (Sundar and Marathe, 2010). In order to decrease these privacy concerns and avoid the generation of distrust, some proposed measures are, for example, to include recommendation explanations (Sharma and Ray, 2016; Arora et al., 2008; Amatriain and Basilico, 2012a), to allow users to express their feelings (Piccoli et al., 2017) and to pay special attention on the website design (Seckler et al., 2015). Moreover, web personalization can also play a positive (Demangeot and Broderick, 2016) or a negative (in case of malfunctioning or biased) (Chau et al., 2013) role affecting these privacy concerns and generation of distrust. Given that it is a complex topic with a big impact on the personalization effects, some authors consider the study of the balance between personalization methods and privacy considerations as an independent research field called *privacy-enhanced personalization* (Kobsa, 2007).

On the other side, trust is considered to be qualitatively different to distrust (Yang et al., 2015). This is because it is more reliant on the brand image and the word of mouth (Guha et al., 2004; Seckler et al., 2015) and it has a global effect on the users' behavior towards an organization beyond the online channel (Gefen et al., 2003; Miceli et al., 2007). In the case of trust, its relationship with web personalization is double sided, as personalization has an influence on trust (Choi et al., 2011; Kalaignanam et al., 2018; Oberoi et al., 2017; Xu et al., 2014b; Zhang et al., 2014a) while trust is needed for personalization to be accepted and adopted (Pappas, 2018; Peppers and Rogers, 2013).

User Feelings

When developing a website and more specifically ,when developing a web personalization strategy, it is important to take into consideration the users' feelings, given its influence on the user's attitude towards the website and the company (Venkatesh et al., 2012; Maruping et al., 2017).

Some user feelings that have gained research interest over time within the website personalization field are obfuscation (Choi et al., 2017b), preference uncertainty (Coelho and Henseler, 2012) and information overload (Arora et al., 2008; Bouras and Poulopoulos, 2012; Gan and Jiang, 2018; Kwon and Kim, 2012; Sharma and Suman, 2013; Thongpapanl and Ashraf, 2011). All of them are considered to be reduced by an effective web personalization (Arora et al., 2008; Hawalah and Fasli, 2014; Xu et al., 2014a; Choi et al., 2017b). However, the last one needs special care when implementing personalization features as they can be a cause for information overload (Schreiner et al., 2019; Zhang et al., 2019).

Other user feelings that have been analyzed withing the field over the last few years, are the feeling of being understood (by other users, by the company or by the website itself) (Blom and Monk, 2003; Demangeot and Broderick, 2016) and user attitudes (Ho et al., 2014; Kalinic et al., 2014; Kim and Gambino, 2016; Oertzen and Odekerken-Schroder, 2019; Xu et al., 2014b).

User Context

Personalization features have typically no impact on the context of the user, whereas, the context has an impact on the user, and may affect how it handles personalization (Knijnenburg, 2012). Taking into consideration the high impact that contextual factors have on the effects of personalization (Salonen and Karjaluoto, 2019), authors have recently started studying how to use these contextual factors to personalize (Hawalah and Fasli, 2014; Salonen and Karjaluoto, 2016). Even personalizing only based on contextual factors has already been proven to have an effect on users (Kim and Sundar, 2012).

The two most commented contextual factors in the literature are users' time and culture (Salonen and Karjaluoto, 2019; Pappas et al., 2017). That is, the specific timing in the relationship between the user and the company, such as the visit number, the exact instant of the visit, the time distance between interactions or the phase in the buying process (Adomavicius and Tuzhilin, 2005a; Ho et al., 2011; Sunikka and Bragge, 2012; Lambrecht and Tucker, 2013). As the user has dynamic needs and preferences (Hawalah and Fasli, 2015; Salonen and Karjaluoto, 2019), personalization at a certain point in time of the user's website journey will require different implementation criteria, but also, will have different effects on the user acceptance of the personalized features (Ho et al., 2011; Huang et al., 2011). On the other hand, regarding the cultural effects, users should be approached by different personalization strategies depending on their cultural background (Pappas et al., 2017; Reinecke and Bernstein, 2013; Wang and Wang, 2016; Wan et al., 2017), as different cultures seem to have different acceptance of individual-based or group-based approaches to personalization (Kramer et al., 2007; Li and Kalyanaraman, 2013; Reinecke and Bernstein, 2013), specially in the case of users with strong ethnic identities (Gevorgyan and Manucharova, 2009; Singh et al., 2008). However, not all authors agree on these cultural differences (Ha et al., 2010).

Other commented context factors in the literature, include the user's social context (Mac Aonghusa and Leith, 2018), the type of products/services(Annamalai et al., 2019), the browsing motivation (Salonen and Karjaluoto, 2019), the user's emotions (Pappas et al., 2017; Pappas, 2018) or the user's mood (Ho and Lim, 2018) as all of them are continuously changing in time.

Even though the results of the studies regarding the contextual factors vary, the general view supports the notion that it is a determinant on the web personalization effect (Hawalah and Fasli, 2014; Huang and Zhou, 2018; Krishnaraju et al., 2016; Pappas et al., 2016; Pappas, 2018).

User Perception

The last subject that we are going to asses within the user specific aspects of personalization is user's perception. This sits between the actual personalization of the website and its impact on the user (Choi et al., 2017b; Kang et al., 2016; Liljander et al., 2015).

In a personalized interaction with the web site, the site behaves in a manner that seems to understand the user, thus, the user may perceive closeness or familiarity with the company (or brand) and it affects their attitude (Demangeot and Broderick, 2016). The user perceives the website personalization or interactivity as the extent to which they believe that the system is understanding them and representing their preferences (Xiao and Benbasat, 2018). Even without actual personalization actions, this perception has a key impact on user's decisions (Liljander et al., 2015; Zhang et al., 2014b).

On the other hand, the perceived interactivity or personalization of the website is also considered to have an effect on other metrics such as usage continuation, perceived enjoyment, perceived user care, adoption intention and perceived quality (Benlian, 2015; Coelho and Henseler, 2012; Knijnenburg, 2012; Liang et al., 2012).

2.1.4 Technical and implementation aspects

The technical aspects and implementation related issues have been the most discussed topics within the website personalization field (Fan and Poole, 2006; Krishnaraju and Mathew, 2013; Salonen and Karjaluoto, 2016; Sunikka and Bragge, 2012). Since it is an extensive topic, some different sub-topics can be identified in the literature. Based on the previous reviews (Adolphs and Winkelmann, 2010; Salonen and Karjaluoto, 2016) those are: (1) Design factors, (2) Data collection and processing and (3) Recommender systems.

Design Factors

This first section, covers the research advances on how to implement personalization in terms of design/interface. In general, website aesthetics and design are critical to building a successful user experience, therefore, considerable efforts have been undertaken to improve and evaluate website design (Fang and Salvendy, 2003; Wang et al., 2011; Yen et al., 2007). This is not different in the case of website personalization where the understanding of design factors is essential to personalize the website successfully (Salonen and Karjaluoto, 2016). Accordingly, authors have studied different factors that should be considered in the design personalization features (e.g. Gerber and Martin (2012); Karat et al. (2003)). With it, some design guidelines have been presented based on user perception (Choi et al., 2017c; Huang et al., 2019; Lin et al., 2010; Parra and Brusilovsky, 2015), user cultural background (Gevorgyan and Manucharova, 2009; Kramer et al., 2007; Reinecke and Bernstein, 2013) or user personal traits (Martin et al., 2005b; Tanya et al., 2017; Wang and Wang, 2016). With a more technical vision, some attention has also been given to the website layout design and adaptability (Ferretti et al., 2016; Kardaras et al., 2013).

In addition to the interface and aesthetic design factors, there is also research on factors to be considered when designing the personalization algorithms. For example, some authors advocate for the inclusion of user feelings in the algorithms (Anand and Bharadwaj, 2013; Lee, 2012; Sahoo and Ratha, 2018) and others promote the use of user contextual factors such as timing of social communities (Hawalah and Fasli, 2014; Salonen and Karjaluoto, 2019; Paliouras, 2012).

Data collection and processing

In this section we include the research addressing data acquisition methods and how to process this data for website personalization. With the purpose of personalizing the website, the more user data we obtain, a better personalization can be delivered. In fact, "the entire web history of a user can potentially be used for personalization" (Bai et al., 2017). But actually, although a company may find it relatively easy to obtain a complete view of 40% of their customers, it may be prohibitively costly to obtain such data for the next 60% (Nesil et al., 2006).

In first place, the most commented topic regarding data collection and processing for website personalization is web mining (also known as web log mining or web usage mining) (e.g. Castellano et al. (2011); Jothi Venkateswaran and Sudhamathy (2015); Senthil Pandian et al. (2016); Umamaheswari et al. (2016)). That is, the usage of statistical and data mining techniques to extract knowledge about user's navigational behavior from the web (Eirinaki and Vazirgiannis, 2003; Jebaraj Ratnakumar, 2010; Sengottuvelan et al., 2017). Web usage mining is not a new topic, however it has recently gained increasing interest from the web personalization research community (Duwairi and Ammari, 2016; Mobasher et al., 2000). At the beginning of the century, the publications on the use of web mining techniques for personalization had a more general view of the topic, mainly presenting and describing the different steps of the mining process (e.g. Adomavicius and Tuzhilin (2001); Eirinaki and Vazirgiannis (2003); Mobasher et al. (2000)). However, most of the recent studies focus on the details of each single step in the process or describe new algorithms for log mining (e.g.Giannikopoulos et al. (2010); Huang et al. (2011);

Yogi and Yamuna (2019)). Special attention has been given to algorithms for navigational pattern classification or prediction (Mishra and Kumar, 2017; Uma Maheswari and Gunasundari, 2017; Wei et al., 2015; Zhang and Liu, 2012; Zhu, 2011), user memorization (Hussein et al., 2013; Verma and Kesswani, 2017) and pattern extraction (Alkan and Karagoz, 2015; Banu and Inbarani, 2011; Lokeshkumar and Sengottuvelan P., 2014; Sengottuvelan et al., 2017).

The second topic to be included is the creation and use of profiles. Although content or products/services can be both profiled for website personalization (Eirinaki and Vazirgiannis, 2003; Instone, 2000), most of the literature focuses on user profiling. Generally, user profiles are created from web mining data (Adomavicius and Tuzhilin, 2001; Hussein et al., 2013). Some authors have presented different user profiling methods (e.g. Alfimtsev et al. (2012); Besbes and Baazaoui-Zghal (2016); Bouras and Poulopoulos (2012); Hawalah and Fasli (2014); Kaptein et al. (2015); Rohm and Swaminathan (2004); Sahoo and Ratha (2018)), however, one of the most discussed issues is the need to include dynamism on the profiles. That is, as user preferences and needs are not fixed, but change over time, the information must be managed accordingly (Hajeer et al., 2016; Hawalah and Fasli, 2015; Mobasher et al., 2000; Prabaharan and Wahidabanu, 2012).

In third place, authors have focused on search engine personalization (also known as web search personalization). Given the vast amount of information available over the Internet, users suffer from information overload and need support systems to find the information they are looking for (Gao et al., 2010). Search engines are the collection of programs used for information retrieval from the Internet (Jayanthi and Rathi, 2014). Therefore, the personalization of search engines is meant to adapt the search results to the needs or interests of the user (Mac Aonghusa and Leith, 2018; Zhang et al., 2013). During the last few years, many new approaches to web search publication have been introduced (e.g. Bai et al. (2014); Choi (2014); Doddegowda et al. (2018); Lee (2012); Prabaharan and Wahidabanu (2012); Sakkopoulos et al. (2010); Sengottuvelan et al. (2015); Subha Mastan Rao et al. (2014)). Accordingly, the need for comparison between models (Song et al., 2016) and detection of biased search engine personalization (Bozdag, 2013) has also emerged in the literature.

In addition to the three above mentioned topics, some attention has also been given to the use of machine learning techniques (Gao et al., 2010; Xue et al., 2019). Clustering has been the most used method, from the use of the classic clustering techniques (Lokeshkumar and Sengottuvelan P., 2014; Manjula and Chilambuchelvan, 2019; Senthil Pandian et al., 2016; Sengottuvelan et al., 2015; Raju et al., 2018; Yogi and Yamuna, 2019), to the adaptation of those clustering techniques (Banu and Inbarani, 2011; Bouras and Tsogkas, 2017) or combinations thereof (Alphy and Prabakaran, 2014; John and Shajin Nargunam, 2013). Moreover, neural networks (Alphy and Prabakaran, 2015; Yang, 2012), deep learning (Zanker et al., 2019) and reinforcement learning techniques (Ferretti et al., 2016) have also been used.

In conclusion, data collection and processing techniques have been very commented topics inside the website personalization field, even though the final decision on what to apply and how to do it is still constrained by factors such as server capacity (Quah and Yong, 2002).

Recommender systems

Recommender systems are the most discussed and adopted of the many applications of website personalization (Adomavicius and Tuzhilin, 2005a; Mobasher et al., 2000; Salonen and Karjaluoto, 2016; Sharma and Suman, 2013; Wu et al., 2003; Zhang et al., 2013). Given their considerable attention and their widespread application on organizations' websites, recommenders have experienced notable development during the few last decades (Senecal and Nantel, 2004; Shambour and Lu, 2011). A recommender system is a web-based technology that collects user preferences and needs (implicitly or explicitly) and tailors the user experience accordingly (mainly by recommending products, services or information) (Castellano et al., 2011; Duwairi and Ammari, 2016; Hussein et al., 2013; Li and Karahanna, 2015).

The recommendation systems are usually classified based on the recommendation approach used (i.e. the filtering technique) (Adomavicius and Tuzhilin, 2005a; Kabassi, 2010; Hussein et al., 2013; Isinkaye et al., 2015; Lika et al., 2014; Lin et al., 2010). The commonly used recommendation approaches are:

- Content-based filtering: The user is seen as an individual and, thus, is suggested items or services which are similar to those bought or searched in the past, by matching the characteristics of the item or service with the characteristics of the user that are maintained in a the user profile (Adomavicius and Tuzhilin, 2005a; Hawalah and Fasli, 2015; Lee, 2012). The cornerstone of this method is the calculation of similarity between the items and the user profile information, and this is usually done by heuristics (such as cosine similarity), Bayesian classifiers and some machine learning techniques (Isinkaye et al., 2015; Lee, 2012; Pazzani, 1999). The main advantage of this method is that is based only on facts about the particular user and, ergo, are true (Kabassi, 2010). Moreover, as it is based on the information of each user may be easier for the system to capture the changes in the users preferences or tastes compared to other recommendation approaches (Adomavicius and Tuzhilin, 2005b). However, this approach suffers from various problems. For instance, it is essential for this approach to collect sufficient information about the user, without it (e.g. for new users), the system will not be able to provide effective recommendations, this problem is known as *user cold-star problem* (also known as *new user problem*) (Bai et al., 2017). Another typical problem is the *over-specialization*, as the user navigates, the profile information becomes ever more specialized and, since the recommender will not select items if the previous user behavior does not provide evidence for that, the system may be unable to make novel suggestions (Hawalah and Fasli, 2015; Kabassi, 2010).

- Collaborative filtering: The user is seen as similar to other users, with it, the recommendations are made based on what similar users (users with similar tasted or behavior) have preferred. Thus, this approach is based on the premise that users with similar interests and tests in the past, can be used to predict the user's interest and tastes in the future (Adomavicius and Tuzhilin, 2005a; Al-Shamri, 2014; Anand and Bharadwaj, 2013; Bouras and Tsogkas, 2017; Lu et al., 2013; Shambour and Lu, 2011; Yu et al., 2004; Zhang et al., 2013). In the literature, the algorithms used in collaborative filtering have been classified in memory/heuristic-based and model-based algorithms (Anand and Bharadwaj, 2013; Adomavicius and Tuzhilin, 2005b; Bouras and Tsogkas, 2017; Isinkaye et al., 2015; Pennock et al., 2000). In some cases, this approach suffers from various problems. For instance, if an item has been chosen few times (or has not been chosen before) it it will not be recommended to any user, this is known as *item cold-star problem* (Hawalah and Fasli, 2015; Kabassi, 2010; Lika et al., 2014). Moreover, collaborative filtering also suffers from the *user cold-star problem* seen in content-based filtering, since, for new users, the system is not able to identify similarities with other users (Bouras and Tsogkas, 2017; Kabassi, 2010; Lika et al., 2014).

- Hybrid filtering: The items recommended to the user are made based on a system developed combining content-based and collaborative methods (Sharma and Ray, 2016). It is possible to create a recommendation based in a content-based system and combine the result with the one from a collaborative system. And it is also possible to directly generate the recommendation in a system using a combination of the two methods (Adomavicius and Tuzhilin, 2005a). With it, the strengths of each of them are emphasized in order to improve the performance of a recommender system (Lee, 2012; Zhang et al., 2013).

Moreover, although not as extensively commented, other filtering techniques can be found in the literature. For example in the early stages of recommender systems, demographic filtering was extensively used (Bobadilla et al., 2013; Malik and Fyfe, 2012; Pazzani, 1999). Another example is knowledge-based filtering (Lu et al., 2013; Malik and Fyfe, 2012; Shambour and Lu, 2011).

Additionally, recommender systems have also been widely studied from the user's point of view, both from the design and the evaluation perspective (Aguirre et al., 2015; Knijnenburg, 2012), paying attention to recommendation explanations (Sharma and Ray, 2016), the user perception of the recommendations given (Choi et al., 2017c; Johar et al., 2014; Xiao and Benbasat, 2018; Zhang et al., 2018) and how to increase the user's trust in the recommendations (Pu and Chen, 2007).

Finally, due to the generalized adoption of recommender systems, they might have an impact on the user's and even on the organizations' environment (Li et al., 2018). Therefore, authors have reached a consensus that the evaluation of recommender systems should consider not only accuracy but also additional measures (Parra and Brusilovsky, 2015). Accordingly, some authors have started presenting user-centric or business-centric approaches to evaluate the performance of recommender systems (Knijnenburg, 2012; Li et al., 2018; Parra and Brusilovsky, 2015).

2.2 Website Personalization Automation

As aforementioned earlier in section Theoretical foundations, personalization historically has been given a variety of attributes within the research literature. Even if it is only included in 4 of the reviewed explicit definitions of personalization (specifically Ho et al. (2014); Huang and Zhou (2018); Salonen and Karjaluoto (2016); Sia et al. (2010)), the term 'automatic' has extensively used as an attribute to personalization (Salonen and Karjaluoto, 2016), mainly in relation to website personalization (e.g.Fan and Poole (2006); Montgomery and Smith (2009)).

Since the first research contributions in website personalization, some authors have used the concept of "web automation" referring to different meanings (Mobasher et al., 2000). On the one hand, the concept of 'automatic' or 'automated' website personalization has been used, to refer to a specific type of personalization. For example in Montgomery and Smith (2009) and in (Salonen and Karjaluoto, 2016), authors consider 'automated personalization' meaning company/system initiated, as opposite to user-controlled. Moreover, 'automatic personalization' has also been used as relative to adaptivity and implicit learning (i.e. the user's preferences are inferred by using the available information gathered, therefore, the user is not directly asked about her preferences) (Mobasher et al., 2000; Fan and Poole, 2006; Soui et al., 2013; Ho et al., 2014).

On the other hand, 'automatic personalization' has also been used to refer to a personalization process with one of the steps self-operated, this is, automatizing one of the steps of the personalization process. For example, in Bai et al. (2017), authors use the concept 'automatic personalization' referring to the specific case of personalization where the process of user profiling is automated (i.e. given some user data, a profile is made for each user, with it, a personalized result if offered). Similarly, in Quah and Yong (2002) and (Ferretti et al., 2016), authors use this concept to refer to the particular personalization case where the process of interface adaptation is automated. Some other examples include **?**, where the input information is automatically processed to then present personalized results. And Vesin et al. (2013), where authors personalize the website content based on scoring the navigational patterns of the user and comparing it with the scoring of other users. Additionally, authors from the field of website testing and optimization, suggest the possibility to automatically present the most suitable content for each segment of users (Kohavi et al., 2009).

Nowadays, there is a wide range of available commercial platforms defined by their owning companies in their websites (or other online sites) as tools for 'automatic personalization' (e.g (Adobe, 2017; Episerver Personalization, 2017; Personalization from Optimizely, 2017)). In most of those cases, 'automatic personalization' refers to automatically select (e.g. based on statistically data) the most suitable content for a user or segment of users. With the most suitable being the one with best performance (depending on the specific performance indicators selected).

Given the variety of interpretation of this concept, we consider it necessary to clarify the meaning of 'automatic website personalization' in this research. With it, in this research, by 'automatic' or 'automated' website personalization we refer to the automation of the entire process of personalization considering all the sub-processes displayed in Figure 2.3 *Website personalization process as described in Adomavicius and Tuzhilin (2005a)*. This is, the creation of self-operated processes in the company in order to, first, collect data from the website (and any other source required) and categorize users based predefined segments or profiles. Second, match each user (given her categorization) with specific personalized options from a previously introduced collection (e.g. specific website images) and deliver them. Third, to measure the impact of assigning the selected personalization option to the specific user (based on predefined measures) and readjust the process according to the obtained result.

2.3 Automotive sector websites

The automotive sector is characterized by its intense competition focused on the product and its development (Lanzini, 2018; Singh et al., 2005) and a lack of disruptive organizational transformations related to other than production systems and product development (Genzlinger et al., 2020; Jacobides et al., 2015). Moreover, several factors, such as the introduction of new players in the car market (eg. Tesla) (Perkins and Murmann, 2018), new mobility needs of the customers (eg. electrical vehicles, mobility services or connected vehicles) (Covarrubias, 2018; Genzlinger et al., 2020; Hoeft, 2021b), new customer needs and desires (eg. improved customer service or car personalization) (Liu et al., 2021; Mourtzis et al., 2014), new regulations (eg. emissions regulations or personal data protection regulations) (Peters et al., 2016; Srivastava et al., 2021) and external factors (eg. COVID-19) (Hoeft, 2021b) have recently challenged the status-quo of this industry Hoeft (2021a). Therefore, the automotive sector is expected to face a profound transformation (Ansart and Duymedjian, 2006). Accordingly, companies of the automotive sector have had to investigate new approaches to solve their problems and to remain competitive (Hoeft, 2021a; Koudal and Wellener, 2003). Some authors point out the need for companies in this sector to focus on doing constant research to improve the service quality (Hanaysha, 2016). With it, in the last decades, many automotive companies have moved from an emphasis on product quality to customer satisfaction and, in a later stage to customer loyalty and retention (Gustafsson and Johnson, 2002). However, a real understanding of the customer-brand relationship is yet to be achieved (Kaufmann et al., 2019).

In this context, since the beginning of the century, companies have tried to be more digital and to design systems to target, satisfy and retain customers (Koudal and Wellener, 2003). An example of this digitalization is the extensive use of social media by most automotive brands (Kormin and Baharun, 2016; Yamamoto et al., 2015). Another example is the use of their brand websites to promote their relationships with their customers (or prospect customers) (Ansart and Duymedjian, 2006). Nowadays, automotive websites usually cover most of the pre-ownership phase of the vehicle customer experience (including awareness, choosing, financing and sometimes even insuring), some part of the ownership phase (including maintaining and repairing) and all the pre-disposal phase (including upgrading and disposing) (Ansart and Duymedjian, 2006). Furthermore, even if the perceived risk of buying automotive products on the websites is higher than other smaller products commonly available online (Bauer and Dorn, 2017), the ordering and actual buying of the vehicle are becoming an available options in some automotive websites (García, 2017; Wertz, 2020). With it, companies try to not only develop the customer-brand relationship but also to predict and influence the purchase intention of the website users (Gu et al., 2018; Kaufmann et al., 2019).

On the other side, nowadays, digital environments provide opportunities for implementing customization strategies, which allow users configure their own individual solutions by selecting from a list of options and components and obtaining personalized products (Mavridou et al., 2013; Perna et al., 2018; Wang and Wang, 2016). In websites of the automotive sector this is usually achieved with online car configuration systems that allow the user to customize the vehicles from a selection of options and a visualization of the resulting car (Mavridou et al., 2013; Mourtzis et al., 2014). With it, automotive brands enable the users to be part of the design of their final car and to have it personalized to their tastes or needs (Mourtzis et al., 2014). However, these systems commonly deal with the problem of mass confusion (the situation where the customer becomes confused by the excess variety of possibilities) and some authors suggest website personalization approaches to adapt the number of options available for each user as possible solution (Felfernig et al., 2002).

Additionally, companies of the automotive sector are also making advances toward the personalization of their websites (Corning, 2018; Kominek, 2019). However, a web personalization strategy may vary among companies due to their different priorities, objectives, the company-user relationship and the kind of website (Ho et al., 2014; Aguirre et al., 2015), and it does not always make sense for a company to personalize (Tuzhilin, 2009). In Wu et al. (2003), a list of key factors is given for companies to know whether if personalization will be effective of not for their websites (including revisit frequency, purchase relationship, product differentiation and content stability). Moreover, their conclusion for a website in the automotive sector was not to implement web personalization, considering that it does not to engender additional business in this particular sector.

In conclusion, even if there is some research in the automotive sector digitalization, more research is needed regarding webs of the automotive sector and the potential effects of using website personalization (Bauer and Dorn, 2016; Genzlinger et al., 2020).

CHAPTER 3

A BROADER CONCEPT OF PERSONALIZATION

In this chapter we present our proposed novel personalization framework. With it, we conceptualize the meaning of personalization as a topic, including the most commonly used terms and classifications. Firstly, we introduce the need for a framework within the personalization field. Secondly, we present the literature review on the topic and the methodology used. Then, the proposed personalization framework is described. Finally, the discussion and conclusions are presented.

3.1 Introduction

Web personalization is a broad topic developed from various fields and perspectives (Soui et al., 2013). Accordingly, its parent topic, personalization, is even broader (Dangi and Malik, 2017). The study of personalization attracts the attention of a wide range of disciplines including, for example, economics, management sciences, information technology, marketing, operations research or computer science (Fan and Poole, 2006; Kwon et al., 2010; Murthi and Sarkar, 2003). This diversity of fields is seen as an advantage for personalization as it gives dynamism to the development of the topic by offering a variety of viewpoints from different knowledge areas (Fan and Poole, 2006; Kaptein and Parvinen, 2015; Leahey and Reikowsky, 2008).

Contrarily, since most research in personalization has been addressed in isolation in the different fields, this same diversity has led to a dispersed state of the literature (Blasco-Arcas et al., 2014; Murthi and Sarkar, 2003). As a result, some major advances have gone relatively unnoticed or have been hidden inside a specific field (Fan and Poole, 2006). Moreover, this variety of fields has generated not only a lack of agreement on how to characterize the most used terminology but also, a controversy around the different definitions and classifications (Arora et al., 2008; Montgomery and Smith, 2009; Sunikka and Bragge, 2012; Vesanen, 2007).

These discrepancies can be seen in the heterogeneity of definitions that can be found in both academic and non-academic environments (Tuzhilin, 2009; Sunikka and Bragge, 2012). Some examples of academic personalization definitions are:

- «Personalization is the adaptation of products and services by the producer for the consumer using information that has been inferred from the consumer's behavior or transaction» (Montgomery and Smith, 2009)
- «Personalization is customizing some feature of a product or service so that the customer enjoys more convenience, lower cost or some other benefit» (Peppers and Rogers, 1997)
- «Process that changes the functionality, interface, information access and content, or distinctiveness of a system to increase its personal relevance to an individual or a category of individuals» (Fan and Poole, 2006)

Some examples of non-academic personalization definitions found in the industry are:

- «[*Personalization is defined as*] A process that creates a relevant, individualized interaction between two parties designed to enhance the experience of the recipient» (George, 2017)
- «Personalization is the process of keeping in mind the needs and preferences of your audience so that you market the right product and experience to the right person at the right time» (Manola, 2019)
- «Personalization is when a brand is able to change the content or experience without your active knowledge» (Proof., 2020)

As a consequence of this fragmented conceptualization of terms and the lack of link between the research advances of the different fields, the successful development of the topic and its general implementation might be threatened (Vesanen, 2007).

Personalization has been experiencing major advances for few decades (Tuzhilin, 2009). In fact, more than one decade ago, *Wired* listed personalization as one of the 6 trends driving the global economy (Kelleher, 2006). Accordingly, the personalization term has become a very commented topic within several fields (Sunikka and Bragge, 2012). However, from the beginning of the topic, its development has mainly focused on personalization implementation rather than on its theoretical foundations (Wu et al., 2003). Consequently, despite its evolution, companies are nowadays still not convinced about their ability to personalize (Boudet, Julien; Gregg, Brian; Rathje, Kathryn; Stein, Eli, Vollhardt, 2019; Evergage, 2019; Qualifio, 2019) and the general application of personalization is still not globally widespread (Boudet, Julien; Gregg, Brian; Rathje, Kathryn; Stein, Eli, Vollhardt, 2019). One of the most commented causes for the slowdown and failure of its application is the lack of understanding of what personalization really is (Kaneko et al., 2018a; Proof., 2020; Sunikka and Bragge, 2012; Tuzhilin, 2009).

In summary, personalization is in the spotlight of a diverse collection of fields (Kwon et al., 2010), which makes it a versatile topic and with a variety of different possible applications (Rossi et al., 2001). Consequently, definitions of the core concepts related to personalization differ from one field to another and there is no common language among them (Fan and Poole, 2006; Kaptein and Parvinen, 2015). Therefore, cross-field understanding of personalization is needed (Al-Khanjari, 2013). In order to address this gap, the research question of this study is:

RQ: What is personalization?

With this broad question, the objective is not only to purely understand the meaning of the term personalization considering a cross-field point of view, but also to understand the meaning of the most used terms related to the topic and the possible personalization strategies.

3.2 Literature Review

During the last few decades, personalization has been classified using a variety of criteria (Sunikka and Bragge, 2008). After conducting a literature review, the different classifications used can be organized in three main groups.

In first place, there is a group of authors that consider personalization to be divisible itself in different categories. This is, authors that explicitly classify personalization as different types, forms, modes or categories (Nasraoui, 2005; Salonen and Karjaluoto, 2016; Verma and Kesswani, 2017). Table 3.1 shows some examples of personalization classifications included in this group.

In second place, a more extended trend to classify personalization is based on how it is reached. This is, to base the classifications on the methods or technologies used to reach personalization (Frias-Martinez et al., 2009; Hongo et al., 2019; Rossi et al., 2001). In table 3.1, some examples personalization classifications of this group are presented.

Table 3.1: Examples of personalization classifications by types, forms, mode and classes

Author(s)	**Categorized by**	**Categories**	**Based on**
Fan and Poole (2006)	*ideal types*	architectural; relational; instrumental; commercial	Philosophical motivation behind personalization
Sakkopoulos et al. (2010)	*categories*	rule-based; content-based	Data used to personalize (Specific for web personalization)

...

Author(s)	**Categorized by**	**Categories**	**Based on**
Salonen and Karjaluoto (2016)	*forms*	extrapolated; interpolated	Data used to estimate the outcome (Specific for web personalization)
Pierrakos et al. (2003); Nasraoui (2005); Verma and Kesswani (2017)	*modes or classes*	memorization; guidance; customization; task performance support	The functionality of personalization

Table 3.2: Examples of personalization classifications based on how to reach it

Author(s)	**Categorized by**	**Categories**
Gilmore and Pine 2nd. (1997)	*methods or approaches*	adaptive; cosmetic; transparent; collaborative
Adomavicius and Tuzhilin (2005a)	*methods*	pull; push; passive
Fan and Poole (2006)	*strategies*	individualization; utilization; mediation; segmentation
Tam et al. (2006)	*approaches*	user-driven; transaction-driven; context-driven
Hawkins et al. (2008)	*tactics*	identification; raising expectations; contextualization
Frias-Martinez et al. (2009)	*techniques*	adaptive; adaptability
Sakkopoulos et al. (2010)	*methods*	implicit;explicit;hybrid
Li and Kalyanaraman (2013)	*approaches*	targeting; tailoring
Thirumalai and Sinha (2013)	*strategies*	transaction; decision

Finally, there is a third group of authors that see more than one only possible classification of personalization strategies or types (Tuzhilin, 2009). These authors perceive personalization as a set of dimensions and, some of them, design frameworks that include the possible dimensions to classify personalization or even personalization strategies (Bleier and Eisenbeiss, 2015b; Fan and Poole, 2006; Hawkins et al., 2008; Kwon and Kim, 2012; Sunikka and Bragge, 2012). It is important to mention that, within the literature, there are different meanings associated with the concept *personalization framework*. First, there are authors that present personalization frameworks as flowcharts or interaction/relationship diagrams of the personalization process (Al-Khanjari, 2013; Instone, 2000). Second, there are authors that present diagrams including different aspects to be considered within the personalization topic, these are also known as personalization concept frameworks (Miceli et al., 2007; Vesanen, 2007). Finally, there are authors that present frameworks including the different dimensions of personalization (Wu et al., 2003; Sunikka and Bragge, 2008). The later being ones used to classify the different personalization strategies.

The personalization frameworks presented in the previous research literature, have been evolving over time (Kwon and Kim, 2012). Two decades ago, Instone (2000) presented the first personalization strategies generated by combining different personalization dimensions. In this first personalization framework there were three dimensions. The first one, *what is profiled?*, was referring to the object of profiling (the user or the content). The second one, *profile setting*, considered the degree of automation of the profile setting process. To the best of our knowledge, none of these two dimensions have been used in any of the following personalization frameworks, however, the second one has been used as an independent criteria to classify personalization types (Tuzhilin, 2009). Conversely, the third dimension of this first framework, *user involvement*, had greater acceptance in the subsequent literature and some authors even considered it essential to understand the meaning of the personalization concept (Arora et al., 2008; Kwon and Kim, 2012). Within the literature, this dimension has been given both different names (e.g. *who does personalization?* (Sunikka and Bragge, 2008; Wu et al., 2003)) and different options (e.g. explicit/implicit (Fan and Poole, 2006) or system/customer-driven (Arora et al., 2008; Kwon and Kim, 2012; Sunikka and Bragge, 2008)), but it has nevertheless been consistently used in every personalization framework (e.g. Fan and Poole (2006); Kwon and Kim (2012)). In the literature, some other dimensions have been widely adopted after their first appearance in a framework. For example *what is personalized?* that was introduced in Wu et al. (2003) or *target of personalization* that was presented in Fan and Poole (2006).

Moreover, despite being more or less complex (i.e. with more or less number of dimensions, options per dimension and allowing or not all the possible dimensions' options), all the frameworks presented in the literature follow the same logic (Sunikka and Bragge, 2012; Kwon et al., 2010). The logic is as follows: Personalization is a complex concept that can not be described by simple classifications because there are different dimensions to be considered, each of them with its own set of possible options (Kwon and Kim, 2012). With it, the combination of the options of each dimension is what gives the personalization type or strategy. For example, the simplest personalization framework is a 2x2 (i.e. formed by two dimensions with two options each) as the one presented in Wu et al. (2003). With this framework there are only 4 possible personalization types or strategies, which is the possible number of combinations of dimensions' options (assuming that all combinations are allowed). Figure 3.1 shows the personalization strategies presented in Wu et al. (2003) by using their proposed framework.

However, even adopting the same logic and sometimes the same dimensions, the different frameworks introduced in the literature presented contradiction or incoherence about not only the dimensions but also their options and meanings (Kwon and Kim, 2012).

Figure 3.2 shows the evolution of personalization frameworks and their dimensions over time. Vertically, the dimensions of each personalization framework are included.

3.3 The proposed personalization framework

After reviewing the literature on personalization with a focus on its meaning and its possible classifications or strategies, we agree with some previous authors in that personalization is a broad topic that can not be understood or broken down with a simple classification (Kwon and Kim, 2012). Moreover, simple classifications tend to have a specific criteria depending on the particular

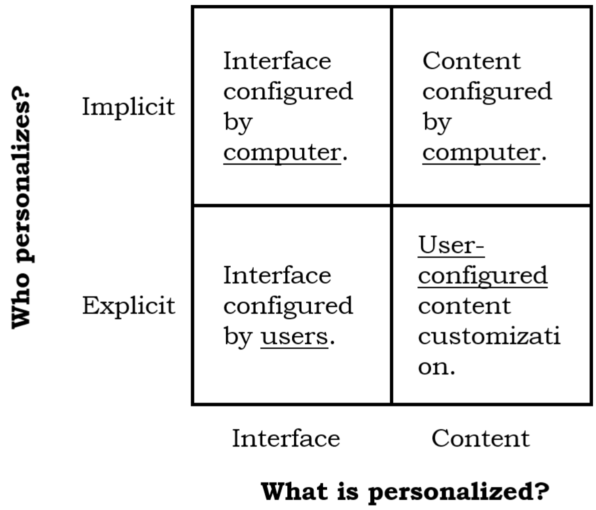

FIGURE 3.1. Example of the use of a personalization framework (Wu et al., 2003)

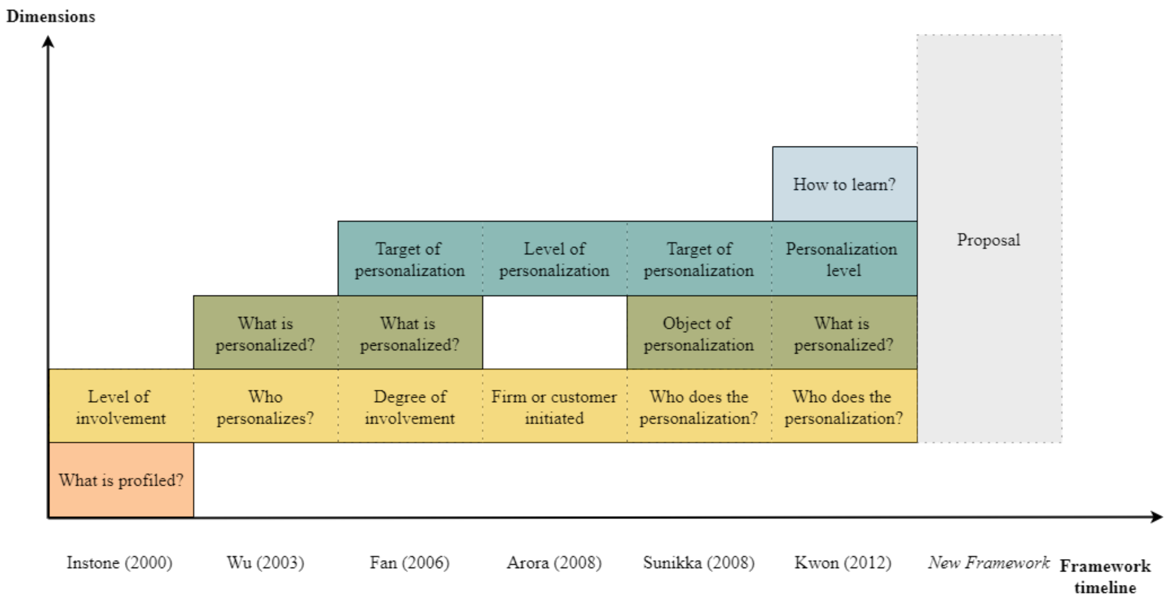

FIGURE 3.2. Evolution and use of personalization frameworks' dimensions

purpose or interests towards personalization, which makes them topic or field-dependent (e.g. Salonen and Karjaluoto (2016); Verma and Kesswani (2017)).

Conversely, personalization frameworks are used in the literature as applicable across domain. For example the framework presented in Wu et al. (2003) is meant for a broader topic spectrum of the personalization field, whereas the framework presented in (Fan and Poole, 2006) is designed specifically for information systems, however, both frameworks share some dimensions. Consequently, personalization frameworks can be considered as more general ways of understanding personalization and, therefore, more appropriate to understand what personalization is (Fan and Poole, 2006).

With that objective, we have developed an inclusive personalization framework which embraces not only previous personalization frameworks but also independent personalization classifications (or their criterion). The result is a comprehensive set of dimensions which cover the foundations to understand and classify personalization and its possible strategies. The proposal framework consists of seven dimensions including different aspects of personalization. All together, the seven dimensions cover the purpose of personalization, the provider-user relationship and the information needed for personalization.

3.3.1 First dimension: The object

The first part of this framework is focused on which is the objective or purpose of the personalization. It is not uncommon to see personalization definitions explicitly indicating what to personalize

Within the literature, previous authors have implicitly included references to the object in their personalization definitions (e.g. 'Personalization is defined here as a process that changes the functionality, interface, information content, or distinctiveness of a system to increase its personal relevance to an individual.' (Blom, 2000)) (Bleier et al., 2017; Li, 2016; Mothersbaugh et al., 2012; Mulvenna et al., 2000; Murthi and Sarkar, 2003). From a general point of view, an object of personalization can be any part of the marketing mix (product, promotion, placement, price and communication) also known as offering (Riecken, 2000; Sunikka and Bragge, 2012; Tuzhilin, 2009). Accordingly, a dimension indicating what is the object of personalization has been included in almost all the previous personalization frameworks (Sunikka and Bragge, 2008; Wu et al., 2003).

Therefore, the first dimensions of this proposed framework is the *Object of personalization*. In this dimension the options are the product/service (either the core product/service or additional attributions of the product/service) (Mourtzis and Doukas, 2012; Sunikka and Bragge, 2008), the website or mobile application (either the content or interface layout) (Kardaras et al., 2013; Wu et al., 2003), the communication between user and organization (either channel or communication attributions) (Fan and Poole, 2006) and the price (Arora et al., 2008; Choudhary et al., 2005).

Consistently with previous authors (e.g. Benlian (2015); Rossi et al. (2001)), for this proposed framework, each option of the Object dimension is considered as individual. This is, even if an organization can perform personalization actions including more than one object, we consider each of these personalization actions as different personalization strategies (i.e. need to be planned, designed and analyzed individually).

A summary of the personalization object dimension and its options can be found in Table 3.3.

Table 3.3: Summary of the object dimension of personalization

Dimension	Description	Options	
Object	The object of personalization defines the part of the provider's marketing mix that is changed or adapted.	Product/Service	Core
			Additional attributions
		Website/App	Content
			Interface layout
		Communication	Channel
			Attributions
		Price	

3.3.2 Second dimension: The subject

The second dimension of this framework also focuses on which is the objective or purpose of the personalization. In this case, after considering the object of personalization, the next step is to determine who does it, this is, the subject of personalization. This dimension is related to the level of involvement of the stakeholders (i.e. the user and the provider) (Kumar and Desai, 2016). The subject of personalization has not only been used in all the previous frameworks (Instone, 2000; Wu et al., 2003), but also, it has been the most used dimension in the literature (Bleier et al., 2017; Cranor, 2003; Karat et al., 2003; Wind and Rangaswamy, 2001). The selection of the subject of personalization has major implications both on the implementation requirements and on the effects of personalization as it has been proven to affect users' satisfaction, loyalty and privacy concern (Kwon et al., 2010; Treiblmaier et al., 2004). For example, the user being the subject of personalization means that they are keeping high degree of control over what is personalized although not every user is willing to invest the necessary effort (Bunt et al., 2009).

This dimension has generated some controversy within the field, both for its meaning and for the names of its options (Kwon and Kim, 2012). On the one hand, for some authors, the subject of personalization is the one who explicitly adapts the object of personalization (e.g. changing the background color of the website can be done directly by the system or can be an option that the user can manually select) (Sunikka and Bragge, 2008). On the other hand, for some authors, the subject of personalization is related with the information acquisition, this is, if users are explicitly asked to provide information about their preferences, they become the subject of personalization (Mothersbaugh et al., 2012).

Finally, it is important to note that some authors do not consider user-driven personalization as a valid form of personalization, thus, they distinguish personalization (as performed by the system) from customization (as performed by the user) (Arora et al., 2008; Ho et al., 2014). In contrast, some other authors consider user-driven personalization as a valid form of personalization since the provider must still prepare the systems to allow the user to personalize (Salonen and Karjaluoto, 2016).

For this framework, performing the personalization actions is considered different from gathering users information, and both the user and the system are valid as personalization subjects. With it, the second dimension of this framework is the *Subject of personalization*, which is, the one (user or system) that performs personalization actions. The possible options for the subject dimension of personalization are system-driven (i.e. the system/firm/organization performs the personalization actions) and user-driven (i.e. the user performs the personalization actions) (Arora et al., 2008; Oertzen and Odekerken-Schroder, 2019; Orji et al., 2017). The first option, system-driven, is also known as adaptive personalization, whereas the second option, user-driven, has been given various names such as adaptable personalization, co-creation or customization (Lu et al., 2013; Perkowitz and Etzioni, 1998; Sunikka and Bragge, 2012).

In summary, an appropriate definition for system-driven personalization could be the extent to which a provider can adapt some element of the marketing mix according to its user (Cranor, 2003) while user-driven personalization is performed by the user using the features that they have been provided with (Blasco-Arcas et al., 2016).

A summary of the personalization subject dimension and its options can be found in Table 3.4.

Table 3.4: Summary of the subject dimension of personalization

Dimensions	Description	Options
Subject	The subject of personalization defines the level of involvement of both the user and the provider in the process.	System-driven (also known as adaptivity)
		User-driven (also known as adaptability or customization)

3.3.3 Third dimension: The target

After considering both what is personalized and who does it, the third dimension of this framework focuses on to whom it is personalized (Kumar and Desai, 2016). With it, the third dimension of this framework addresses what is known as the level or degree of personalization (Arora et al., 2008; Bleier and Eisenbeiss, 2015b; Riecken, 2000). Personalization can range from being specific for a unique user, to be adapted to a group or segment of N users or to present the same personalization object to all the target users (Hawkins et al., 2008; Li, 2016). This third dimension has attracted the attention of both researchers and practitioners, as it is largely commented both in research literature (e.g. Bleier et al. (2017); Fan and Poole (2006); Sunikka and Bragge (2012)) and companies' online publications (e.g. Annas (2020); Boag (2018)).

The extreme case of personalizing to an individual level, also known as individualization or tailoring (Kaneko et al., 2018a), is, for some authors, the only valid form of personalization (Krishnaraju et al., 2016). Accordingly, it is becoming a trend in the industry (mainly by the name of hyper-personalization) as most companies consider it to be the only really effective way of personalization (Lebo, 2019; Qualifio, 2019). However, some studies have shown that this type of personalization does not always significantly outperform group personalization (Kwon et al., 2010). While individual level personalization may suffer from biases and not enough data, group level personalization suffers from heterogeneity of population inside segments or groups (Tuzhilin, 2009). Finally, the other extreme case, 1-to-all personalization (also known as mass personalization) has not always been included as a personalization option (Hawkins et al., 2008).

The decision of the target of personalization is key for the personalization strategy selection, as it has major implications not only from a technical or an economic point of view, but also affects the user's attitude towards personalization and the personalization effectiveness (Kalyanaraman and Sundar, 2006; Montgomery and Smith, 2009). Although there is not a general agreement (Ha et al., 2010), according to some authors, personalization approaches with different target (e.g. individual-based or group-based personalization approaches) are tolerated differently by users pertaining to distinct cultures (e.i. individualistic vs. collectivist cultures) (Kramer et al., 2007; Li and Kalyanaraman, 2013; Reinecke and Bernstein, 2013). Specifically, users with strong ethnic identities tend to show greater acceptance of 1-to-N personalization approaches (Gevorgyan and Manucharova, 2009; Singh et al., 2008).

Accordingly, the third dimension of this framework is the *Target of personalization*. Which is the degree in which an object can range from no personalization (or mass personalization) to high personalization (or individualization) (Arora et al., 2008; Hawkins et al., 2008). Therefore, the possible options of the target dimension of personalization are 1-to-all (mass personalization), 1-to-N (targeting, segmentation or group personalization) and 1-to-1 (tailoring or individualization) (Arora et al., 2008; Li, 2016).

Finally, within this dimension, it is important to point out that 1-to-1 personalization does not mean that the object of personalization will necessarily be unique for the user. This is, 1-to-1 personalization means to personalize targeting the individual user (e.g. by selecting an specific combination of options), however, the result might coincide with other users' results.

A summary of the personalization target dimension and its options can be found in Table 3.5.

Table 3.5: Summary of the target dimension of personalization

Dimension	Description	Options
Target	The target of personalization defines the degree to which the object is adapted to the individual user.	1-to-all (also known as mass personalization)
		1-to-N (also known as targeting or group-based)
		1-to-1 (also known as tailoring or individual-based)

3.3.4 Fourth dimension: The approach

After considering the first three dimensions of the framework (object, subject and target), the purpose of the personalization strategy is already defined. The next two dimensions focus on the provider-user relationship within personalization. This fourth dimension tackles the benefit that personalization aims to provide to the user, in other words, how personalization approaches the user.

Over the last decades, some authors have been studying persuasion and user attitudes based on information processing and social cognition (Chen et al., 2002; Ho et al., 2014). While some scholars contemplate the existence of various influence principles used in personalization to change the attitudes and behaviors (Kaptein and Parvinen, 2015), others state that personalization can only modify users' attention towards information or information processing (Li and Liu, 2017; Tam et al., 2006). Conversely, a third group of authors see personalization as a useful tool to avoid information overload and user time consumption (Hawalah and Fasli, 2015), to reduce users' effort (Liang et al., 2006) or to increase enjoyment (Piccoli et al., 2017), disregarding the psychological viewpoint. With such a variety of possibilities, numerous authors agree on the importance of deciding the value addition for the user within the design of the personalization strategy (Kalyanaraman and Sundar, 2006; Surprenant and Solomon, 1987; Verma and Kesswani, 2017), and that is the core intention of this dimension.

Although none of the previous personalization frameworks have included a dimension regarding how to approach the user, some personalization classifications are based on it (Nasraoui, 2005; Verma and Kesswani, 2017). For example, in Hawkins et al. (2008) the possible tactics of personalization are identification (which is equivalent to self-reference), raising expectation (which is to inform the users about the personalization actions) or contextualization (which is also equivalent to self-reference but in a more indirect manner).

Accordingly, some personalization definitions include that, for it to have an effect, it has to entail a benefit for the user (Kardaras et al., 2013; Mothersbaugh et al., 2012; Wind and Rangaswamy, 2001). For some authors, this benefit for the user can only be self-reference (references to the user's self identity) (Li and Kalyanaraman, 2013), while for others, personalization will have no effect on the user if the adaptation presented is not relevant (the content is relevant for the user and at the specific time) (Jayanthi and Rathi, 2014; Li and Liu, 2017). In line with these, some other authors study the different benefits that personalization can have for the user (such as to make the personalization object pleasant to use or more efficient) or compare between them (e.g. self-reference vs. content relevance) (Balan U and Mathew, 2020; Das and Ranganath, 2013; Gao et al., 2010; Mothersbaugh et al., 2012).

All in all, the fourth dimension of our framework is the *Approach of personalization*. According to previous authors, the options are self-reference (to refer in some way the user's context and perception of the self, both self-identity and group-identity), content relevance (to provide personalization based on the user's goals at a given time) and sequence (to adapt the sequence of events based on the user's preferences or needs) (Blom, 2000; Krishnaraju et al., 2016; Tam et al., 2006). Apart from these options, this framework also includes a fourth one which is the combination of any of the previous three. This fourth option is included because a personalization strategy might be designed to approach the user in more than one of the three first options (including any combination of two or three options), and this decision might affect both the design of personalization and its potential effect on the user.

Table 3.6 presents a summary of the personalization approach and its options.

Table 3.6: Summary of the approach dimension of personalization

Dimension	**Description**	**Options**
Approach	The personalization approach defines how the personalization subject tries to reach the user.	Self-reference
		Content relevance
		Sequence
		Combination

3.3.5 Fifth dimension: The notification

Continuing with the focus on the provider-user relationship within personalization, the fifth dimension of this proposed framework focuses on the user awareness about personalization actions. However, as far as the personalization provider can not manage what each user knows or is aware of, the only decision that can be made in the design of a personalization strategy is regarding the information given to the user about the presence of personalization activities.

In the literature, some authors consider covert marketing techniques more efficient as they prevent the user from wasting time (Milne et al., 2008). However, transparent marketing techniques are considered to prevent users from feeling vulnerable regarding privacy concerns (Aguirre et al., 2015). Additionally, some authors insist on the perception of personalization as the real driver of personalization effectiveness, meaning that the users need to perceive personalization for it to have any effect (Xiao and Benbasat, 2018). Therefore, it seems necessary to consider this issue within the design of a personalization strategy (Sundar and Marathe, 2010).

Although none of the previous personalization frameworks have included a dimension regarding the user awareness about personalization activity or its notification, it has been an extensively studied topic within the personalization literature due to its importance on the user response (Aguirre et al., 2015; Hawkins et al., 2008; Liljander et al., 2015; Sundar and Marathe, 2010). For example, some authors have examined how the consciousness that users have over the personalization actions and strategy affect how they react to it (Aguirre et al., 2015; Liljander et al., 2015). Moreover, in the case of overt personalization (i.e. the user is informed about the presence of personalization actions), the quantity of information given to the user can vary depending on the provider's determination and, therefore, have different impacts on the user (Cramer et al., 2009). Users can, for example, be informed about the presence of personalization actions, about criteria used to personalize or about the information collected.

Finally, in the last few years, an increasing research interest has been given to the importance of users' trust in the performance of personalized systems (Kimery and McCord, 2002; Peppers and Rogers, 2013). Particularly, some research on this topic studied the effect of using explanations about the personal recommendations given as a trust-inspiring tool (Pu and Chen, 2007; Sharma and Ray, 2016).

Overall, the fifth dimension of this framework is the *Notification of personalization*, that is, the extent to which the provider informs the user about the personalization actions (Sundar and Marathe, 2010). The options for this dimension are overt (providers inform the user about the personalization activities) or covert (the provider does not inform users about personalization).

A summary of the notification dimension and its options is presented in table 3.7.

Table 3.7: Summary of the notification dimension of personalization

Dimension	**Description**	**Options**
Notification	The notification dimension defines if the provider informs the user about the personalization actions.	Overt
		Covert

3.3.6 Sixth dimension: The learning

The first five dimensions of the framework have mainly covered both the personalization purpose and the user-provider relationship, therefore, next two dimensions are related to the information used to personalize. This sixth dimension defines how the information used to personalize is acquired.

In order to personalize, information is needed and the two main methods of acquiring it are directly asking the user about their preferences or indirectly learning about their preferences (e.g. by observation of their behavior) (Kalaignanam et al., 2018; Sharma and Ray, 2016). Additionally, the decision of which of the two methods to use will affect the user experience and their perception regarding personalization (Adomavicius and Tuzhilin, 2005a; Peppers and Rogers, 2013). Accordingly, authors have been studying the effects of selecting one of the two methods. On the one hand, some authors consider that asking too much information and feedback from the users might be intrusive and that it might break the user's experience (Adomavicius and Tuzhilin, 2005a; Murthi and Sarkar, 2003; Mulvenna et al., 2000). Moreover, some concerns have arisen about the reliability of the information directly provided by the user (Murthi and Sarkar, 2003). On the other hand, some authors see proactivity as an important trust driver and even as an enhancer of the perceived connection between the user and the personalized object (Peppers and Rogers, 2013; Sundar and Marathe, 2010). Accordingly, and based on its implication for the personalization strategy design, several authors have used the information acquisition method as basis to classify personalization strategies (Balan and Mathew, 2016; Cranor, 2003; Kalaignanam et al., 2018; Kaptein et al., 2015; Li and Liu, 2017; Murthi and Sarkar, 2003).

As previously introduced, some authors of previous frameworks associate the concept of *learning method or information acquisition* with *subject of personalization* (e.g. Instone (2000); Wu et al. (2003)). For those authors, explicit personalization refers to the subject of personalization whereas implicit personalization refers to the information acquisition method (Wu et al., 2003). This mixed conceptualization generates confusion within the literature (Kwon and Kim, 2012). Therefore, the learning method was not formally included as an independent dimension in a personalization framework until 2012 with the publication of Kwon and Kim (2012).

In accordance, the sixth dimension of this framework is the *Learning of personalization*, which is, the acquisition method used to gather information about the user in order to personalize. The possible options for this dimension are the explicit learning method (which is, acquiring information about the user by directly asking them), the implicit learning method (which is, indirectly inferring the information about the user without asking them) and a combined learning method (which is any combination of the previous two learning methods).

Using a hybrid approach to the learning method (this is, combining to some extent explicit and implicit acquisition) might not only have specific technical requirements but also specific effects or results. These mat or may not be equivalent to use separate explicit and implicit personalization strategies to the same user (Weinmann et al., 2013). For that reason, we consider combined learning methods as a different personalization strategy. A summary of the sixth dimension of this framework and its options is presented in table 3.8.

Table 3.8: Summary of the learning dimension of personalization

Dimension	Description	Options
Learning	The learning method defines how to acquire the information needed to personalize.	Explicit
		Implicit
		Combination

3.3.7 Seventh dimension: The information

Personalization definitions often include references to the need of users' information, however, it is not that common to see explicit references or details about the type of data that is required (e.g. Chellappa and Sin (2005); Kwon and Kim (2012); Montgomery and Smith (2009); Salonen and Karjaluoto (2016)). Therefore, the seventh and last dimension of this framework targets the type of information needed to personalize.

Some previous authors presented different classifications for the information used in personalization, for example, in Bai et al. (2017), authors classified the information as endogenous or exogenous depending on its origin. Another example can be found in Tam et al. (2006), where authors distinguished between transaction and context information based on the nature of this information.

As a personalization framework, this is not the first one to introduce the need to include a dimension regarding the information used. This need was originally introduced in Weinmann et al. (2013) where authors included a dimension called *type of data* with their options for this dimension (user, usage, context or social information) based on the information's relation with the user (Kobsa et al., 2001; Weinmann et al., 2013). However, we consider the information to be classified based on how it can be used to personalize.

In accordance, the seventh dimension of this framework is *the Information of personalization*, and the options for this dimension are individual information (information dependent on each exact user), pre-clustered information (the available options are organized in pre-existent groups) and a combination of both.

The decision on whether to implement personalization based on individual or pre-clustered information might have both technical and performance implications (Murthi and Sarkar, 2003). On the one side, considering technical implications, in order to collect and use individual information, the system needs to be prepared for the input of information not previously identified and tagged (e.g. a personalization including the name or nickname of the user should be able to include almost any combination of characters) whereas, in order to collect and use pre-clustered information, the system needs previously specified options in order to capture or use the user information regarding those specific clusters (e.g user gender or buyer type). On the other side, users might potentially react differently to a personalization system using their individual information (e.g their name is used by a website) than to a pre-clustered information (e.g. their city is automatically filled in a digital form) (Hawkins et al., 2008).

This dimension might seem correlated with the target of personalization (section 3.3.3), with 1-to-1 personalization seeming equivalent to using individual information and 1-to-N seeming equivalent to using pre-clustered information. However, this is a mistaken assumption since pre-clustered information can also be used to implement 1-to-1 personalization. For example, a phone case could be personalized to the individual level (1-to-1 personalization) based only on a combination of pre-clustered information, such as the users' phone model, favorite color theme, case texture, case material, name of a city or favorite animal. This is why the present framework includes two separate dimension for the target of personalization and the information used to personalize.

Table 3.9 shows a summary of the seventh dimension, the information of personalization.

Table 3.9: Summary of the information dimension of personalization

Dimension	Description	Options
Information	This dimension defines the type of information gathered and used to personalize.	Individual
		Pre-clustered
		Combination

3.4 Discussion

Since the beginning of the topic, personalization has attracted the attention of a diversified group of fields and it has been addressed from a variety of viewpoints (Fan and Poole, 2006). Consequently, the concept of personalization is used to cover a wide range of ideas meaning something different to each research field and there is no basis of knowledge for mutual understanding among fields (Blasco-Arcas et al., 2014; Riecken, 2000). Moreover, given that each area of investigation had a different research agenda and assumptions, some key aspects of personalization have been overlooked (Kwon et al., 2010). Additionally, this is not only affecting the research development of the topic but also its implementation in the industry (Tuzhilin, 2009; Sunikka and Bragge, 2012). Therefore, a cross-domain understanding of the personalization concept is needed (Vesanen and Raulas, 2006). With the presented framework we aimed to fill this gap.

The personalization framework introduced in this chapter presents the concept of personalization not as a unique closed term, but as a versatile idea conformed by the variation of seven dimensions. This conceptualization is not only consistent with previous personalization frameworks but also with personalization classifications and definitions from different research fields. For example, in Frias-Martinez et al. (2009) the authors present two possible approaches for website personalization, adaptivity and adaptability. The main distinguishing attribute between these two approaches is who does personalization, that is, the subject of personalization (second dimension of this framework). Therewith, adaptivity and adaptability can be respectively used as synonyms of system-driven and user-driven personalization, regardless of the options selected in the other dimensions.

A more complex example is the classification proposed in Gilmore and Pine 2nd. (1997). In that case, the authors distinguish four personalization approaches: collaborative, adaptive, cosmetic and transparent, where the main differentiating attributes among the four options are a combination up to four of our dimensions. For example, collaborative personalization is defined as "a dialogue with individual customers to help them articulate their needs, to identify the precise offering that fulfills those needs, and to make customized products for them". Considering the seven dimensions of personalization, that definition is consistent with individually (the target of personalization is 1-to-1) asking users about their preferences (the learning of personalization is explicit) to adapt the product (the object of personalization is the product) for them (the subject of personalization is the system). Therefore, explicit system-driven 1-to-1 personalization of products would be the equivalent to collaborative personalization. In a similar way, our framework is consistent with the other three approaches proposed in Gilmore and Pine 2nd. (1997). Table 3.10 presents some examples of how representing the personalization concept in the seven proposed dimensions covers a variety of personalization classifications given in the literature.

Table 3.10: Examples of the personalization framework consistency with other classifications

		Dimensions considered							Synonym expression
		Object	Subject	Target	Approach	Notification	Learning	Information	
Gilmore and Pine 2nd. (1997)	Collaborative	x	x	x			x		Explicit system-driven 1-to-1 personalization of product
	Adaptive	x	x						User-driven personalization of products
	Cosmetic	x							Personalization of the product attributes
	Transparent	x		x		x			Covert 1-to-1 personalization of products or services
Murthi and Sarkar (2003)	Asking						x		Explicit learning personalization
	Tracking						x		Implicit learning personalization
Adomavicius and Tuzhilin (2005a)	Pull		x			x			Overt user-driven personalization
	Push	x	x						System-driven communication personalization
	Passive	x	x		x				System-driven communication personalization based on content relevance
Tam et al. (2006)	User-driven	x	x						User-driven website personalization (layout and content)
	Transaction-driven	x	x				x		Implicit learning system-driven website personalization (layout and content)
	Context-driven	x	x	x			x		Implicit learning 1-to-1 system-driven website personalization (layout and content)
Hawkins et al. (2008)	Identification	x						x	Individual information communication personalization
	Raising expectation	x				x			Overt communication personalization
	Contextualization	x			x				Self-reference communication personalization
Frias-Martinez et al. (2009)	Adaptivity	x	x						User-driven website personalization
	Adaptability	x	x						System-driven website personalization
Li and Kalyanaraman (2013)	Targeting			x					1-to-N personalization
	Tailoring			x					1-to-1 personalization
Krishnaraju et al. (2016)	Self-reference	x			x				Self-reference website personalization
	Content relevance	x			x				Content relevance website personalization
	Navigational content	x			x				Sequence website personalization
Bleier et al. (2017)	Customization		x						User-driven personalization
	Personalization		x	x					System-driven 1-to-1 personalization

Seeing the consistency of the proposed framework with both previous personalization frameworks and classifications, we can use it to answer the research question of this chapter:

RQ: What is personalization?

Answer: Personalization is any process or action that changes or adapts any part of the provider's marketing mix based on certain knowledge to increase the personal relevance to an individual or group of individuals.

According to some of the previous authors (Riemer and Totz, 2003; Salonen and Karjaluoto, 2016; Sunikka and Bragge, 2012; Tam et al., 2006), we consider personalization as a broad concept that can be approached by a wide range of strategies. The given definition of personalization is consistent with each of the dimensions included in the personalization:

- **The object:** The definition explicitly states that personalization includes «any part of the marketing mix». That is, any offering from the provider to the user can be personalized.
- **The subject:** The previous definition does not limit the subject of personalization, therefore implying that it is not restricted to the system (including not only the system as a technical entity but also the provider itself as a person) nor the user, and both are considered valid forms of personalization.
- **The target:** The proposed definition explicitly states that personalization can be targeted to both «an individual or group of individuals».
- **The approach:** As can be seen in the definition, personalization aims to increase the personal relevance. This could include any action that intends to make the personalization object more related to the subject self-identity, more relevant or more convenient.
- **The notification:** The proposed definition does not limit the potential awareness of the user about personalization or even the notification given by the provider, implying that personalization includes the user being (or not) aware of personalization actions, and the system/provider displaying (or not) information about the personalization actions being performed.
- **The learning:** As can be seen in the definition of personalization, it does imply the use of knowledge about the target, however, there is no restriction about how this knowledge is acquired.
- **The information:** Finally, the definition does not limit the type of information needed in order to perform personalization actions.

However, even if the proposed conceptualization for personalization is consistent with previous definitions, classifications and frameworks, there are some dimensions in our framework that may seem conflicting with definitions of personalization existing in the literature. For examples, some authors consider that personalization needs to necessarily meet several conditions, such as to be system-driven (Montgomery and Smith, 2009; Orji et al., 2017; Sundar and Marathe, 2010), to be individualized (1-to-1) (Arora et al., 2008; Bleier and Eisenbeiss, 2015a; Murthi and Sarkar, 2003), to not require users explicit input (Ho et al., 2014) or to always match the users' notion of self (self-reference) (Li and Liu, 2017). Nevertheless, even in the cases where the provider (or system) seems not to have a leading role in personalization, there is still a need for designing a strategy in order to create an environment able to be adapted or personalized. That is the reason why those cases are also included as valid personalization strategies in our proposed framework.

Moreover, as previously commented, the objective of this chapter was not only to purely understand the meaning of the term personalization from a cross-field point of view, but also to understand the meaning of the most used terms related to the topic. According to previous authors, some of the most used terms in relation with personalization are: adaptive/adaptivity, adaptable/adaptability, customization, one-to-one marketing, segmentation, tailoring and targeting (Fan and Poole, 2006; Hawkins et al., 2008; Montgomery and Smith, 2009; Vesanen, 2007).

Adaptive: As previously commented, adaptivity and adaptability are often used terms in the personalization topic mostly adopted to classify different approaches (e.g. Bunt et al. (2009); Frias-Martinez et al. (2009)). A system is considered adaptive when it is able to adapt something without user intervention (Karat et al., 2003). Accordingly, any part of the marketing mix is adaptive when it is personalized with the system being the subject of personalization (Fan and Poole, 2006). Therefore, considering our proposed framework, within the context of personalization, saying that something is adaptive would mean the same as saying that it is system-driven personalized.

Adaptable: In a similar way, adaptable or adaptability are terms used to classify personalization strategies and are related to the subject of personalization (e.g. Bunt et al. (2009); Sundar and Marathe (2010)). Consequently, a system is considered adaptable when it is able to allow the user to change something in the marketing mix (Karat et al., 2003). This is, considering our proposed framework, within the context of personalization, something is adaptable when it is user-driven personalized.

Customization: Customization is the term most compared with personalization (e.g.Bleier et al. (2017); Davis (2018); Orji et al. (2017); Sundar and Marathe (2010); Sunikka and Bragge (2012); Treiblmaier et al. (2004)). According to our framework, customization is any form of user-initiated personalization. This is, the subject of personalization is the user, thus, customization is a synonym for user-driven personalization. Therefore, personalization and customization should not be directly compared, as customization is under the umbrella term personalization (Fan and Poole, 2006; Instone, 2000; Kramer et al., 2000; Kumar and Desai, 2016).

One-to-one marketing: This expression is commonly used to describe any form of personalization where the object is adapted to the individual level (Montgomery and Smith, 2009). Therefore, according to the previously presented concepts, one-to-one marketing is a personalization strategy where the target of personalization is the individual user (1-to-1), thus, being synonym of 1-to-1 personalization.

Segmentation: Within the personalization topic, segmentation is a frequently used term (e.g. Miceli et al. (2007); Sands et al. (2016); Wind and Rangaswamy (2001)). Segmentation can be defined as the degree to which the users are divided into groups that share different features (Hawkins et al., 2008). Segmentation is considered to be a basic strategy to develop personalization because the same criteria used to divide the audience into different groups can be used to personalize the marketing mix to each group (Fan and Poole, 2006; McDonald and Dunbar, 2004a; Simkin, 2005; Webber, 2011).

Tailoring: The term tailoring has been given two main purposes within the personalization topic. On the one hand, the term has been commonly used as part of the personalization definition itself (Simkin, 2005; Sunikka and Bragge, 2012). For example, in Chellappa and Sin (2005) the authors use it inside their definition of personalization as «Personalization refers to the tailoring of products and purchase experience [...]». On the other hand, the term tailoring has also been used as a synonym for individualization, with a specific reference to adaptation to the individual user (Camerini et al., 2011; Hussein et al., 2013). With this second approach, the term tailoring refers to a specific category in a personalization classification that splits personalization strategies based on who is the target of personalization (Hawkins et al., 2008). According to our proposed framework, this second application of the term tailoring can be interchangeably used with any form of 1-to-1 personalization.

Targeting: Similarly, the term targeting has also been adopted in two different ways. On the one hand, the term has been used to refer to the act of identifying a portion of the population as the objective of personalization actions (Mendoza and Marasinghe, 2013; Simkin, 2005). However, on the other hand, the term targeting has been used in classifications to categorize the personalization strategies not focused on the individual user but on groups of users (Hawkins et al., 2008; Noar et al., 2009). Therefore, according to our proposed framework, in the latter application of the term, targeting can be used as a synonym for 1-to-N personalization. Finally, it is important to comment that, for some authors, the difference between tailoring and targeting does not only depend on how small the segments of population are (degree of segmentation), but also on how adapted the object of personalization is (degree of adaptation) (Hawkins et al., 2008). However, according to the proposed framework the only distinction between tailoring (understood as 1-to-1 personalization) and targeting (understood as 1-to-N personalization) is to whom are intended the personalization actions.

As commented during the chapter, the first and main contribution of this framework is to address the personalization concept interpretation considering the viewpoints of different research fields. However, it is important to clarify that this framework and personalization conceptualization do not intend to be established as the standard personalization definitions or approaches. As stated above, the diversity of fields involved in the personalization study and development is a signature feature of the topic, giving it dynamism and a diversity of viewpoints and applications (Fan and Poole, 2006; Leahey and Reikowsky, 2008). Consequently, the variety of terminology and vocabulary used in regards to personalization is but a mere reflection of this reality (Arora et al., 2008; Sunikka and Bragge, 2012). Accordingly, the objective of this personalization framework is not to standardize concepts or terms, but to break-down the personalization concept in different dimensions to ease its understanding. Along with this purpose, the proposed framework has additional contributions to the personalization field.

As a second contribution, this framework outlines an interconnection map of the different personalization terms and definitions used among the different fields. The proposed personalization framework does not aim to be a standardization of terminology, but to assist researchers from different fields and backgrounds to understand each other. For example, the terms explicit and implicit personalization are used differently across the topic literature. In Fan and Poole (2006), within the human computer interaction literature, authors use explicit or implicit personalization to refer to who does the personalization (that is, for them, the subject of personalization can be explicit or implicit). In contrast, in Bo and Benbasat (2007) and in Duwairi and Ammari (2016), within the business and computer systems fields respectively, authors understand those terms as related to the learning method (referring to asking or not the user for the information needed to personalize). Another case can be found in Hawkins et al. (2008), from the health communications perspective. They use explicit or implicit personalization as associated with the users' awareness of personalization actions, this is, if users are informed about the presence of personalization. Moreover, in Kaptein et al. (2015), from a persuasive technologies viewpoint, authors use the terms indicating both reference to the notification and the learning of personalization, with it, explicit personalization implies both the user being asked about their preferences and being notified about personalization actions. As final examples, in Instone (2000) and in Wu et al. (2003), both from the information systems perspective, authors use a mixed approach considering what they call «user involvement» where explicit personalization alludes to the subject of personalization (this is, explicit personalization is used as synonym for user-driven personalization) whereas implicit personalization alludes to the information acquisition (this is, implicit personalization is used to refer to acquiring users' information without asking). The previous example illustrates the difficulty of trying to compare personalization concepts and research advances within fields merely by the terminology. By using the proposed framework, the comparison does not need to be done based on the terms utilized in each field (or author) but based on the dimension of personalization that they are referring to. This contribution to the mutual understanding from the different fields represents a gain in the transversal visibility of personalization and its now field-isolated advances, which may also help easing the cross-field identification of research gaps yet to be solved (Arora et al., 2008; Riecken, 2000).

The third and last contribution of this framework is related to the evaluation of personalization. As previously commented, the inability to measure the effects of personalization is one of its main drawbacks, concerning both researchers and practitioners. Even being categorized as the potential decline of the personalization development and implementation efforts (Gartner, 2019; Vesanen, 2007). According to the literature, one of the most recurrent errors when trying to measure personalization effects is the comparison of personalization as a whole. That is, comparing the results of personalizing against not personalizing without considering any variation in personalization dimensions (Kwon et al., 2010; Vesanen and Raulas, 2006). Considering personalization as a whole and trying to measure it regardless of the specific personalization strategy selected (seen as the combination of specific option selected for each dimension) may result in inconsistent results (e.g. Kalaignanam et al. (2018); Thirumalai and Sinha (2013)). The proposed framework identifies the different dimensions compressing personalization, therefore, easing the measurement of personalization effectiveness when considering the dimensions independently. For example, in order to measure the effect of self-reference versus content relevance personalization (this is the approach of personalization, the fourth dimension of the framework), the six remaining dimensions should be fixed so that they do not interfere in the comparison results (e.g. Mahesh Balan et al. (2019)). In conclusion, in order to measure the results of personalization, each dimension needs to be considered and evaluated separately, and the specific set of dimension options effective for a specific case will not necessarily be valid for other scenarios (Kwon and Kim, 2012; Tuzhilin, 2009), the proposed framework contributes to ease the identification and understanding of the personalization dimensions to be considered.

As a summary, by using the proposed personalization framework we are able to conceptualize personalization by combining seven dimensions. Moreover, using the presented framework, other related terms often used in the topic can also be defined. Additionally, this framework is consistent with previous definitions and classifications used across different fields. Altogether, this framework contributes to easing the general comprehension of the personalization concept, the connection of concepts between fields and the evaluation of personalization effectiveness.

3.5 Conclusions

In order to understand web personalization it is important to clearly conceptualize its parent topic, personalization. As seen in the literature, personalization has been addressed from various research fields and industrial viewpoints. This made it become a dynamic and flourishing topic, with an element of controversy and lack of agreement (Fan and Poole, 2006; Murthi and Sarkar, 2003; Sunikka and Bragge, 2012). This siloed environment, together with the difficulty to understand and implement effective personalization, has created a general concern about the industrial abandonment of personalization (Gartner, 2019; Kaneko et al., 2018a), and the opinion that personalization persistence has only an opportunity if defined clearly, is becoming increasingly supported (Proof., 2020; Riecken, 2000; Vesanen, 2007)

In order to address this gap, the research objective of this study was to understand the meaning of personalization as a concept including definitions for the most used terms within the topic. With this goal, we proposed a personalization framework based on seven dimensions entailing the object, subject, target, approach, notification, learning and information of a personalization strategy. Breaking down personalization as a set of options, respectively selected in each of the seven dimensions allows us to understand a complex concept as is personalization.

Moreover, since the framework has been developed considering terminology and classifications from distinct standpoints (both different research areas and industrial practitioners' viewpoints), it can be used as an interconnection map for the jargon used in different domains. Additionally, this broken-down vision of personalization may ease the evaluation and comparison of strategies.

Chapter 4

Finding persons: audience segmentations

In this chapter we evaluate different segmentation criteria by using real data from the SEAT's website. With it, we study de possibility of using these personalization criteria for to personalize the website.

4.1 Introduction

Unarguably, segmentation is closely related to personalization not only as a practice but also as a term itself (Sunikka and Bragge, 2012). On the one hand, we can find in the literature, almost a general agreement about segmentation being an important (and usually the first) step when trying to implement website personalization (Fan and Poole, 2006; Mobasher et al., 2000; Simkin, 2005; Slaninová et al., 2010). Moreover, on the other hand, as previously seen, the term segmentation itself has been eventually used as a synonym of personalization (mostly referring to one-to-N personalization) (Kwon and Kim, 2012; Simkin, 2005; Sunikka and Bragge, 2012).

Since its first definitions, market segmentation has mainly been seen from two different perspectives (Florez-Lopez and Ramon-Jeronimo, 2009; Smith, 1956; Yeo, 2005). The first one is to see segmentation as a strategy related to distinguishing different groups of customers in order to target marketing efforts, which is synonymous to personalization (Bijmolt et al., 2010; McDonald and Dunbar, 2004a; Miceli et al., 2007; Simkin, 2005; Sinha and Uniyal, 2005). The second one is to see segmentation as a collection of techniques and methods employed for user clustering with the overall objective of understanding the users and their behavior (Bughin, 2011; Vellido et al., 1999; Yeo, 2005; Zhou and Mobasher, 2006).

Anyhow, segmentation has historically been a basic tool for almost any company as it involves viewing a heterogeneous market as a number of smaller homogeneous markets with different preferences and different response to the marketing mix (Florez-Lopez and Ramon-Jeronimo, 2009; Lieberman, 2016; Prashar et al., 2016; Smith, 1956). Accordingly, having the market segmented might not only include knowing the geographical or cultural similarities between users, but also understanding their shared needs, desires and capabilities (such as ability to pay or ability to communicate through online channels) (Hassan and Craft, 2003). Therefore, even if there are some website personalization strategies where the use of segmentation might not be evident (such as in one-to-one personalization or user-driven personalization), the user knowledge of a particular website given by user segmentation is a core part of the foundations needed in order to start any personalization initiative in the website (Jiang and Tuzhilin, 2009; Miceli et al., 2007; Simkin, 2005; Slaninová et al., 2010; Yuksel and Yüksel, 2002).

Unfortunately, one of the main advantages and also drawbacks of user segmentation relies on the fact that it is completely context dependent (Florez-Lopez and Ramon-Jeronimo, 2009; McDonald and Dunbar, 2004a; Yeo, 2005). This dependence on the context does not only includes considering the type of users to be segmented, but also the objective of the segmentation (e.g. loyalty actions, advertisement campaigns, etc.), the type of organization (e.g. retailing, business-to-business, etc.), the relationship between the organization and the user (e.g. recurrent transaction, one time interactions, etc.), the data available (e.g. personal data, general navigation data, etc.) and the segmentation technique to be used (e.g. nearest neighbor, support vector machine, etc.), among others (Sinha and Uniyal, 2005; Webber, 2011). Not considering the context of a segmentation technique or criteria often leads to meaningless or valueless results resulting in losses in time, efforts and business opportunity (Bijmolt et al., 2010; Webber, 2011).

Moreover, previous research has proven that the navigational behavior of the users varies depending on the type of goods or services they are looking for (Huang et al., 2009; Klein, 1998). Therefore, the fact that the main product of an automotive brand is a major durable product will have an impact on the overall relationship that a user has with the organization and specifically, the use of the organization's website (Kulkarni et al., 2012; Taylor-West et al., 2020; Rutz and Bucklin, 2012; Yan et al., 2018). Both the fact that cars are not recurrent purchases and that vehicles are often seen as complex products have an effect on the website visits, affecting the amount and type of data that automotive organizations will be able to gather about their website users (Taylor-West et al., 2020; Yan et al., 2018). Consequently, the amount of users together with the information that the organization can gather from a unique user are usually not sufficient to personalize or even to segment (Lessard, 2019; Mattos et al., 2020).

Accordingly, given the context dependency of segmentation, the importance of website user segmentation to personalize and the particularities of websites in the automotive sector, the objective of this study is to understand how to segment in order to be able to personalize. With it, the goal is not to study segmentation techniques but to depict segmentation criteria informative enough to understand the website users' needs. With it, the research question of this study is:

RQ: Which users' segmentation criteria can we use that are informative enough in the implementation of website personalization?

With it, the aim is to test if common segmentation criteria can be blindly adopted regardless of the context of the organization by directly adapting it to the specific available user data. In accordance with this objective, in this chapter, we present commonly recommended website segmentation criteria and test their applicability in the specific case of the SEAT's website.

4.2 Literature Review

Segmentation is based on observing the market in order to distinguish several groups where only one was recognized before (Smith, 1956). Subsequently, marketing segmentation means knowing your users or customers and understanding their preferences (Hassan and Craft, 2003; Yeo, 2005). With it, to be able to comprehend what customers want, build stronger relationships with them or target products (or services) to specific market segments (Miceli et al., 2007; Simkin, 2005; Yeo, 2005). Consequently, website user segmentation is a widely used approach in website environments for characterizing user behaviors, navigation and interests (Bijmolt et al., 2010; Zhou and Mobasher, 2006). However, despite the extensive literature on the topic and the overall agreement on the user segmentation value, there is no consensus about the optimal segmentation methodology (Florez-Lopez and Ramon-Jeronimo, 2009). The importance of considering contextual factors while implementing user segmentation, the need for the segments be adaptable to the dynamism of the user (i.e. adapted over time) and the user preferences or the use of machine learning models to build user segments are only some examples of the variety of discussions that can be found in academia regarding website user segmentation (Florez-Lopez and Ramon-Jeronimo, 2009; Hosseini and Shabani, 2015; Yeo, 2005).

On the one hand, one of the most used and recommended segmentation criteria based on their simplicity is considering the context of the user (Florez-Lopez and Ramon-Jeronimo, 2009; Webber, 2011). This criteria is considered easy to implement although it is less informative compared to other criteria such as purchase behaviors (Peker et al., 2017). In this case, with context, authors include a wide variety of variables, for example demographics, geographical data, psychographic (e.g. personality or attitude), temporal indicators (e.g. time of the day or day of the week), culture or economical factors (Beheshtian-Ardakani et al., 2018; Chen et al., 2012; Hosseini and Shabani, 2015; Juarez et al., 2004; Kohavi and Parekh, 2004; Zhou et al., 2021). On the website, without explicitly asking the user, it is not always possible to identify some of the recommended segmentation criteria, for example, psychographic criteria, lifestyle or attitudes are not easy to obtain as they are not directly observable (Florez-Lopez and Ramon-Jeronimo, 2009). However, some other website-specific variables can be used, for example website events (such as pageviews or visits), device type or time spent on the website (Slaninová et al., 2010).

On the other hand, one of the earliest segmentation criteria, not based on the user context, and currently one of the most well known and widely used methods used for user segmentation (and also for user analysis) is the RFM analysis (Kohavi and Parekh, 2004; Peker et al., 2017).

This segmentation methodology is based on creating groups of customers based on combinations of three variables from the users' previous purchase: Recency, Frequency and Monetary (Gupta et al., 2006; Jiang and Tuzhilin, 2009). Specifically, this method is based on evaluating each user at a given time by user by recency of the last purchase (R) , frequency of past purchases (F) and monetary value of the purchases (M). Therefore, RFM model is based on three premises valid across multiple industries. First, the recency variable is based on the premise that customers who purchased recently (compared to someone who has not purchased recently) are more likely to respond to marketing actions and purchase again. Second, the frequency variable is based on the assumption that customers who continually purchase are more likely to buy than infrequent buyers. Finally, the monetary value is based on the premise that customers used to spend more money, respond better than lower spenders (Kohavi and Parekh, 2004). The usual method of the RFM model consists in, first, preparing data based on each variable and then dividing them into 5 subsets. For each variable, the data is ordered according to each premise, with the top subset getting a maximum score of 5 and the last subset getting a score of 1 (e.g. for the recency score, the most recent buyers would be scored 5). In the simplest approach each customer is given 3 scores based on each of the variables, giving 125 cells or segments (i.e.$5x5x5$) (Kohavi and Parekh, 2004; Zhou et al., 2021). Another commonly used approach is adding the three scores given to each customer and dividing the total customer database in 5 segments based on their score (Gupta et al., 2006; Hosseini and Shabani, 2015). These three general purchase history variables are easily understood, relatively available in organizations' databases including purchase history and have been extensively reported to predict future purchases (Juarez et al., 2004; Kohavi and Parekh, 2004). Consequently, given their simple understanding and applicability, RFM models have been used in market segmentation for decades (Bauer, 1988; Kohavi and Parekh, 2004; Magliozzi and Berger, 1993). However, the model has some limitations, for example, RFM model does not perform well for prospect users or first time visitors, as it depends on a prior purchase history (Juarez et al., 2004). Therefore, as a consequence of these limitations, different adaptations have been presented including extra parameters depending on the industry or the objective of the segmentation (Hosseini and Shabani, 2015; Juarez et al., 2004). Some examples of this adaptations include adding loyalty, time, churn probability, group or weights and resulting in models such as LRFM, RFMTC, WRFM or GRFM (Hosseini and Shabani, 2015; Peker et al., 2017; Zhou et al., 2021). Moreover, despite the commented limitations, this model (or any of its adaptations) is based on the evaluation of each independent user, which has been seen as an opportunity to use it for personalization (Arora et al., 2008; Hutchison and Mitchell, 2007; Jiang and Tuzhilin, 2009).

Additionally, regarding website personalization, there is no discussion about the importance of segmentation to personalize (Arora et al., 2008; Fan and Poole, 2006; Mobasher et al., 2000; Simkin, 2005; Slaninová et al., 2010; Sunikka and Bragge, 2012). However the criteria used to segment the website audience have an impact on the effectiveness of personalization (McDonald and Dunbar, 2004b; Miceli et al., 2007; Slaninová et al., 2010). Lately, some research attention has been given to the differences on the user behavior depending on the time spent on the website, the number of interactions with the organization of knowledge acquired about the product (Churchill, 2013; Ho et al., 2011). According to those authors, the motivations and attitudes of the user evolve not only because of the natural temporal dynamics (i.e. normal evolution of a person when time passes) but also because of the evolution of user-organization relationship (Salonen and Karjaluoto, 2019). This evolution is tracked by using a 'customer journey' (Santana et al., 2019). The customer journey (also known as customer journey map) is a tool developed in the customer relationship management field in order to analyze and understand the user experience in relation to the organization from the user point of view (Mangiaracina et al., 2009). In other words, the customer journey is a linear, time-based representation of the main stages that a user goes through in interacting with an organization (Maechler and Neher, 2016). This customer is tracked by organization by means of the interactions with the user (Pointillist, 2019). In summary, the user preferences evolve during the time of the user-organization relationship and this evolution can be tracked based on the customer journey (Thirumalai and Sinha, 2011). Accordingly, some authors advocate for the use of the customer journey (or the stage of the user in the customer journey) to segment the website audience and also to personalize (Mangiaracina et al., 2009; Santana et al., 2019; Thirumalai and Sinha, 2011).

4.3 Methodology

In order to answer the research question, and given the context dependency of segmentation, in this study, we are going to present an applied case example. The studied company, SEAT, S.A. wants to understand if they can implement personalization in their site with the user navigation data they are currently tracking from their website. Specifically, their idea of this personalization is: to be system-driven (i.e. not managed by the user), targeted one-to-N (i.e. not individual but based in groups of users), covert (i.e. not informing the user), implicit learning (i.e. not asking the user about her preferences) and with a sequential approach (i.e. adapting the sequence of events based on the users preferences). In other words, the objective of the company is to understand if, with the data currently available, they would be able to generate user segments usable to forecast the user preferred website section at a given time of her navigation.

Given that the user's preferred website section is dynamic preference (i.e. the desired section is changing during the navigation of the visit), per page data is used. This is, the complete independent information is collected at each website page viewed by the user. For example, if a user accesses the website at a given time, and navigates through 4 different pages of the website (e.g. home page, car model page, car configurator page and home page), the data gathered contains four independent data points. Table 4.1 shows an illustrative example of the different data points.

Table 4.1: Illustrative example of the different data points used to evaluate segmentation

User ID	Visit number	Page number	Page name	Time spent (sec)
1	1	1	Home	15
1	1	2	Car model	30
1	1	3	Car configurator	30
1	1	4	Home	10

Subsequently, with this purposed of identifying different information currently tracked in the company and test if it can be used to forecast the user section, we evaluate different segmentation criteria divided in three blocks.

Based on the literature reviewed, the segmentation criteria used to personalize should be based on contextual variables regarding the user (Webber, 2011). Subsequently, the first block consists of a list of segmentation criteria based on context variables commonly recommended in the literature (Longley et al., 2006; Prashar et al., 2016). The segmentation criteria evaluated in this block are:

- Geographical region
- Time of day
- Day of the week
- Weekdays vs weekends
- Website entry channel

Similarly, the second block is also based on the literature. In this case, the segmentation criteria is based on the assumption that users have different interests depending on their stage in relationship with the brand (Hamilton et al., 2019; Santana et al., 2019). In other words, in the SEAT's case, this is assuming that the users section of interest will vary along with her customer journey. As previously described, the customer journey is a hypothetical process postulated in order to understand the different stages in the relationship of a customer (or user) and an organization (Maechler and Neher, 2016). This customer journey is tracked by organizations throughout the different interactions with the user (Pointillist, 2019). When tracking the customer journey through website interactions, commonly used variables are; event (such as website visits or page views) and time spent on the website (Slaninová et al., 2010). Consequently, the segmentation criteria evaluated in this block are:

- Current Visit number
- Total time spent on the website

- Page views

Finally, the third block consists of a single segmentation criterion developed based on the RFM and customer journey literature. The name given to this criterion is the Customer Journey Moment, its calculation is further detailed later within this section.

In order to measure the strength of association of each segmentation criteria with the target variable (i.e. website section), a statistical test is used. In this case, Pearson's chi-squared statistic is discarded based on its sensitivity to sample size and to not independent and identically distributed observations (OkekeCharles, 2019). Therefore, the commonly used Cramer's V is used. This statistic is based on Pearson's chi-squared statistic. It varies from 0 to 1, with a 1 indicating a perfect association (Cramer, 1946). Moreover, in order to evaluate if the data currently available is informative enough to personalize, the Goodman and Kruskal's *lambda* statistic is used. This statistic is used to estimate the strength of the association between two categorical variables. It also varies from 0 to 1, being a 1 the indication of perfect association (Goodman and Kruskal, 1972). The main reason why this statistic was selected over more commonly used measures of association for nominal variables (such as *phi*) is because Goodman and Kruskal's *lambda* is formulated so that one of the variables (independent variable) is used to predict the other one (dependent variable) (Goodman and Kruskal, 1954; Mangiafico, 2016; Pearson, 2020). Therefore, by using this statistic, we can measure whether each segment is informative of the objective variable (i.e. website section). The decision to keep both statistics instead of limiting the calculations to Goodman and Kruskal's *lambda* is due to the extreme sensitivity of this statistic to highly skewed distributions (Stavig, 1979).

4.3.1 Customer Journey Moment calculation

The customer journey moment (hereinafter referred to as CJM) is a variable developed in order to be used as a segmentation criterion. Considering the proven effect of including the user purchase history in the segmentation criteria (Kohavi and Parekh, 2004), an adaptation of the RFM premises has been used in the calculation of the CJM. Moreover, the CJM is also based on the need to include changes over time in the user-organization relationship Thirumalai and Sinha (2011).

The CJM is calculated in two phases. First, the CJM is based on an adapted version of the RFM model where the terms are multiplied in order to obtain a unique RFM value (i.e. $RxFxM$). As previously commented, the RFM model is completely based on the customer purchase history (Juarez et al., 2004) and, at the time of this study, the SEAT's website does not include purchase options, therefore, no purchase history is collected. In spite of that, each of the main premises used in the formulation of the RFM model have been adapted considering a website visit equivalent, in terms of RFM calculation, to a purchase. With it, the value of the purchase is considered equivalent to the pageviews visited. Consequently, we translate 'previous purchase' to 'previous visit'. Thereby, adapted versions of each of the RFM terms are calculated as follows:

Recency

The Recency term is based on the premise that customers who purchased recently are more likely to purchase again compared to customers with no recent purchases (Kohavi and Parekh, 2004). Adapted to the SEAT's website scenario, this translates as: visitors who visited the site recently, are more likely to visit again. With it, the recency value depends on the time since the previous visit ($Time_{pv}$) and is calculated as $1/Time_{pv}(days)$. However, there are two cases that can not be calculated with this formula. Those are, first the case when the previous visit has occurred on the same day, in this case, given the aforementioned recency premise, a recent visit is assumed to be positive. Therefore, in the cases where the previous visit has occurred on the same day the R is assigned a value of 2 (i.e. affecting RFM calculation positively). Second, the case when there is no previous visit (i.e. the case of new visitors) in this case, there is no previous information about the user, therefore, in order for the to R term not to affect the overall RFM calculation, the R is assigned 1 (i.e. $1xFxM$). With it, the R term is calculated as follows:

$$R \begin{cases} \nexists PrevVisit \rightarrow R = 1 \\ \exists PrevVisit \begin{cases} Time_{pv}(days) = 0 \rightarrow R = 2 \\ Time_{pv}(days) > 0 \rightarrow R = \frac{1}{Time_{pv}(days)} \end{cases} \end{cases}$$

Frequency

The Frequency term is based on the premise that customers with more frequent purchases are more likely to purchase again compared to infrequent purchasers (Kohavi and Parekh, 2004). Adapted to the SEAT's website scenario, this translates as: visitors who regularly visit the site, are more likely to visit again. Consequently, the frequency value depends on the total number of visits previous to the calculation and the total time since the first visit to the current visit. With it, the frequency value is calculated as the total number of visits divided by 1 plus the differences between the current date and the date of the first visit (in days) ($Vt_{num}/(1+Date_{dif})$). By adding 1 unit in the denominator, the frequency term equals 1 for new visitors, therefore, not affecting the later RFM term calculation (i.e. $Rx1xM$). With it, the F term is calculated as follows:

$$F \begin{cases} \nexists PrevVisit \rightarrow F = 1 \\ \exists PrevVisit \rightarrow F = \frac{Vt_{num}}{1+(Date_{now}-Date_{first})} \end{cases}$$

Monetary

The Monetary term is based on the premise that customers that spend mode money are more likely to purchase again than lower spenders (Kohavi and Parekh, 2004). Adapted to the SEAT's website scenario, this translates as: visitors who have seen more pages on the website are more likely to revisit compared to visitors that have navigated less pages. Consequently, the monetary term directly depends on the page view number (PV). Therefore, for any given pageivew (p) the term M is calculated as the number of this page view PV_p. With it, the M term is calculated as follows:

$$M_p = PV_p$$

Once the three terms are calculated the global RFM value is calculated as $RxFxM$.

As aforementioned, the calculation of the CJM is made in two phases, the first being the above described calculation of the RFM term. The second phase, consist in calculating the Customer Journey Moment term. The CJM is calculated for each individual pageview. Accordingly, the CJM is calculated for a given pageview as the CJM_p of the previous page CJM_{p-1} plus the time spent on the page t times the RFM_p. With it, the CJM term is calculated as follows:

$$CJM_p = CJM_{p-1} + t \times RFM_p$$

The results obtained in the calculation of the CJM are described in the following section (subsection 4.3.2) along with the other variables used to obtain the tested segmentation criteria.

4.3.2 Data description

With the purpose to evaluate if the data currently available is informative enough, we are going to use a dataset including information from the company's Spanish website, ranging from May 1st to December 31st, 2019. In order to understand the navigation of a website user, and considering that users navigate differently depending on the device of their visit (i.e. desktop, mobile or tablet) (Huang and Zhou, 2018; Zhang and Yang, 2017). Only the information of the website navigation in the 'Desktop version' (i.e. the mobile and the tablet versions of the webiste have not been included).

The used dataset contains information of of 701,865 different users in 1,092,916 different website visits, containing information of 7,524,291 website page views. Figure 4.1 shows the distribution of the number of visits per unique user (left) and the distribution of the number of pageviews per visit (right). As shown by the figure, almost two thirds (74.6%) of the total number of users visit the website only once during the studied period. Moreover, approximately 50% of the visits have fewer than 6 pageviews. The data described has already been cleaned and prepared, therefore does not contain missing values, duplicates or invalid values. The original dataset before the cleaning process contained more than 15 millions of pageviews, therefore, more than 50% has been discarded during the cleaning process due to the quality of the data received. However, outliers with valid information have not been removed. For example, a visit number equal to -1 would have been removed, but a user with a visit number equal to 700 would not have been removed. However, some users have been removed from the dataset based on one of the following three criteria. First, visits from computers inside the SEAT, S.A. network or its collaborating marketing companies are excluded from the dataset. Second, users with only one website visit including a single page view with total time lower than 15 seconds have been removed from the dataset as no information can be extracted from their navigation.Finally, as the complete vision of the user is needed for the calculation of the CJM, all the users whose first visit in the dataset did not correspond with visit number 1 (i.e. with visits prior to May 1st 2019) have also been excluded from the dataset.

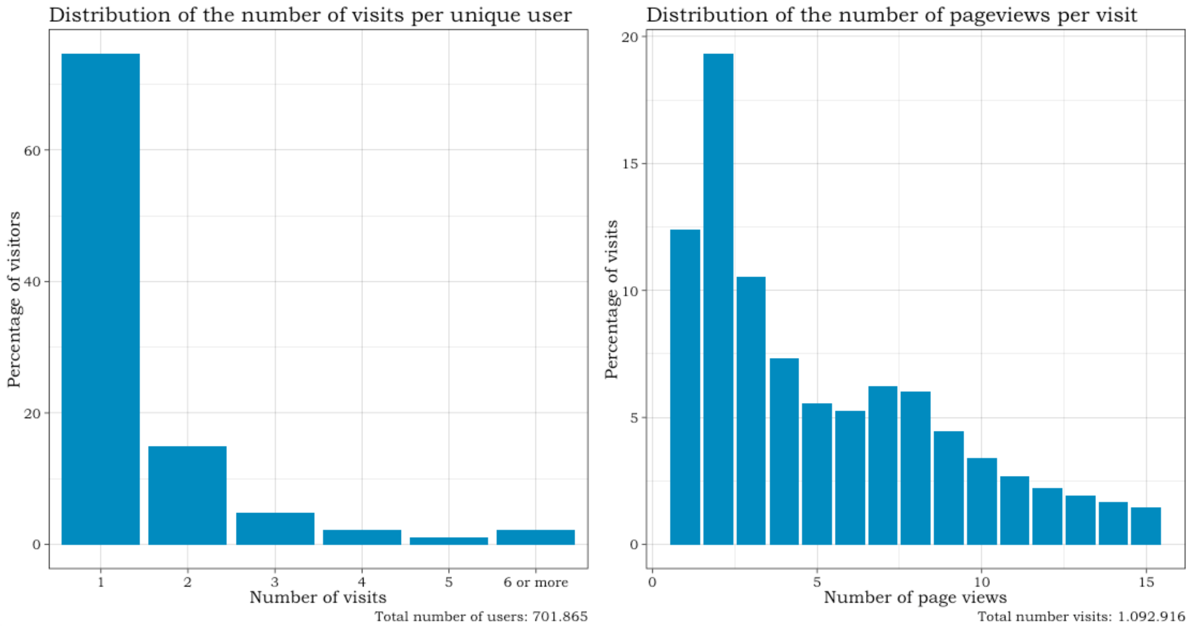

FIGURE 4.1. Distribution of the number of visits per unique user (left) and the distribution of the number of pageviews per visit (right)

Objective variable: Website Section

As previously commented, the objective of the segmentation criteria evaluated is to predict the users' website section of interest. All the pages included in the used dataset have been classified in 13 main website sections (other sections with less than 0.1% representation in the dataset have been reassigned to a 14th section names 'other section'). Each of the 13 website section are briefly described below (the described sections are alphabetically ordered by name):

- After-sales Page: This section includes all the website pages with information related with after-sales services, car's warranty, vehicle's manuals, official workshop's information, accessories and merchandising.
- Brand Page: This section includes all the website pages related to the brand. This is, general information about SEAT, history of the organization, news and events.
- Canarias Page: This section includes all the pages related to the information regarding SEAT in Canary Islands.

- Car Configurator: This is a specific section of the website dedicated to car customization. In this section, the user is interactively guided through the car-building process and allowed to select different options for the car and its optional accessories. In real time, the user can see a visual presentation of the generated results. At the end of the configuration process the user is given information of the specific car generated including details such as price or consumption.
- Car Model Page: The SEAT website has a section dedicated to detailed information of each of the vehicles included in their product range.
- Contact Page: This section includes the contact page of the website. This page contains an online form where the user can leave her personal information (i.e. name, email, region, phone number, etc.) in order to be contacted.
- Dealer Search Page: This section includes a search engine where the user can look for the most convenient dealer of the official dealer network depending on her needs (e.g. dealer vs. workshop).
- Finance Page: This section includes all the pages dedicated to information about financial services, car rental options and vehicle assurance options.
- Fleet Page: This section, includes all the website pages dedicated to 'SEAT for Business', which is a section dedicated to industrial customers, including to fleet options information, special offers for companies, etc.
- Form Page: This section contains all the contact forms included in the website (other than the main contact form page). Those forms are mainly specific temporal campaigns or pop-ups that appear depending on the users' actions during the navigation.
- Home Page: This is the main page of the website. Includes general information about the brand, the morels of the product range and contains links to all the other sections.
- Legal Note Page: This section includes the legal-note page of the website along with the pages including cookie management information.
- Offers Page: This is a section dedicated to special (temporal) offers of currently available vehicles.

Figure 4.2 shows the representation (in percentage of pageviews) of each commented section. As seen in the figure, the distribution of pageviews is highly unbalanced, with more than 50% of the pageviews corresponding to the car configurator section. This behavior can be explained by the fact that the car configurator is the most interactive section of the website. With it, while customizing a car in the car configurator sector, the user can easily navigate both forward and backwards to include (and remove selected items and accessories) while seeing the resulting car.

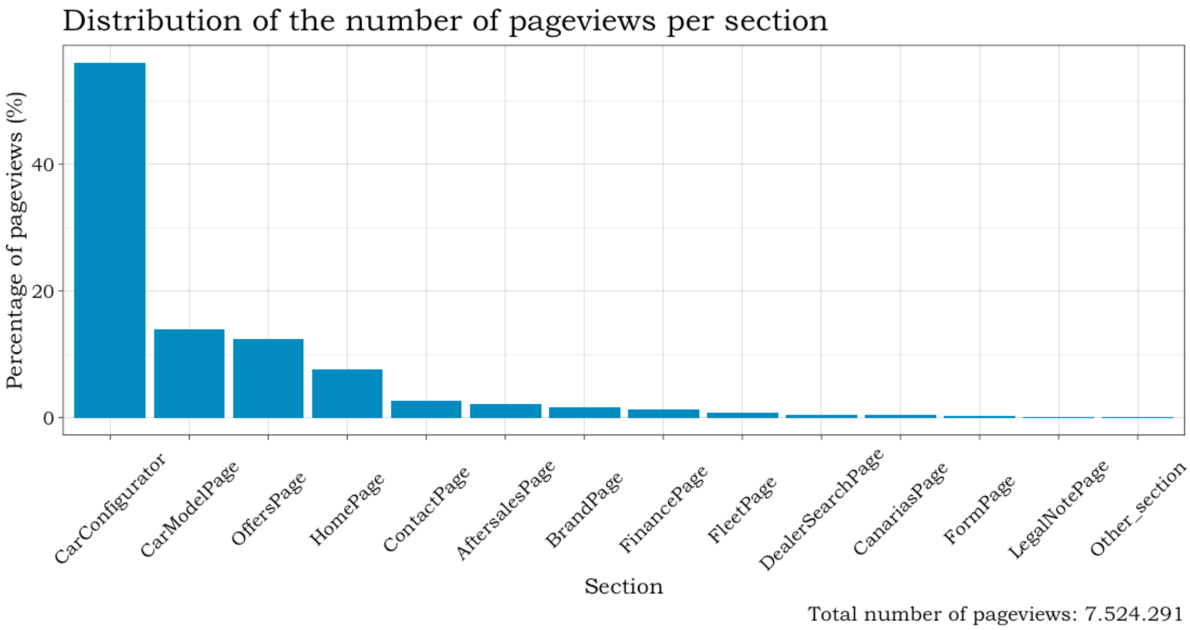

FIGURE 4.2. Distribution of the number of pageviews per section included in the dataset

Once the objective variable (i.e. website section) the different data used for segmentation can be described. As aforementioned, three different data blocks have been tested in order to understand which is the best personalization segmentation criterion based on currently available data usable for personalization purposes. The first block contains five different segmentation criteria based on the context of the user (those being geographical region, time of day, day of the week, weekdays vs weekends and website entry channel). The second block consist in segmentation criteria based on the stage of the user in the user-organization relationship (those being visit number, total time spent on the website and total number of pages seen). The third and final block, includes the segmentation based on presented variable CJM. The description of each of the variables used in each block is described below.

Contextual variables: Geographical Region

In first place, the data used to segment based on the user context going to be described. The first used criterion has been *geographical region*, the geographical region is obtained based on the zip code assigned to each visit. Each zip code has been assigned to a Provincia and then to a region based on the information provided by the *Instituto Nacional de Economia* (INE, 2021). Table 4.2 presents the percentage representation of pageviews of each region.

Contextual variables: Time of day

The second used criterion has been the *time of day*. The hour of the day has been divided in five intervals including night, morning, lunchtime, afternoon and evening. Table 4.3 presents the detail of the interval assignment and the percentage representation of the hour of the day

Table 4.2: Percentage representation of pageviews of each region sorted by decreasing percentage

Region	Percentage of pageviews (%)
Madrid	26.32
Catalunya	26.30
Andalucia	11.39
C. Valenciana	8.17
Pais Basco	4.04
Galicia	3.80
Castilla y Leon	2.99
Castilla la Mancha	2.45
Murcia	2.43
Canarias	2.40
Aragon	2.16
Asturias	1.90
Baleares	1.72
Extremadura	1.21
Navarra	1.11
Cantabria	1.01
Rioja	0.43
Melilla	0.08
Ceuta	0.07

variable.

Table 4.3: Percentage representation of pageviews of each time of day segment

Time of day	From	To	Percentage of pageviews (%)
Night	0:01	6:00	6,58
Morning	6:01	13:00	36,35
Lunchtime	13:01	16:00	16,00
Afternoon	16:01	20:00	27,06
Evening	20:01	0:00	14,01

Contextual variables: Day of the Week

The third and forth criteria have been *Day of the week* and *Weekdays vs Weekends*. In order to create the variable *Weekdays vs Weekends*, pageviews have been segmented in two intervals, *weekdays* include all the pageviews with dates relative to Monday, Tuesday, Wednesday, Thursday or Friday (representing78% of the pageviews included in the sample) while *weekends* include all pageviews with dates relative to Saturday or Sunday (representing 22% of the total number of pageviews). Table 4.4 presents the percentage representation of each day of the week.

Contextual variables: Website entry channel

The final criterion in the block of contextual factors is the *Website entry channel*. In this case, the channels representing less than 0,1% of the pageviews have been reassigned to a segment

Table 4.4: Percentage representation of pageviews of each day of the week

Day of the week	**Percentatge of pageviews (%)**
Monday	16,72
Tuesday	16,26
Wednesday	15,60
Thursday	15,39
Friday	13,96
Saturday	11,67
Sunday	10,41

named 'Other channel'. Moreover, even if 'Refresh' is considered as an entry channel, the visit number has not been increased after a 'Refresh' entry channel. This is, if a visitor was on visit number *X*, and the next visit has an entry channel equal to Refresh, the navigation of this second visit has been assigned to visit number *X* instead of visit number *X+1*. Table 4.5 presents a description of each of the website entry channels and their percentage representation.

Table 4.5: Percentage representation of pageviews of each website entry channel

Entry channel	**Percentage representation (%)**	**Description**
Paid Search Branded	41,10	Click in the link placed in search engine (for searches including the brand name)
Natural Search Unbranded	33,23	Click in the result obtained after a search in a search engine
Direct	10,49	Directly introducing URL of the website
Referral	4,35	Click in a recommendation placed in another website
Display	3,12	Click in graphical advertisement placed on a website by previous agreement
Programmatic Buying	1,64	Click in graphical advertisement placed on a website by online bidding
Paid Search Other	1,65	Click in the link included in a campaign tagged as paid search
Session Refresh	1,69	Visits that continue their navigation after 30 or more minutes of inactivity

...

Entry channel	Percentage representation (%)	Description
Paid Search Branded	1,08	Click in the link placed in search engine (for searches including generic terms)
Natural Search Branded	0,91	Click in the result obtained after a search in a search engine including the brand name
Social Networks	0,69	Click in a social media post
Other channels	0,05	-

Customer Journey variables: Visit Number

Once all the contextual segmentation criteria included in the first block have been described the second block of variables can be presented. As aforementioned, the second block of variables consist in variables that are assumed to provide information of the user's phase in the customer journey. The firs variable described in this block is the *visit number*. The visit number variable describes the number of the visit the user is currently in. Therefore, for each pageview of during the same visit, the visit number is repeated. As seen in figure 4.1, most users only visited the website once during the studied period. Accordingly, more than 65% of the pageviews correspond to first visits (i.e. visit number equal to 1). Moreover, the visit number in percentile 95% is 7. Nevertheless, the maximum visit number in the dataset is 145. However, the percentage of pageviews with corresponding to a visit number equal or greater than 20 is less than 0.8%). Table 4.6 presents the percentage representation of visit number in the dataset (visit numbers equal or greater than 10 are are shown in the group 'More than 9' for the sake of visualization). In order to use the visit number as a segmentation criteria, 10 groups have been created. Groups 1 to 9 are equivalent to the visit number (i.e. group 1 includes visit number equal to 1), group 10 includes all the data points with visit number equal or higher than 10.

Customer Journey variables: Page Number

Similarly to the visit number, the *page number* variable describes the number of the page viewed the user is currently in. Therefore, it is also related with the customer journey. The page number considers all the previous pages viewed by the user independently of the number of visits. As aforementioned, most users only perform one visit in the website, therefore, using the page number instead of the visit number can be a more informative version of the same information. As seen in figure 4.1, more than 40% of the visits include 1 to 3 pageviews. Considering the information per user instead of per visit, while the average page view per unique visitor is 10.72, 50% of the visitors see 6 or fewer pages in total (i.e. regardless of the number of visits). In order to use it as a segmentation criteria, the values obtained have been divided in groups. According to

Table 4.6: Percentage representation of visit number in the dataset

Visit number	%
1	65.18
2	15.17
3	6.69
4	3.68
5	2.26
6	1.54
7	1.09
8	0.79
9	0.60
More than 9	3.01

the RFM literature, 125 is a reasonable number of groups for segmentation (Kohavi and Parekh, 2004). Consequently, 126 groups have been created by 0.8% quantiles (i.e. 100/125).

Customer Journey variables: Time Spent

Finally, the third variable included within the second block (i.e. related with the customer journey), is *total time spent on the website*. The total time spent on the website is calculated by adding the time that a user has spend in each of all the pageviews seen previous to the current one. Therefore, it represent the total time (regardless of the number of visits or the number of pages visited) that a user has spent in the website. Table **??** presents the summary statistics of the total time spend on the website (in minutes) per pageview included in the dataset, per visit and per visitor. As shown in the table, most visitors spent less than 3 minutes navigating the website (median equals 2.5). Moreover, only 1/4 spends more than 5 minutes on the website (percentile 75% equals 5.25). Similarly to what has been done with the previous variable, in order to use time spend as a segmentation criterion, groups need to made. Accordingly, 126 groups have been created by 0.8% quantiles (i.e. 100/125).

Table 4.7: Summary statistics of the total time spent in the website (minutes)

Reference	Min	Median	Mean	Std	Max
Per Visitor	0.26	2.5	5.38	11.08	1498.01
Per Visit	0.01	2.87	8.85	21.52	1498.01
Per Pageview	0.01	3.25	10.11	24.52	1498.01

Customer Journey Moment

Now that, both the contextual segmentation criteria and the customer journey criteria, have been presented, the data obtained from the Customer Journey Moment calculation is described.

Given the nature of the dataset, where the majoritarian visit number is 1 (65% of the data points), both the Recency and the Frequency terms of the RFM calculation are equal to 1 for almost 70% of the data points. Therefore, as the Monetary term is equivalent to the page number, the RFM term is equivalent to the page number for more than approximately 65% of the data points.

Regarding the CJM, the values for CJM range from 0 to 959228.8, the average is 449 while 50% of the data points have CJM values equal or lower than 10.6. In order to use it as a segmentation criteria, the values obtained have been divided in groups. The same procedure done with the two previous variables has been followed. Therefore, according to the RFM literature, 125 is a reasonable number of groups for segmentation (Kohavi and Parekh, 2004). Consequently, 126 groups have been created by 0.8% quantiles (i.e. 100/125).

4.4 Results

Given the described data, Goodman and Kruskal's *lambda* statistic is independently calculated for each of the segmentation criteria described as independent (i.e. predictor) variables with *Section* as the dependent variable.

The results obtained for each criteria in the block of context related segmentation are presented in Table 4.8. As seen in the table, the tested segmentation criteria related to the context of the user show small to non association with the website section regarding the Cramer's V statistic. Moreover, none of them should be used as predictors of the Section, as all of them show lambda coefficients equal or close to zero, meaning a weak to nonexistent association between them. Given the Cramer's V result, the most associated criterion with the website section is the website channel entry, however its association is considered small since it is lower than 0,17 (Mangiafico, 2016).

Table 4.8: Results obtained for Cramer's V and Lambda indexes for each criteria in the block of context related segmentation

Criteria	**Cramer's V**	**Lambda**
Geographical region	0,069	0
Time of day	0,024	0
Day of the week	0,012	0
Weekdays vs weekends	0,026	0
Website entry channel	0,115	0,030

The results obtained for each criteria in the customer journey related segmentation are presented in Table 4.9. As seen in the table, the tested segmentation criteria related to the customer journey of the user show small to non association with the website section regarding the Cramer's V statistic. Moreover, none of them should be used as predictors of the Section, as all of them show lambda coefficients close to zero, meaning a weak to nonexistent association between them. Given the Cramer's V result, the most associated criterion with the website section is the page number, however its association is considered small since it is lower than 0,17 (Mangiafico, 2016).

Table 4.9: Results obtained for Cramer's V and Lambda indexes for each criteria in the block of context related segmentation

Criteria	**Cramer's V**	**Lambda**
Visit number	0,036	0
Page Number	0,134	0,043
Time spent	0,118	0,027

The results obtained for each criteria in the block of context related segmentation are presented in Table 4.10. As seen in the table, the segmentation created by using the CJM value show small association with the website section regarding the Cramer's V statistic. Moreover, it should not be used as a predictor of the Section, as it shows a lambda coefficient close to zero, meaning a weak to nonexistent association between them. Given the Cramer's V result, the CJM segmentation is the most associated criterion with the website section of all the tested ones, however its association is considered small since it is lower than 0,17 (Mangiafico, 2016).

Table 4.10: Results obtained for Cramer's V and Lambda indexes for each criteria in the block of context related segmentation

Criteria	**Cramer's V**	**Lambda**
Customer Journey Moment	0,14	0,036

4.5 Discussion and conclusions

One of the main focuses of personalization is to provide value to the end user, therefore, understanding what the users' want or need is a fundamental part of personalization (Kramer et al., 2000). Market segmentation has historically been used to understand users' needs, desires and capabilities (Hassan and Craft, 2003). Accordingly, website audience segmentation is closely related with website personalization, and most authors include it as the first step of the personalization process (Fan and Poole, 2006; Mobasher et al., 2000; Simkin, 2005; Slaninová et al., 2010).

Nowadays, website audience segmentation is a basic tool used by almost any company (Florez-Lopez and Ramon-Jeronimo, 2009; Lieberman, 2016; Prashar et al., 2016; Smith, 1956). However, website segmentation is highly dependent on the context (i.e. the specific objective of segmentation, the organization sector specifications or the users' relationship with the organization). Unfortunately, some companies still fail at considering the context of their segmentation activities resulting in losses in time, efforts and business opportunity (Bijmolt et al., 2010; Webber, 2011).

With it, our research includes an analysis on the possibility of acquiring knowledge about the preferences of the web users through segmentation criteria considering the specific context of a company in the automotive sector (i.e. by using the specific data, personalization objective and website). We also consider whether these criteria can be used to personalize websites. With this, we create a variable that can be applied for segmentation based on the premises of the two segmentation criteria highly recommended in the literature (the RFM model and the 'Customer Journey'), and we further assess its potential to be used in web personalization.

The results show that, for the given website, none of the tested segmentation criteria is informative enough to be used for personalization. This is due to several factors. First, poor data quality led to the loss of more than 50% of the dataset. Second, given the nature of the organization (i..e. automotive sector) and the user-organization relationship, websites in the automotive sector are mainly informative (Kulkarni et al., 2012; Taylor-West et al., 2020; Rutz and Bucklin, 2012; Yan et al., 2018). Therefore, the website does not collect any personal information (i.e. users do not have a login area with personal information or preferences) or purchase history, therefore, the data set does only contain genetic information such as visit number, zip code or date of the visit. Third, the number of visits and pageviews per unique are abnormally skewed to 1. Even if a website in the automotive sector is not as recurrent as other retail websites, according to the literature, users visit the brand website several times before going to a dealership (CoxAutomotive, 2019). Therefore, this unexpectedly low number of visits per unique visitor might indicate an error in the collection or assignment of visitor IDs. This is, if a repeated user (i.e. a user that has already visited the website) is not 'recalled' by the system when entering in the website, a new ID is generated and assigned with visit number equal to 1, instead of assigning the new information to a previously generated ID. Therefore, losing the traceability of the user. This could be due to technical problems in the system or due to cookie churn (i.e. intentionally clean or reset of cookies made by users) (Hohnhold et al., 2015). Finally, traditionally industrial companies, such as companies of the automotive sector, have relatively small website traffic as compared with big tech companies(Liu et al., 2021; Mattos et al., 2020). This represents an additional challenge for those companies in gathering a clear idea of the user needs and preferences and, therefore, difficult the implementation of website audience segmentation and website personalization.

This research was based on the specific case of a company of the automotive sector, therefore, even if this company can have some similarities with other traditionally industrial companies none of the results can be generalized to other companies or other sectors. Moreover, this research was limited to segmentation criteria using the data currently available on the website therefore, the use of segmentation criteria based on additional data or the development of different segmentation techniques have been left out of the scope of the study. Given the bad results obtained in this study further research is needed in assessing the viability of effectively using different segmentation criteria in traditionally industrial companies.

Despite not obtaining a specific segmentation criteria usable to personalize the website. Different conclusions can be drawn from the performed analysis. Namely, with the data currently available, we have not found evidence that any of the segmentation criteria explored can be used to personalize, considering the specific objective personalization strategy (i.e. forecasting the visitors' preferred website section at any given time during her navigation). However, both including new data (such as including information not only the entry channel of the website but the specific campaign clicked by the user) or changing the personalization objective. Moreover, even if the available data, the value of the CJM as segmentation criteria could not be validated, the principles used to create the CJM term are based in the literature, therefore, its potential validity given a different dataset should not yet be dismissed.

As a consequence of the research performed and the aforementioned discussion of the results, we can answer the research question of this chapter:

RQ: Which users' segmentation criteria can we use that are informative enough in the implementation of website personalization?

Answer: None of the evaluated users' segmentation criteria has been proven effective to be usable for the personalization strategy selected by the company (i.e. system-driven personalization able to forecast the preferred website section for the user at any given time of the navigation without explicitly asking it to the user). However, the poor data quality, the nature of the data currently tracked in the website and possible errors in the visitor identification have been identified as possible causes of the obtained results. Therefore, the research could drive different results after addressing these issues.

In conclusion, effective website segmentation is a fundamental part for website segmentation, however some traditionally industrial companies are still not able to segment their website audiences effectively enough to implement personalization. In this study, different segmentation criteria have been evaluated, and, despite the fact that none of them has resulted effective personalization, some problems in the data have been identified. Moreover, in this research, we presented a variable intended to be used to segment audiences.

CHAPTER 5

DOS AND DON'TS IN THE EVALUATION OF PERSONALIZATION

In this chapter we study the evaluation methods for personalization. Part of the content presented in this study was included in a conference paper presented in th *Adaptive and Personalized Persuasive Technology* section rt of the *27th Conference on User Modeling, Adaptation and Personalization*) (Esteller-Cucala et al., 2019), a journal article published in the journal *Frontiers in Artificial Intelligence* (Esteller-Cucala et al., 2020a) and an informative publication in the new report of *Societat Catalana de Matemàtiques* (Esteller-Cucala et al., 2020c) all of which have been derived from the resulting work of this doctoral research.

5.1 Introduction

As seen in previous chapters, website personalization is a broad concept that has gained research and market attention during the last years (Salonen and Karjaluoto, 2016). Its proven positive effects in user persuasion, trustworthiness perception, satisfaction, engagement, loyalty and the reduction of user uncertainty and obfuscation, among others, have set excellent conditions for web personalization to flourish (Bleier et al., 2017; Coelho and Henseler, 2012; Demangeot and Broderick, 2016; Kaptein et al., 2015; Oinas-Kukkonen and Harjumaa, 2008; Salonen and Karjaluoto, 2016; Lee and Lin, 2005; Tam et al., 2005; Piccoli et al., 2017; Xu et al., 2014a). However, while the general effects of website personalization have been proven by the academia, and some authors claim that personalized experiences improve the effectiveness of online marketing (Bleier and Eisenbeiss, 2015a), determining the specific impact of particular personalized features on an organization's website remains an elusive goal (Kaptein et al., 2015; Kwon et al., 2010). Therefore, there is still not a consensus on how to capture this positive effect of the website personalization on the final user, website performance or business goals (Kaptein and Parvinen, 2015; Li and Liu, 2017). Accordingly, a majority of marketing executives have reported to be struggling with measuring actual website personalization impacts (Forbes, 2019). Moreover an increasing number of marketers report dissatisfaction with their personalization efforts and their lack of confidence about their ability to achieve successful personalization results (International, Researchscape (Evergage, 2018). This has been predicted to compromise the evolution of personalization development (Vesanen, 2007) and even to cause the abandonment of personalization efforts (Gartner, 2019).

Given such a generalized need to explore and understand which methods can be used to evaluate personalization, authors have proposed different solutions. On the one hand, the most extended method to evaluate website personalization are randomized control trials, also known as online controlled experiments or A/B tests) (Amatriain and Basilico, 2012b; Dmitriev et al., 2016; Govind, 2017; Letham et al., 2018). This assessment method is a common practice in website evaluation and with the inclusion of personalized features in marketers websites, it has been extended to the evaluation of these features. Both in academic and industrial literature, online controlled experiments have been widely commented and discussed (Govind, 2017; Kohavi et al., 2009; Lazarova, 2020; Ros and Runeson, 2018; Tang et al., 2010; Xu et al., 2015). However, some authors claim that this method, as traditionally used, is not suitable for the purpose of evaluating personalization (Chen et al., 2019; Das and Ranganath, 2013; Jiang et al., 2019) and propose adapted A/B testing techniques or alternative new methods (Athey and Imbens, 2016; Haupt et al., 2020; Pouget-Abadie et al., 2018; Tu et al., 2021). On the other hand, it is not always possible to run A/B tests as they might be expensive, time-consuming, at times unethical or even not feasible (e.g. if the website alteration has already been done without an experiment) (Salimkumar et al., 2021). In these cases, other techniques, such as causal inference, can be used to estimate the effect of new features in the website (Goldenberg et al., 2021; Govind, 2017; Adam Kinney, 2019).

Accordingly, in order to understand how an organization can assess the results of their website personalization efforts, we need to have a complete overview of the most used evaluation methods in the field. Taking this into consideration, the research question formulated for this study is:

RQ: How can we evaluate website personalization?

With this broad research question we aim not only to get a clear idea of the most common techniques applied for website personalization evaluation but also to comprehend how they can be used.

With this broad research question we aimed not only at getting a clear idea of the most common techniques applied for website personalization evaluation but also to comprehend how these methods can be used. In accordance with this objective, in the present chapter, we describe in detail the two most commented methods for website personalization evaluation. First we introduce website evaluation through online controlled experimentation and then we focus on causal inference for website personalization evaluation.

5.2 Online controlled experimentation

5.2.1 Introduction

Online controlled experiments are one of the most common methods used to evaluate the impact that website alterations has on users(Chen et al., 2019; Olsson and Bosch, 2014; Ros and Runeson, 2018; Xu et al., 2015). Given its extensive use by both academics and practitioners, it has been given various different names in the literature such as randomized control trials, A/B tests, split tests or bucket tests (Das and Ranganath, 2013; Tu et al., 2021).

The basic objective of online controlled experiments is to estimate the causal effects of a treatment in a controlled online environment (Rubin D. B, 1974). In the most basic case, the participants of an A/B test are randomly split into two comparable groups. The only difference between those two groups is some variation X intentionally included by the experimenter. Assuming the experiment to be correct (i.e. designed and executed without inducing any bias), external factors will be distributed evenly between the groups. Consequently, the only consistent difference between the groups is the variation X. Therefore, any detectable difference in metrics between the groups can only be due to a random change or to the variation X, although the former can be ruled out using statistical testing. Because of this, a causal relationship can be established between the variation and the quantified difference in metrics between the groups (Kohavi et al., 2007; Crook et al., 2009; Fabijan et al., 2016; Zhao et al., 2016; Johari et al., 2017).

The simplicity of the A/B testing concept has lead to an increasing use of this method to evaluate the inclusion of new features on websites (Amatriain and Basilico, 2012b; Bakshy et al., 2014; Dmitriev et al., 2017; Knijnenburg, 2012). Moreover, with the rise of internet connectivity, online controlled experimentation presents an unprecedented opportunity to make causal conclusions between website alterations and customers‚Äô reaction in almost real-time (Fabijan et al., 2016). Consequently, both big tech companies (e.g. Amazon, Facebook, Google, Netflix, Uber, etc.) as well as small companies are using A/B tests as a scientifically solid method to evaluate variations and compare different alternatives in their websites (Amatriain and Basilico, 2012b; Bakshy et al., 2014; Deb et al., 2018; Deng et al., 2016; Dmitriev et al., 2016; Hohnhold et al., 2015). Accordingly, the evaluation of personalization or recommender systems have also become popular applications of online experimentation (Fabijan et al., 2016; Govind, 2017; Letham et al., 2018).

However, even if the fundamental idea of split testing can be considered simple, there is a variety of A/B testing types and techniques such as A/A testing, multi-variant testing and multivariate testing (Kohavi et al., 2009; Kotapalli, 2020), as well as testing adaptations for different fields or objectives (i.e. adapted A/B testing method for websites of the automotive sector or adapted experimentation methods considering the specific case of personalization) (Liu et al., 2017, 2021; Tu et al., 2021). Moreover, even if online controlled experimentation has traditionally been done based on the statistical basis of a frequentist hypothesis test (the null hypothesis statistical testing) using Bayesian models or even Sequential adaptations are also popular (Deng et al., 2016; Johari et al., 2017; Rivasseau, 2019a; Su and Yohai, 2019).

Additionally, not all the companies are able to develop in-house tools capable of randomly splitting variants of the website to the different users in real time when they are navigating on their websites. Therefore, it is considered that at least 25% of the companies performing A/B tests use third party experimentation platforms (Fabijan et al., 2018c). Accordingly, there are thousands of open source and commercially available platforms categorized as 'Optimization, Personalization & Testing' for organizations to choose from (Dmitriev et al., 2017; Fabijan et al., 2018b; Johari et al., 2017; Pam, 2017; UserConversion, 2020).

All of this makes A/B testing a simple concept but still, it is not routinely applied by most organizations (Kohavi et al., 2009), which are not always able to accurately perform those experiments (Chen et al., 2019). Accordingly, even though companies usually need to follow A/B testing guides to start experimenting, authors frequently report sets of experimental errors or misinterpreted conclusions that companies make when performing those tests (Dahl and Mumford, 2015; Dmitriev et al., 2017; Kohavi et al., 2014; Kotapalli, 2020). Unfortunately, the incorrect implementation or analysis of A/B tests has led some authors to the conclusion that online controlled experimentation is not an effective practice (SiteSpect, 2018).

In order to address the research question of this chapter, we have used different techniques (described in the methodology) to gather the information needed to present the typically recommended process to perform online controlled experiments. We also discuss the most common testing pitfalls committed in each part of the process.

5.2.2 Methodology

In order to get a clear vision of how to evaluate new features in the website, we wanted to include information from academia, companies already experimenting in their websites (with different experience levels) and field experts. Therefore we suggest a mixed data gathering approach. The data collection procedures used in this study were:

a. Academic literature: General literature review on the online controlled experimentation topic (considering its different given names) limited to academic literature. These include papers from companies with expertise in using website experimentation published in research journals or academic conference proceedings.

b. Specific companies of the automotive sector: Collection of test reports and participative observation in a website experimentation project of a company in the automotive sector.

The analyzed company manages multiple websites and, at the time of the study, more than 10 websites were being tested independently by different teams.

c. Extension to other companies in the automotive sector: Collection of information from other 7 companies in the automotive sector including:

  - Documentation from the companies' experimentation project plans (from five out of the seven companies)
  - Group meetings (with six out of the seven companies)
  - Open answer surveys (from three out of the seven companies)

d. Extension to companies in other sectors: Collection of 18 open-ended interviews (the interviews were individual, written and anonymous), corresponding to participants from 18 different companies currently performing online experimentation. The interviews included three demographic questions aiming at figuring out the interviewee‚Äôs company sector, their position in the company and the approximate number of tests annually performed by the company. Additionally, the interview consisted of 10 questions focused on the standard experimentation routine of the company. The interview design was validated with a pilot respondent from an additional external company.

e. Literature from experts in the field: In order to extend the data acquisition to the field experts, we analyzed the online blogs of the companies with the current most recognized personalization and experimentation platforms of the market. The companies included are the ones reported in the Gartner's annual report *Gartner Magic Quadrant for Personalization Engines 2021* (Gartner, 2021) and the Forrester's quarterly report *The Forrester Wave^{TM}: Experience Optimization Platform, Q4 2020* (McCormick, 2020). This resulted in a total of 14 companies. The complete list of companies analyzed is shown in Table 5.1. For each of the companies we analyzed all the posts related to website personalization, experimentation, optimization and A/B testing available in their public websites at the time of the study.

The data gathering methods *a* to *c* were used in Esteller-Cucala et al. (2019) for the purpose of listing the most common experimentation pitfalls in the automotive sector. Moreover, the previous research was extended in Esteller-Cucala et al. (2020a) with the data gathering method *d* with the objective of analyzing if the pitfalls identified in the automotive industry were also present across other industries.

5.2.3 Results

After the gathering and analysis of data from different website sources, we went on to define the guideline for online controlled experimentation, which is composed of three main phases, each of

Table 5.1: Summary of experimentation field expert companies included in the revision of blog sites

Company	Mentioned in	Blog Site
AB Tasty	*FW*	AB Tasty expertice-hub
Adobe	*GMQ / FW*	Adobe experience league
Algonomy (previously RichRelevance)	*GMQ*	Algonomy Blog
Attraqt	*GMQ*	Attraqt Blog
Boxever (acquired by Sitecore)	*GMQ*	Sitecore Knowledge Center
Dynamic Yeld	*GMQ / FW*	Dynamic Yeld Blog
Insider	*GMQ*	UseInsider Blog
Kameleoon	*FW*	Kameleoon Blog
Kibo (previously Monetate)	*GMQ / FW*	Kibo Commerce Blog
Optimizely (previously Episerver)	*GMQ / FW*	Optimizely Insights
Oracle	*GMQ / FW*	Blogs Oracle Marketing Cloud
Salesfoce	*GMQ / FW*	Salesforce Blog
SAS (previously Emarsys)	*GMQ / FW*	Blogs SAP
SiteSpect	*GMQ / FW*	SiteSpect Blog

GMQ = Gartner Magic Quadrant for Personalization Engines 2021; FW = The Forrester Wave^{TM}: Experience Optimization Platform, Q4 2020

which including different steps. Namely, (1) pre-experiment conceptualization, (2) experiment design and execution and (3) post-experiment analysis and learning. Even if some authors describe the process as a succession of steps describing the execution of one single test (e.g. Kao (2020); Kotapalli (2020)), the majority of them emphasize the need to see it as a cycle or an iterative process (e.g. Attraqt (2021); Deng and Shi (2016); Eckles (2016); Fabijan et al. (2018a); Kohavi et al. (2009)).

Phase 1: Pre-Experiment Conceptualization

The rationale of this first phase is to include all the ideas and planning previous to the actual elabora tion of the experiment (Fabijan et al., 2018a). In order to start any experiment or experimentation initiative, the company needs to first be able to gather data from the existing website. (Fabijan et al., 2018b). Even if this might seem evident, being able to picture the current state of the website with sufficient data quality is a crucial step sometimes forgotten (Maassen, 2020). Once the data is available, it has to be analyzed in order to really understand the current website performance and to get an idea of the users' preferences. This can include qualitative and quantitative data (Attraqt, 2021; Kotapalli, 2020). By having a clear idea on the current state of the website and the users‚Äô preferences, hypotheses of how certain alterations of the website can have an effect on the user can be formulated (Kao, 2020). After working on the different hypotheses, reinforcing (or discarding) them based on data, prioritizing them and deciding how to validate them, a test plan can be created (Eckles, 2016). The test plan includes the grounded definition of the hypothesis and the draft idea of the variation to be implemented and tested in order to validate the hypothesis (Fabijan et al., 2018a). Additionally, the test plan should include: the number and description of variants to be tested, how to measure or calculate the indicators needed to validate the hypothesis, the audience segments to test on (if any), any known contextual factors at the time of the test, the first calculations of the experiment duration and the sample size needed (Eckles, 2016; Kao, 2020). This phase harbor some of the most commented pitfalls when performing online controlled experiments. These pitfalls are especially relevant since, if they arise in the first phase of the process, they may completely invalidate the test results (Kohavi et al., 2009). The five most commented experimentation pitfalls in this phase are:

- Not choosing the right evaluation metric. Even if this might not result in a risk for the experiment itself, repeatedly testing random hypotheses or ideas not based in data might result in irrelevant testing, bad used experience, opportunity cost of not performing other A/B tests or even the abandonment of the testing initiative (Benlian, 2015; Crook et al., 2009; Dmitriev et al., 2017; International, Researchscape (Evergage, 2018). A/B tests should be evaluated using metrics that represent the business objectives (Dahl and Mumford, 2015) and at the same time, these metrics should be understandable, do not include easily misinterpretable ratios, they should be relevant to optimize and also represent the good performance of the website (i.e. if the user experience is declining, the metric should not yield positive results) (Crook et al., 2009; Kohavi et al., 2014; Saux, 2020; White, 2019). In order to avoid this pitfall, some organizations decide to evaluate a large group of metrics in each experiment, resulting in a new caveat, which is not having a clear unique indicator of hypothesis validation (Kohavi and Longbotham, 2016). In line with the *Experimentation Growth Model* presented in Fabijan et al. (2018a), the interviewed companies with greater experience in split testing reported to use stable thoughtfully selected metrics across experiments while less-experienced companies were reported to use specific sets of evaluation metrics depending on the particular A/B test used.
- Not having a data grounded hypothesis. Even if this might not result in a risk for the experiment itself, repeatedly testing random hypotheses or ideas not grounded in data might result in irrelevant testing, bad used experience, opportunity cost of not performing other A/B test or even the abandonment of the testing initiative (Eckles, 2016; Saux, 2020; White, 2019).
- Not determining the experiment length beforehand. When using frequentist statistical approaches one of the requirements of the Null Hypothesis Statistical Testing requirements is to obtain a minimum sample size (Dahl and Mumford, 2015; Dmitriev et al., 2017; Kohavi et al., 2007; Robinson, 2018; White, 2019). This problem has been extensively commented in the literature and it is related to many different actions.

For example, if the minimum required sample size for the experiment is calculated for the entire population of the test, the results will not be evaluable by segments (which is a common practice in evaluation for personalization) (Keser, 2018). Moreover, another well known bad practice is *test monitoring* (or *test peeking*) which results in a premature abortion of the experiment (Dahl and Mumford, 2015; Dmitriev et al., 2017; Johari et al., 2017). Given the abundance of this pitfall, there is extensive literature on statistical methods to avoid misinterpreted conclusions when continuously monitoring an experiment (Deng et al., 2016; Dmitriev et al., 2017; Johari et al., 2017; Koomen, 2018; Su and Yohai, 2019). Additionally, there are other aspects to be considered when determining the experiment length. For example, longer experiments (i.e. samples longer than needed) can also invalidate or difficult the test (Dmitriev et al., 2016). Moreover, the length of each independent experiment should be calculated taking into account the dissipation of temporal effects (such as hour-of-day or day-of-week effects), business cycles and seasonality effects (Dmitriev et al., 2016; Kohavi et al., 2007; QuickSprout, 2019; Su and Yohai, 2019). All the companies of the automotive sector interviewed calculated the experiment length beforehand while companies in other sectors reported mixed responses.

- Not adapting the experiment if more than one comparison is going to be done. The so-called *multiple comparison problem* is also an extensively commented experimentation pitfall (Kohavi et al., 2014). Comparing more than one variable of the website is a common practice when evaluating website personalization (Arora et al., 2008; Letham et al., 2018).

  However, on the basis of a frequentist approach, when the sample size is calculated for a given significance level (e.g. significance levell of 10%, equivalent to a 90% confidence level) each comparison (e.g. variant A vs variant B) has a false positive rate equivalent to the significance level. If there are multiple comparisons (i.e. multiple variants, multiple variations in each variant or multiple metrics) within the same test, the whole-test false positive rate increases. This is, considering the binomial probability ($b(X;n,P)$) of finding at least one false positive ($X \geq 1$) within n comparisons (independent trials) considering $P(0.05)$ as the probability of finding a false positive in a single comparison:

$$P(X) = \frac{n!}{(n-1)!X!} p^X (1-p)^(n-x)$$

  As the specific typical example of considering a significance level of 5% de calculation can be simplified by:

$$P(\text{at least one false positive}) = P(X \geq 1) = 1 - P(\text{at least one false positive})$$

$$P(\text{at least one false positive}) = 1 - P(X = 0) = 1 - 0{,}95^n$$

Because of this comparisons including 15 variants, lead to a probability of obtaining a false positive (51%) almost equivalent to flipping a coin and getting a head. Consequently, some adjustments have been proposed in the literature (e.g. Bonferroni correction) (Dahl and Mumford, 2015; Robinson, 2018; Kohavi et al., 2007).

In line with what was observed in the literature, two thirds of the companies we interviewed were performing experiments with more than two variants whereas only a minority were using proper adjustment for their sample size calculation.

- Not taking the test context into account. Considering the specific context of the website during the time of the experiment is needed to be able to extrapolate the results to the normal website performance (Kohavi et al., 2009). This means taking into account the presence of special events or atypical factors that could affect the performance of the website during the test (such as private sales periods) (Brebion, 2015).

Phase 2: Experiment design and execution This phase is mainly performed inside the experimentation platform (in case of using one) (Attraqt, 2021).The idea of this second phase is to first design the actual website variant (or variants) that are going to be displayed in the experiment (Fabijan et al., 2018a). This includes: (1) the construction of the monitoring of the experiments (such as including the data gathering for the designed evaluation metrics), (2) the analytical part of the experiment (defining the user segments) and (3) building/designing the mechanisms in order to include in the experiment only the desired audience (if applicable) (Kao, 2020; Maassen, 2020). Moreover, this phase includes all the quality assessments which need to be performed to each element of the experiment according to the organization and the test plan (Eckles, 2016). This phase often includes the refinement of the calculations done in the previous phase (Fabijan et al., 2018a). Finally, this phase also includes the execution of the test itself (Fabijan et al., 2018a).

The most commented experimentation pitfall in this phase is the following:

- Not controlling the balance among experiment samples. This is commonly known as *unbalanced sampling, sample ratio mismatch* or *bucketing skew* and refers to the situation where the split of users between variants does not satisfy the expected ratio (Dmitriev et al., 2017; Robinson, 2018). The test unbalance can be produced manually (Dahl and Mumford, 2015) or technically (Kohavi et al., 2009). Some of the most common unbalance causes are, for example, changing the sample ratio during the experiment (e.g. using ramp-ups to activate the test), post-experiment segmentation, post-experiment grouping of samples tested with different ratios or bugs in the implementation (e.g. a bug that affects only a specific browser) (Crook et al., 2009; Keser, 2018; Kohavi et al., 2007). As previously commented, the main objective of an online controlled experiment is to be able to establish a causal relationship between the test variation and a measurable change in the evaluation metric. This causal relationship is based on the premise that any external alteration to the metric other than the tested one will be evenly balanced between the test variant due to the randomized variant split (Zhao and Zhao, 2016). Therefore, it is necessary to avoid the sample ratio mismatch in order to ensure the validity of the experiment results (Crook et al., 2009). Proactive actions to mitigate this pitfall include technical quality assessments of the experimentation platforms (e.g. A/A testing) and the test designs (Crook et al., 2009; Kohavi et al., 2007). Moreover, the use of stratified sampling is specially recommended to avoid this pitfall when evaluating personalization (Das and Ranganath, 2013). This technique consists on including audience segmentations in the test that are not used for the analysis but in order to monitor that all the variants are representative of the studied population. One example of this technique would be to include a segmentation by browser in order to ensure that each variant has been seen by proportion of users from each browser, therefore, ensuring that a problem with one of the browsers will uniformly affect all the variants at the same proportion (Keser, 2018; Urban et al., 2016).

In addition to the proactive actions, another recommended action is to track the balance of the test variants during the experiment. A possible approach is to check the balance between the cumulative count of the assignment units (i.e. cumulative count of users in each variant). Moreover, knowing the expected proportion of assignment units for each group, a Chi-square goodness of fit test can be used to test their supposed steadfastness. More detailed information on this regard can be found in Esteller-Cucala et al. (2019).

From the interviewed companies within the automotive sector, approximately 50% of them reported to be taking actions to prevent monitor unbalanced sampling. However, this pitfall could not be confirmed for the companies other than the automotive sector.

Two other caveats such as test constant monitoring and early stopping are also related to this phase of the process since they take place when the experiment is actually running. However, since both of them have already been discussed, they have not been included in this section.

Phase 3: Post-Experiment analysis and learning

This last phase includes the analysis of the results in order to evaluate if there are statistically significant changes in the evaluation metrics. Predictions are compared with the experiment outcomes in order to make decisions on whether the hypothesis has been validated or not (Fabijan et al., 2018a; Kao, 2020; Kotapalli, 2020; Maassen, 2020). Additionally, this phase includes further evaluation of the results which will eventually lead to the implementation of specific actions depending on the obtained test results (Eckles, 2016; Fabijan et al., 2018a). Documenting, identification or learning and communication of the results are other actions that are included in this phase although they are often forgotten (Attraqt, 2021; Eckles, 2016; Fabijan et al., 2018a; Rivasseau, 2019b; White, 2019). The results of those last actions can be used as the basis of next experiments (Kao, 2020)

This last phase of the experiment also include some extensively commented experimentation pitfalls, the most common ones are:

- Not considering the statistical significance to declare a winner. When using frequentist approaches for A/B testing, a variant can not be considered a winner without the needed statistical significance (Dahl and Mumford, 2015). Moreover, considering a winner with borderline statistical significance is also not recommended (Kohavi et al., 2014). This practice is especially common as the absence of significant results is commonly seen as an indication that the new variant 'does not hurt' the metrics (Robinson, 2018; White, 2019). This practice is considered to be related to 'being too attached to the hypothesis' or generating organization dynamics where experiments are used to validate which team member's idea is the best, therefore losing the scientific perspective of online experimentation (Brebion, 2015). Additionally, this pitfall also includes the blind adoption of unexpectedly good results (Dmitriev et al., 2017). Even if they are statistically significant, unexpectedly bad results are often analyzed in order to 'see what happened', however, this practice is not so common when the unexpected results are positive (i.e. favorable to the hypothesis) (Kohavi et al., 2014). After the evaluation of our pool of interviews we have seen that, for the companies in the automotive sector, almost all of them directly apply the new variants in case of a positive outcome with statistical significance. However, from the companies outside of the automotive sector, approximately half of them apply directly the new variant in case of a winning result.
- Not considering the effect of outliers. Neglecting to filter outliers can also lead to inaccurate test conclusions (Crook et al., 2009). This includes, for example, not filtering possible robots interacting with the website, uncommon heavy users, novelty effects of the new variants (especially important in personalization evaluation) and differences in the consideration periods of the different variants (Crook et al., 2009; Dahl and Mumford, 2015; Dmitriev et al., 2017; Kohavi et al., 2009).

Even if the commented pitfalls are some of the most extensively described in the literature, some authors also describe other pitfalls such as testinting useless elements or unlikely scenarios of the website (Brebion, 2015), failing to prioritize experiments (entailing the opportunity cost of not performing the most relevant experiments) (Saux, 2020), failing to validate each step of the analysis pipeline (Crook et al., 2009) or testing complete webpage redesigns at once (Brebion, 2015).

5.3 Causal inference

5.3.1 Introduction

As previously commented, even if online controlled experiments are the simplest scientifically grounded way to evaluate variations and compare alternatives in the website (Kohavi et al., 2009), it is not always possible to run A/B tests. As they might be expensive, time-consuming, sometimes unethical or even not feasible (e.g. if the variation has already been done without a test) (Salimkumar et al., 2021). For example, in the cases where the organization can expect interferences between the users assigned to different website variants of an A/B test (e.g. mass media, offline marketing campaigns or even through word-of-mouth) it can not be done, since this result could be biased by this interference (McFarland et al., 2018).

Therefore, in those cases, the company is not able to gather experimental data of their variations on the website (i.e. to assign users at random to different experimental groups) but to gather observational data. However they still want to establish causal relationships between website variations and the users' responses (Govind, 2017; Rosenbaum, 2004). In these cases, other techniques, such as causal inference, can be used to estimate the effect of new features in the website (Goldenberg et al., 2021; Adam Kinney, 2019).

Causal inference involves the application of statistical procedures to this observational data in order to estimate causal relationships (Pearl, 2003).

5.3.2 Methodology

In order to illustrate the use of causal inference in the context of a real company's evaluation website we are going to use an applied case example.

Case description

The case of this study consists of the evaluation of the performance of the release of a new design for the company's website (Company A). In this case, the studied company launched the redesign of their website. This could not be evaluated through an online controlled experiment as the new design was going to be launched for all the devices. Therefore, the same user could see different versions of the website if connecting from different devices (i.e. they could be assigned to the old version when connecting from the computer but to the new version when connecting from the mobile phone). Company A manages several independent websites including a global website '*.com*' and separate websites for each market where the brand is present (e.g. France '*.fr*', Spain '*.es*', Italy '*.it*', UK '*.uk*'). In March of 2019 the new redesigned website was launched in France.

After the release of the new website, all the indicators already used by the company (e.g. total number of visits, number of unique users or time on page) were still tracked. Figure 5.1 shows the evolution of one of the indicators (average page views per unique visitor) before and after the release of the new website design. As it can be seen in the graph, the average number of page views per visitor is higher after the release of the new website. However, this increase cannot be directly attributed to the release of the new website, as other external factors can also be affecting the users behavior (e.g. any temporality effect or any competitors' action such as a sale). Because of this, in our study case, causal inference was used to obtain the impact of the new website in the evaluation metrics. .

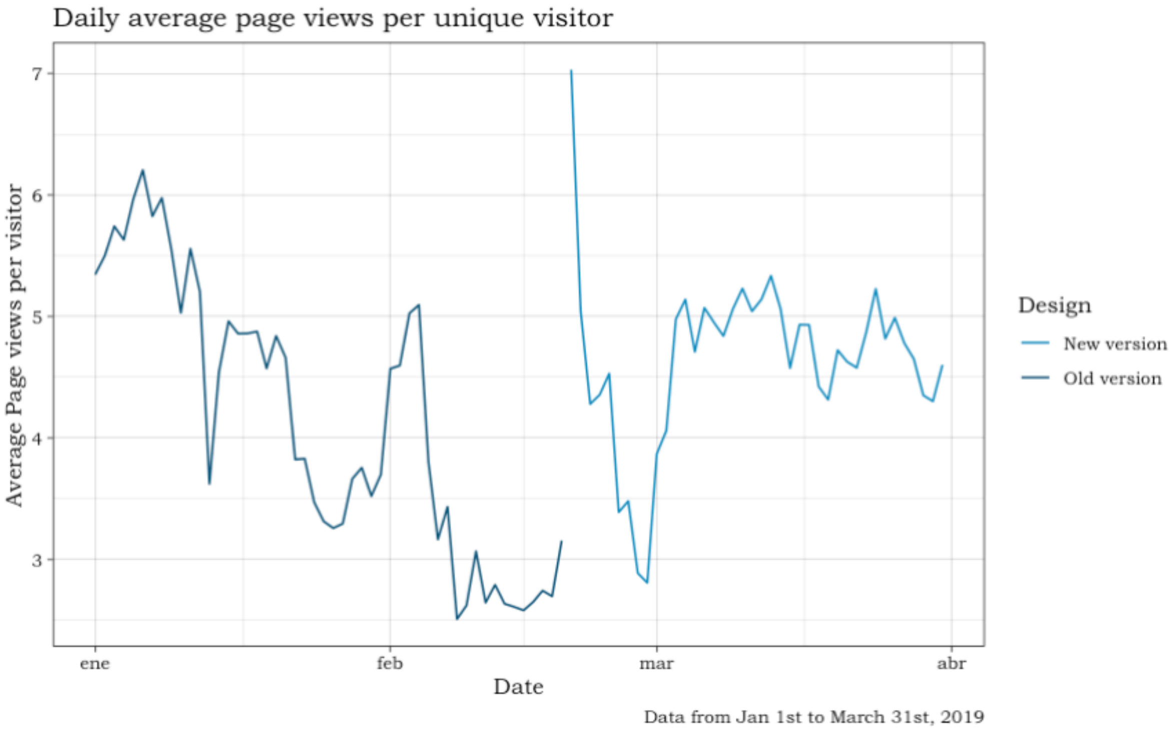

FIGURE 5.1. Evolution of the average number of page views per unique visitor and day in the French website of Company A

The main objective of Company A is to know if the new design has had an impact on the overall user's interest on their website. In order to simplify the calculations, we are going to describe the process using one single metric:daily average number of page views per unique visitor (hereinafter referred to as PvUv). This is, the number of pages that a visitor has seen within the website regardless of the number of visitors needed.

Counterfactual inference method

Causal inference consists of a family of loosely connected statistical methods, and because of this, there is an overwhelming variety of methods available in the different fields (Harinen and

Li, 2019). In this study, we have used counterfactual inference, as they are one of the most used methods for marketing applications (Rossi, 2018).

The main idea of counterfactual inference is giving a probabilistic answer to a 'what would have happened if' question (Huszár, 2019). This is, in this case, we know that the new website was released in France, this is called the *intervention* (McFarland et al., 2018). To use counterfactual inferences is to predict which would have been the website,Äôs performance without the intervention. In our case, what would have happened if the new design had not been released. With it, the causal estimate of the intervention on the website performance is the difference between the actual performance and the conter-factual performance (i.e. the performance estimated without the new design release) (Rajendran, 2019).

The most extended method to solve this type of problems is known as Differences-in-Differences and it is based on attempting to mimic an experimental research design but with observational data instead of experimental data. This is done by selecting a control group that is assumed to have parallel trends in outcome (i.e. the objective metric) to the studied group and using it to infer the trends of the treated group without the intervention (Lechner, 2011). Two of the main limitations of this method are, first, most Differences-in-Differences analyses only consider two time points (before the intervention and after the intervention) not considering the temporal evolution of the intervention impact. And second, they do not consider the existence of multiple sources of variation influencing the outcome of the studied group (Bertrand et al., 2004; Brodersen et al., 2015).

With the aim of overcoming these limitations, Google, Inc. presented in Brodersen et al. (2015) a method to infer causal impact based on Bayesian structural time-series models. This approach is based on using the trend in different control groups of data to forecast which would be the trend in the treated group without the variation (in this case, the new design release) (Brodersen et al., 2015). Accordingly, one of the main advantages of using this method is that we can get an idea of the effect of the intervention, not only at the very moment after the intervention but also how it evolves over time (Rajendran, 2019). Moreover, this method differs from other similar ones (e.g. the use of a synthetic control group) by including full pre and post-intervention time series of the predictor variables (instead of only using pre-treatment variables) (Rajendran, 2019).

Given the previous advantages of the causal impact approach proposed by Brodersen et al. (2015) this is the method used in this study.

In order to apply this method it is necessary to have temporal data from different control sources as correlated with the objective metric as possible but ensuring that none of them has been impacted by the intervention Pearl (2003). For example, if launching a new design in France is considered to have an effect on the brick-and-mortar store number of visits, this number of store visits can not be used as a control data source for the forecasting.

Once the data from the different sources has been collected and cleaned, the calculations are made using the CausalImpact R package provided in Brodersen et al. (2015), (http://google.github.io/

CausalImpact/) (Brodersen and Hausen, 2015).

Data description

In order for our analyses to be as informative as possible, four different types of data types were collected and then used:

- Website data from the same automotive brand (Company A) but in different markets. This data included four other markets.
- Website data from other automotive brands in the same market (France). This data was gathered from two other automotive brands' websites (Alternative company B and Alternative company C).
- Campaign data from the same brand and the same market. This data included two online types of campaigns (direct display and programmatic).
- Economical data of the market. This information was gathered by using the French trade sales volume index provided by the Insee (French National Institute of Statistics and Economic Studies) (Insee, 2021).

All the data spans from October 1st, 2018 to March 23rd, 2019 being the intervention (new website design release) made on February 20th, 2019.

The data used consists in four datasets one from each of the used data sources. The first dataset is the one obtained from Company A's websites. It comprises daily website tracking information from five Company A's markets (France, Germany, United Kingdom, Italy and Spain). This website information includes the daily average page views per unique visitor. Summary statistics of this data are presented in Table 5.2.

Table 5.2: Summary statistics of Company A's daily PvUv per country website included

Market	Min value	Max value	Mean	Median	Std Dev
France	2.41	7.03	4.07	4.09	0.93
Germany	3.13	7.35	5.67	5.69	0.71
UK	2.74	5.12	4.37	4.46	0.40
Italy	0.63	6.87	3.79	3.39	1.32
Spain	1.00	5.84	3.87	4.10	1.07

The second dataset contains daily information about the digital campaigns conducted in the target market (i.e. the French market) during the studied period. This data includes both impressions and clicks for direct display and programmatic campaigns. The summary statistics of this dataset are displayed in Table 5.3.

The third dataset includes tracking website data from Company B and Company C, both for their international websites and for their France market websites. In the case of Company B, the data includes daily website number of visits. In the case of Company C, the data gathered

Table 5.3: Summary statistics of digital campaigns included in the dataset

Campaign	Min value	Max value	Mean	Median	Std Dev
Direct Display Impressions	30	85244408	3476869	1864078	5370869
Direct Display Clicks	6	139596	16630	13968	15560.99
Programmatic Impressions	0	11043741	3120038	2533362	2369626
Programmatic Clicks	0	85591	8168	4314	12722.67

includes daily information of PvUv. Table 5.4 presents summary statistics of Company B. The summary statistics of Company C are presented in Table 5.5.

Table 5.4: Summary statistics daily number of visits for company B

Market	Min value	Max value	Mean	Median	Std Dev
France	284	3362	1903	1836	410.16
International	212	14970	6719	6648	1603.52

Table 5.5: Summary statistics of Company C's daily PvUv per country website included

Market	Min value	Max value	Mean	Median	Std Dev
France	1.373	3.274	2.499	2.551	0.4026213
International	1.951	3.508	2.873	2.904	0.2942917

The final dataset includes the French monthly trade sales volume index. Table 5.6 displays summary statistics of this dataset.

Table 5.6: Summary statistics of the monthly sales volume index

Variable	Min value	Max value	Mean	Median	Std Dev
Sales volume index	108.7	113.6	111.3	111.5	1.32

5.3.3 Results

Using the R package CausalImpact provided in Brodersen et al. (2015) to both the forecasting and the impact calculation, we obtain the absolute effect. This is, the difference between the real observed PvUv and the forecasted counterfactual value. During the post-intervention period, the PvUv had an average value of 4.63, while the forecasted value in the absence of an intervention was 3.99, (with 95% confidence interval values 3.72-4.30). Therefore, subtracting this prediction from the observed value, the causal effect of the intervention obtained is an increase of the daily average of 0.64 $[0.34, 0.91]$ page views per unique visitor. In relative terms, the PvUv showed an increase of +16% [+8%, +23%]. A summary of the obtained results is presented in Table 5.7.

The Bayesian posterior tail-area probability result is 0.00103. This number indicates that the probability of obtaining this result by chance is very small. Because of this, the causal effect is considered to be statistically significant.

Table 5.7: Summary of the obtained results for causal inference calculation

	Average Values	**Absolute effect**	**Relative effect**
Actual PvUv	4,63	0,64 [0.34,0.91]	+16%[8.4%,23%]
Predicted PvUv [CI 95%]	3,99 [3.72,4.30]		

However, it is important for the company to not only obtain the value of the causal effect of the new website design, but also to understand the evolution of this effect over time. Figure 5.2 presents the evolution of the forecasted and the observed PvUv. The actual measured values for daily page view per unique visitor are represented in black whereas the blue dashed line represents the predicted for this same metric (with the blue area being the confidence interval). The intervention date is represented with the dashed gray vertical line on 20th February, 2021. This graph shows how the effect of the new design is not completely sustained over time. Therefore, this can be an indicator that, even though there is an effect of the new design on the website performance, part of it can be due to a novelty effect (Kohavi et al., 2014). This is, including a new feature in a website has a combined impact, the impact of something new, which is (temporal and not sustained over time, and the real impact of the feature included, which tends to be sustained over time (Kohavi et al., 2009). In this case, the impact of releasing the new design of the website has been calculated to have an overall impact on the website performance, specifically in PvUv. However, we are not able to determine the proportion of this impact due to the novelty and the impact of the design itself.

5.4 Discussion and conclusions

Even if the general effectiveness of website personalization has already been proven in academia (Bleier and Eisenbeiss, 2015a), organizations are still not confident in their ability to capture the specific effect that personalization actions have in their websites (Kaptein et al., 2015; Kwon et al., 2010). This lack of evaluation fluency is seen as a potential obstacle for the extension of personalization effort in the industry (Gartner, 2019; Vesanen, 2007). Given the generalized need to explore and understand how to evaluate personalization, the research question of this study was:

RQ: How can we evaluate website personalization?

In order to answer this question, the nowadays most commonly applied website evaluation method (A/B testing) has been presented and described. Moreover, given that there are some specific cases where online controlled experiments can not be used, an alternative method has

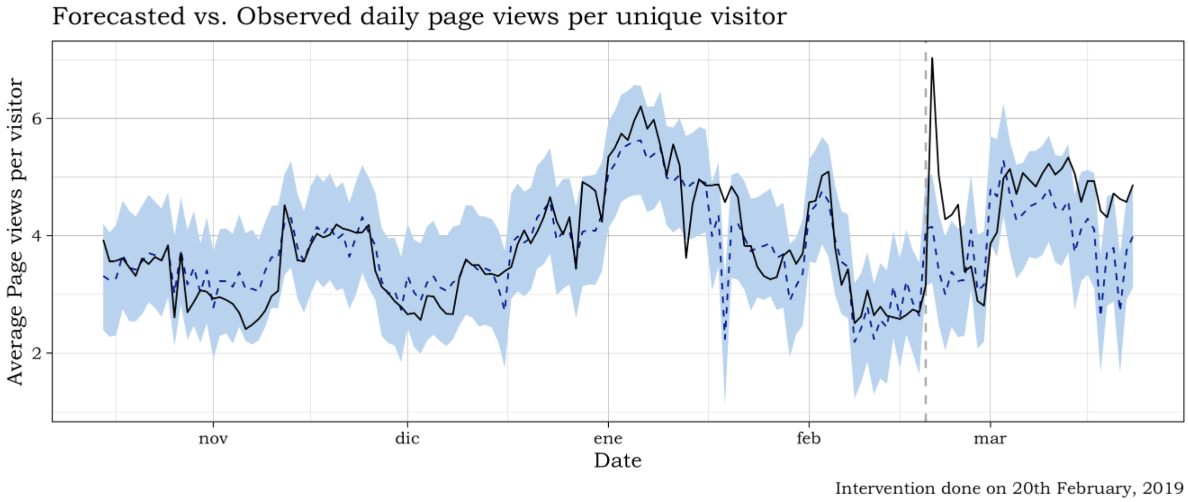

FIGURE 5.2. Evolution of the predicted and observed daily page view per unique visitor

also been introduced. As seen in the study, online controlled experiments are gaining increasing attention as evaluation methods for website general advances and website personalization (Govind, 2017; Letham et al., 2018). Given the simplicity of the A/B test concept, its use has been widely extended through the industry (Amatriain and Basilico, 2012b; Bakshy et al., 2014; Dmitriev et al., 2017; Knijnenburg, 2012). Accordingly both big and small companies are applying A/B tests as a scientifically grounded alternative to evaluate variations and compare different options in their websites (Amatriain and Basilico, 2012b; Bakshy et al., 2014; Deb et al., 2018; Deng et al., 2016; Dmitriev et al., 2016; Hohnhold et al., 2015). However, even if the fundamental idea of split testing can be considered simple, the wide variety of techniques, adaptations, statistical methods and testing tools to choose from has made A/B testing not always easy to be applied correctly by organizations in their website evaluation (Chen et al., 2019; Kohavi et al., 2009).Moreover, even if online controlled experimentation is already being used and recommended in the evaluation of personalization (Urban et al., 2016) and its effectiveness has been proven (Govind, 2017; Tu et al., 2021), not all authors agree on its direct use (i.e. without adaptation) (Liu et al., 2017). Accordingly, some A/B testing adaptations have been presented with the purpose of evaluating personalized features (Das and Ranganath, 2013; Hill et al., 2017).

In this study, we examined different approaches to evaluate web performance. To do so, we have used a variety of data sources including an academic literature review along with interviews to some companies currently performing A/B tests in their websites and a review of expert field companies online publications on the topic. As a result, we presented a guideline to implement online controlled experimentation on the website based on different data sources including both academia and industry experts. Additionally we describe some critical A/B testing pitfalls and assess whether these mistakes are recurrent in the automotive sector and in other sectors based on interviews. The results show that most of the respondent companies not experienced in experimentation do not have a clear procedure for the selection of their evaluation metrics, which is the starting point of an A/B test. Moreover, most of the surveyed companies (specially the ones from the automotive sector) directly apply winner results without further analysis of the test without further evaluation and two thirds of the interviewed companies are not aware of the multiple comparison problem and its possible corrections. After a decade of publications from expert practitioners and big digital companies, the most common and critical pitfalls are substantially well-documented. Despite this, our results show that some of these well-known experimentation pitfalls in academia are still present in the experimentation initiatives of companies relatively inexperienced with A/B testing.

However, this study has some limitations. First, the experimentation pitfalls commented in this paper are focused on traditionally industrial companies or other companies without expertise in A/B testing, therefore some pitfalls relevant for other sectors might be missing. Second, the total number of analyzed companies is not large enough to statistically determine the generalizability of each of the described experimentation pitfalls. Further research could extend the study to larger samples. Finally, this research is only focused on examining the state of website experimentation, being able to present a simple guideline and assess the presence of testing pitfalls across the industry. However, determining the causes why companies are still not confident in their ability to implement A/B testing and are unaware of some of the most common pitfalls was out of the scope of this study and could be addressed on further research.

Moreover, as previously discussed it is not always possible to run A/B tests as they might be expensive, time-consuming, at times unethical or even not feasible (Salimkumar et al., 2021). In these cases, other techniques, such as causal inference, can be used to estimate the effect of new features in the website (Goldenberg et al., 2021; Govind, 2017; Adam Kinney, 2019). Given its complexity and its applicability (i.e. recommended only when A/B tests can not be performed), causal inference is not so widely commented in marketing (Adam Kinney, 2019). However, it is widely discussed and applied in other fields such as economics and social sciences (Pearl, 2009).

In this chapter, we have also presented a case of causal inference to evaluate the website performance in a case where an online controlled experiment was not feasible. The presented causal inference method applied case was by no means a representation of the extensive and complex causal inference field. Given the lack of literature on this topic, further research is needed in the applicability of different causal inference methods to evaluate personalization actions.

In conclusion, the answer of the RQ proposed in this chapter, which focused on how to evaluate website personalization could be summarized with the following: when possible, website personalization should be evaluated by using online controlled experiments or specifically adapted methods based on those experiments. However, when it is not possible to use A/B tests, causal inference methods should be used instead.

Chapter 6

Organization readiness for personalization strategies

In this chapter we present the last study of this doctoral thesis. The content discussed in this chapter has been summarized and published in the *Journal of Industrial Engineering and Managment*, 'Towards Data-Driven Culture in a Spanish Automobile Manufacturer : A Case Study' (Esteller-Cucala et al., 2020b)

6.1 Introduction

As previously discussed in the present thesis, in order to start personalizing a website, an organization needs to understand what this concept means and evaluate how to implement this process by finding (1) the adequate user segmentation for their specific context and (2) how to assess the effect of personalization in their website. However, even after understanding these concepts, having a clear strategy and addressing the technical details of the implementation, most organizations are still not confident on their ability to implement personalization (Qualifio, 2019; Evergage, 2019; Boudet, Julien; Gregg, Brian; Rathje, Kathryn; Stein, Eli, Vollhardt, 2019). Implementing website personalization requires an organizational shift of mindset regarding the company-customer relationship but also the importance of data and how to rely on it for decision making (Forbes, 2019; Harvard Business Review Analytic Services, 2018; McKinsey&Company, 2018). Accordingly, organizations might need to perform internal, structural and cultural transformations in order to achieve real personalization in their websites (BVACCEL, 2020; Lazarova, 2020).

On the one hand, in the nowadays fast-changing world, organizations from almost any field have realized the critical need for digitalization in their businesses (Kohnke, 2016; Matt et al., 2015). Currently, digital transformation (also referred to as digitalization) is broadly understood through the so-called IT mega-trends which mainly include: analytics or big data, mobile device access and management, cloud computing, social media technologies and smart systems (Cray, 2014; Legner et al., 2017).Because of that, now organizations are required to make massive socio-technical transformations in order to move towards digitized business (Germanakos et al., 2021; Serrano-Cobos, 2016). These transformations, commonly known as digital transformations, include changes on their organizational structures, strategies, IT architectures, methods and business models (Legner et al., 2017; Matt et al., 2015). Data-driven agility, digital platform management and customer-partner engagement are some of the key areas that are subject to this substantial transformation when companies aim to go digital (Legner et al., 2017). Overall, today's users are presenting some challenges for organizations with their new demands including, among others, personalized interactions (Cay et al., 2019).

On the other hand, the automotive industry has traditionally been considered a competitive but relatively stable industry (Jacobides et al., 2015). This stability has been possible mainly because of the capital investment needs and the original equipment manufacturers' (OEMs') brand heritage that have historically represented notable barriers for new entrants to get into the market, ensuring classic OEMs' strong market position (Genzlinger et al., 2020). Therefore, automotive organizations have mainly focused their development and transformational efforts on their final product: vehicles (Lanzini, 2018; Singh et al., 2005). However, the conditions have changed. First, regarding the product, customers no longer perceive vehicles as isolated tangible goods, but as a service-objects that provide different value depending on their immediate needs (Covarrubias, 2018; Genzlinger et al., 2020; Hoeft, 2021b). Second, concerning the market competition, novel technologies (such as autonomous car) have changed the field, allowing new competitors to enter the automotive market (Perkins and Murmann, 2018). Third, regarding the OEMs clients, buyers not only demand products from providers but also improved customer-company relationships (Liu et al., 2021; Mourtzis et al., 2014). Finally, in regards to the organizations' context, digitalization has been pointed as one of the major trends transforming society and business and, therefore, featured as the strategic priority for science, industry and society (Knobbe and Proff, 2020; Legner et al., 2017; Parviainen et al., 2017). All of these four factors are driving OEMs to complete organizational reexaminations and transformation (Perkins and Murmann, 2018). Some authors describe this as 'the last automotive revolution' (Covarrubias, 2018; Hoeft, 2021a), predicting that companies unable to adapt to the new environment and to bring significant innovations to market quicker or more efficiently will be replaced by their competitors (Grieger and Ludwig, 2019).

In summary, in order to implant personalization, specific cultural changes in the organisations are needed (Serrano-Cobos, 2016). This transformation can range from the company's culture (e.g. decision-making culture) to structural organization change, including internal communications, working procedures and information organization and management (Knobbe and Proff, 2020). Companies will only be successful if they adapt to such increasingly changing business environment (Christopher, 2011; Wassner and Brebion, 2018). However, these cultural transformations are complex and most organizations fail (O'Reilly and Tushman, 2008). Moreover, even though companies of the automotive sector are now facing the so-called 'automotive revolution' they haven been traditionally known for their stability and cultural resistance to change (Genzlinger et al., 2020; Hoeft, 2021a).

Therefore, in order to fully understand how to implement personalization in an organization of the automotive sector, we first need to understand how companies in this sector manage to implement change. Taking this into account, the research question of this study can be formulated as:

RQ: Which are the potential factors that may affect the success of an organizational change in a company from the automotive sector?

This research question does not aim to point out overall challenges of the organization in order to understand the need for change (e.g. lack of understanding of the importance of data, lack of financial support for the transformation), but instead, to identify causes that may affect the success of a company (and their potential solutions) when already implementing a specific transformation.

6.2 Literature Review

As previously commented, in order to implement personalization in a company,Äôs website, becoming truly data-driven and adapting to the new digital environments is necessary. And this change requires a digital organizational transformation (Fabijan et al., 2017; SiteSpect, 2013). In order to make these changes more manageable, companies can address these transformations in the so-called 'incremental organizational changes' (Cao et al., 2000), which have different phases (Imran et al., 2016). However, since digital transformation strategies cut across various other strategies at the same time, complex coordination efforts are needed (Matt et al., 2015). Therefore, making the processes highly dependent on the context and far from intuitive, end up with companies facing considerable difficulties achieving organizational change (Attaran, 2000; Hughes, 2011; Imran et al., 2016). Because of that, and even if there is no agreement on the specific failure rate of organizational change, authors do agree on a significant failure rate in the implementation of these changes (Cândido and Santos, 2015; Hughes, 2011; Kotter, 2006; O'Reilly and Tushman, 2008).

One of the first known and most extended change models is the Lewin's organizational change model (Elrod and Tippett, 2002). This model describes change with a simplistic three phase model: Unfreeze, Move/Change and Freeze (Lewin, 1951). For a long time, from Lewin's model first presentation (Rashford and Coghlan, 1989) and especially since the mid 80s, a wave of practitioners presented their organizational change models or approaches (Johansson and Heide, 2008). Some of the most well-known ones are Bullock and Batten's four-phase model (Bullock and Batten, 1985), Kanter's ten commandments for executing change (Kanter et al., 1992) and Kotter's eight-stage model on how to manage change successfully (Kotter and Rathgeber, 2005; Kotter, 1996). However, these three models harmonize with the original idea of the unfreeze-change-freeze model, like most of the models presented after Lewin's one (Elrod and Tippett, 2002; Erwin and Garman, 2010; Johansson and Heide, 2008).

Knowing that the change process is not easy (Hughes, 2011) and given the extensive amount of existing organizational change models in the literature (Elrod and Tippett, 2002), selecting and applying a particular model to a specific organization are key factors in the success of the transformation (Imran et al., 2016). However, the application of a change model does not ensure the success of the organizational transformation and various authors have presented a wide variety of causes of failures of organizational change efforts (Appelbaum et al., 2017; Aslam et al., 2018).

After conducting an exhaustive literature review on the topic focusing on causes of change success (and failure), we identified seven key causes recurrently highlighted in the literature and often interconnected. The seven causes of organizational change failure frequently commented and studied in the literature are:

1. **Not following an organizational change procedure:** Organizational transformations are uneasy processes, and thus unsuccessful cases are commonly reported (Aslam et al., 2018). According to several authors, defining a methodology, alienating it with the business structure and executing it properly enhances the probability of a positive result (Attaran, 2000; Brisson-Banks, 2010; Rajan and Ganesan, 2017). Developing a road-map of the transformational process beforehand is considered a key factor for a successful transformation(Chrusciel and Field, 2006). This includes, not only to outline a management strategy, but to carefully detail the entire organizational change process/model to follow (Appelbaum et al., 2017; Galli, 2019). Moreover, this plan should include the need, context, intention and possibilities of the proposed transformation (Grieger and Ludwig, 2019).

2. **Not filling the knowledge gap:** Independently of how complete the change strategy is and how many details have been considered, transition can make the stakeholders feel uncomfortable and alarmed (Neely and Stolt, 2013). When there is a transformation within an organization, a gap of knowledge is generated, positions and roles might be changed and new abilities might be needed (such as new digital skills or learning how to use new tools). This scenario will inevitably generate uncertainty during the process (Virili and Ghiringhelli, 2021). Specifically, digital transformations or changes in the decision-making process can produce the shared belief within the team members that the team is not safe and this could be considered as part of the emotional response to change (Erwin and Garman, 2010; Grieger and Ludwig, 2019). It is essential for the success of the transformation to

make teams understand that they will need some learning (Fabijan et al., 2018b). Adequate training is the main solution for filling the knowledge gap (Imran et al., 2016; Vakola and Wilson, 2004). Users are required not only to adopt the transformation but also to support, understand and maintain it after the change process, therefore, they need to be effectively trained and provided with documentation (Wong et al., 2005). With it, building the needed capabilities (e.g. digital capabilities) is considered part of the change itself (Kohnke, 2016).Moreover, providing proper training is not enough to fill the knowledge gap and other actions are also required. Such actions include: providing the team with support at all stages of the change process, continuously monitoring the level of understanding of the initiative, creating a knowledge sharing-and-learning culture, fostering idea generation and encouraging competence and innovation (Aslam et al., 2018; Attaran, 2000).

3. **Failure to cope with resistance to change:** When planning an organization change, two key topics to be taken care of are employees' response to change and human-related factors (Erwin and Garman, 2010). Accordingly, those are the most studied failure causes in organizational transformation (Hamdi and Abouabdellah, 2018). Resistance to change, change cynicism and change anxiety are some of the main concerns for organizational change initiatives, as they can slow down or even terminate the transformation efforts (Appelbaum et al., 2018; Attaran, 2000; Erwin and Garman, 2010; Imran et al., 2016; Vakola and Wilson, 2004). Behavioral responses to change can be identified as supportive or resistant, active or passive and covert or overt (Bovey and Hede, 2001). Moreover, resistance to change is considered to be a multi-dimensional response including behavioral, cognitive and emotional dimensions (Piderit, 2000). This makes it a complex concept to be taken care of (Attaran, 2000; Erwin and Garman, 2010). Failure to cope with resistance to change is strongly correlated with failing to fill the knowledge gap as the lack of training might produce on employees the fear of being unable to perform in the new way, leading to a reluctant response to change (Martin et al., 2005a). Oppositely, self-efficacy (the feeling of being able to perform) and perception of personal gain might raise employees' willingness to welcome change (Aslam et al., 2018; Chrusciel and Field, 2006; Martin et al., 2005a). Moreover, if the employees perceive an alignment of change proposal with the organization's vision, they tend to be less resistant to the change (Appelbaum et al., 2017). As further explained in the following paragraphs, employees' resistance to change is also correlated with other success/failure factors (i.e. change readiness and management involvement).

4. **Lack of sense of urgency:** A significant proportion of the organizational change models described in the literature start with an unfreeze phase (especially the ones based on Lewin's model) (Elrod and Tippett, 2002; Erwin and Garman, 2010; Johansson and Heide, 2008; Kotter and Rathgeber, 2005). This phase mainly consists in generating a sense of urgency in the organization, which is considered equivalent to feeling motivation for the change and to intend to be prepared for the change (Martin et al., 2005a; Ouedraogo and

Ouakouak, 2018). This feeling of urgency should not be spread to the employees alone, but also to the team management (Antony and Banuelas, 2002; Kotter, 2006). This motivational attitude needs to be sensed by all the participants of the change and it should persist from the first planning phases up to the end of the transformation process (Soja, 2016). The lack of sense of urgency is one of the primary causes of failure of organizational change efforts (Aslam et al., 2018) and it is specifically significant and challenging for digital transformations (Kohnke, 2016). However, an excessive sense of urgency is considered to produce feeling of instability and uncertainty, which might end up leading to resistance to change (Genzlinger et al., 2020).

5. **Insufficient organizational readiness for change:** Readiness to change is a widely commented factor related to the unfreezing phase (Aslam et al., 2018). The readiness for change comprises both the beliefs about the need for change (its benefits and implications) and the positive thoughts regarding the change itself (Aslam et al., 2018; Imran et al., 2016). Although this factor might seem similar to the sense of urgency, readiness for change is more deeply connected with the previously existing organization culture: attention to the teams' psychological responses, sharing of information, trust and teamwork (Brisson-Banks, 2010; Kohnke, 2016). The organization structure beforehand plays a critical role in the company's readiness change and, thus, in the likelihood of change success (Antony and Banuelas, 2002; Soja, 2016). For example, flat (i.e. non-hierarchical) organizations are more familiar with open communication channels and tend to facilitate participation in decision-making, easing the transformation processes, whereas hierarchical and complex organizations with strong dependence on third parties and external factors face more difficulties to implement change (Jacobides et al., 2015; Vakola and Wilson, 2004). Moreover, the culture of dynamic adaptability, contiguous innovation and internal collaboration are found to be core drivers of change success (Knobbe and Proff, 2020; Long et al., 2018). Additionally, it is not only the actual readiness for change of the company but the staff's perception of this readiness to cope with change that has a critical effect on the process (Chrusciel and Field, 2006).

6. **Insufficient management support and involvement:** Relevant changes require determined leadership, therefore, real involvement from the management positions in the process is critical for the success of the change effort (Aslam et al., 2018; Attaran, 2000; Genzlinger et al., 2020; Hoeft, 2021b; Widianto et al., 2021; Wong et al., 2005). The viewpoint taken from management towards the change has an impact on the success not only because of the management‚Äôs authority itself but also because managers' attitudes induce employees' positive disposition towards change and boost their level of commitment (Martin et al., 2005a). Even though the actual managerial support (i.e. resources dedicated, communication efforts, empowerment of the leading team) and involvement (stakeholders conflicts resolution, task prioritization and monitoring, internal leadership through the process) are critical factors to be taken care of (Alsulami et al., 2013; Kohnke, 2016), part of

the effect of these actions relies on how they are perceived by the team (Appelbaum et al., 2017). Employees perceiving enthusiasm and coherent vision for the change in their leaders or managers tend to manifest more positive attitudes and commitment and less resistance to change (Kohnke, 2016; Martin et al., 2005a). Moreover, consistency between managerial actions and the change proposal, drives organizational trust (Erwin and Garman, 2010). Consequently, the management support and involvement in the change process needs to be visible, consistent, overt and continued (Venugopal and Suryaprakasa Rao, 2011). In this regard, many authors emphasize the risk of insufficient management support particularly in the case of digitalization (Genzlinger et al., 2020; Hoeft, 2021a; Knobbe and Proff, 2020). Because of that, it is important for managers to legitimize the transformation plan also in terms of time, money and effort in order to prevent employees to feel fearful of their self-efficacy temporary loss (i.e. employees need to feel that losing efficacy in their work because of the change will be accepted by the management) (Neely and Stolt, 2013).

7. **Lack of or ineffective communication:** The role of communication in organizational transformation processes is one of the most commented factors in the literature (Johansson and Heide, 2008). Given the extensive amount of literature on communication and its effects in organizational change, this factor has been analyzed from different perspectives. First, the existent communication culture before the transformation (i.e. communication with immediate supervisors, communication frequency and information sharing) is known to have both direct and indirect effects on the change process (e.g. by affecting commitment to change, readiness for change and job satisfaction) (Attaran, 2000; Martin et al., 2005a). At the first stages of the change process itself, fluent communication is needed in order for all the involved employees to understand and share the goals, vision and processes of transformation (Ouedraogo and Ouakouak, 2018; Venugopal and Suryaprakasa Rao, 2011). Moreover, during the transformation, communication efforts have an effect on the teams' commitment, perception of situational control and trust (Appelbaum et al., 2017; Martin et al., 2005a; Vakola and Wilson, 2004). Finally, during the whole process, keeping an constant flow of communication and empowering teams' input and feedback (i.e. bidirectional communication) promotes acceptance of the change, gives employees the opportunity to actively contribute to the change and increases productivity (Brisson-Banks, 2010; Martin et al., 2005a; Rivasseau, 2019b). Accordingly, and given the importance of communication in the final result of organizational changes, some authors are analyzing the effect of new variation such as inclusion of new communication channels (e.g. social media) or the use extensive communications (e.g. creating general awareness of the importance of digitalization) (Aslam et al., 2018; Kohnke, 2016).

During our exhaustive literature review, other factors for the organizational change success (or failure) have also been identified. Some examples are: the extent and turbulence of the change (i.e. how significant is the change and many people are involved) and how close is the change to the core business of the organization (e.g. affecting the core business or introducing secondary activities), however both have an undetermined effect on the change result (Antony and Banuelas, 2002; Appelbaum et al., 2017; Grieger and Ludwig, 2019; Mourtzis et al., 2014). Another example is the effect of external influences or events (e.g. supplier attitudes or governmental regulations), this factor has been found to be one of the primary motivations for change (i.e. the change is made motivated by external events), but also to have major impact on the transformation process outcome (Antony and Banuelas, 2002; Covarrubias, 2018; Hoeft, 2021b; Long et al., 2018; Peters et al., 2016; Perkins and Murmann, 2018). Moreover, specific internal practices, such as having a tracking system to monitor the transformation results and determine anchoring points, has been shown to have a positive impact on the change result (Antony and Banuelas, 2002; Fui-Hoon Nah et al., 2001; Soja, 2016).

6.3 Methodology

In order to answer the RQ of this study we used a case study approach (Yin, 2002). Case studies are particularly useful to provide greater insights on contemporary problems when the boundaries between the phenomenon and its context are not clearly evident (Perna et al., 2018; Yin, 2003). As we want to explore a situation in which the set of outcomes is not clear (i.e. the type of results are not clear beforehand), the specific method used is an exploratory case study (Baxter and Jack, 2008). Our case selection criterion was a traditional company of the automotive sector currently performing a digitization process.

At the time of the study, the analyzed organization was planning its digitalization process with a series of different initiatives and approaches, one of them being the transformation of their decision-making process. This case study is centered on the change of this decision-making process switching from traditional intuition-driven decision making model to a data-driven model in the websites' management team. To that end, it was planned to introduce data-driven user-feedback in the decision-making by adopting continuous online controlled experimentation (A/B testing). With the adoption of online controlled experiments, proposed changes or questions should always be structured and treated as experiments (Fabijan et al., 2018a; SiteSpect, 2013). Therefore, the decision-making switches from opinions based on previous experience to a scientific data-driven process directly (based on users) (Crook et al., 2009; Kohavi et al., 2009; Spear, 2004; Kohavi et al., 2007). As previously discussed, even if they are currently facing a change of mindset, OEMs have historically been process-oriented organizations mainly centered on the quality and manufacturing of their main product, in our case vehicles (Covarrubias, 2018; Genzlinger et al., 2020; Grieger and Ludwig, 2019). Accordingly, the team involved in this case study, despite being a digital team focused on software products, is part of an OEM, and thus played a critical role in the processes and decision-making procedures for the development of the website. By the end of this study, the decision-making initiative within the websites' management team was still ongoing, the duration of which had been 1.5 years and all the teams related to the planning, design, development, operation and use of the organization's external websites (i.e. excluding internal HR websites and intranets) had been involved.

After selecting the case study, a protocol to conduct this study was developed accordingly. This protocol contained, among others, the details about scope of the project, the study objectives, the profile of interview respondents and the corresponding data collection and analysis. Data collection comprised four out of the six main case study sources of evidence for case studies research (Yin, 2003), namely:

a. Participant-observation. During the time of the study two of the researchers were employees in the company, one of them in a managerial position and the other one directly involved in the case study project. Therefore, the data collection was based on action research.

b. Unstructured interviews. Non-directive interviews were selected in order to gather more details about the employees' perception and thoughts during the change.

c. Project documentation. The project documentation includes documents generated within the scope of the project and also materials used for organizational communication were included in the analysis.

d. Project communications. In order to track the formal project progress communications, written information (including meeting minutes and email records) were collected.

The results obtained in the project have been analyzed and compared with those existing in the literature in order to discuss the resulting conclusions. Figure 6.1 indicates the steps of the methodological procedure conducted in this research. The general procedure is represented by grey boxes (steps) linked by arrows, additional information specific to this case is included in white boxes.

6.4 Case description

The context of the case is the websites' management team inside an organization of the automotive sector. The participants of this project can be classified in different groups, each of them including from managerial roles to workforce employees. In this company, websites' management team is organized around their two main products: (1) the master website, a template of the website used by market local teams to generate their websites by adapting the content to each market needs and specifications, which is not visible to the final user and (2) the customer websites, which are the set of final websites that users can access. There is only one master website and more than 40 customer websites. Figure 6.2 shows the approximate diagram of the stakeholders' landscape. As shown in the figure, there is not overall communication nor coordination between teams. Moreover, some teams have 'external collaborator agencies' (e.g. the central data team works

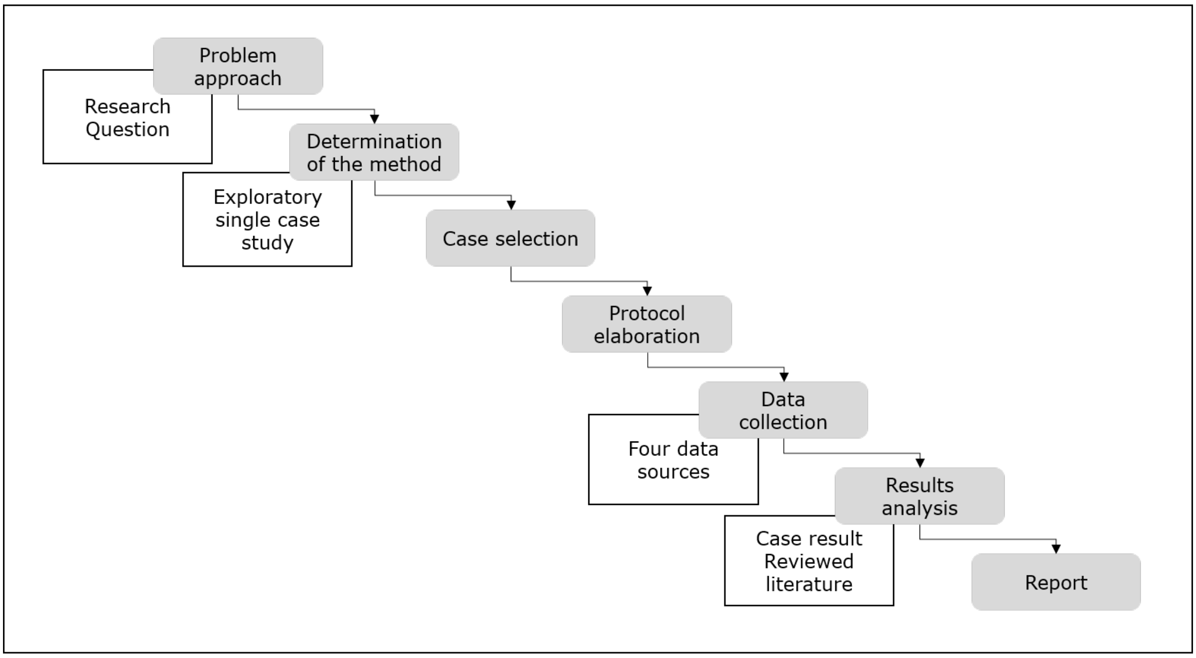

FIGURE 6.1. Methodological procedure followed in the study. Figure published in Esteller-Cucala et al. (2020b)

with an external analytic team also included in the project), however, the external collaborator agencies do not interact with the rest of the teams.

With the given network of collaborations and communications, including teams located in different countries, the organizational change needed to transform the decision making from intuition-driven to data-driven was considered a complex transformation. Therefore, in order to maximize its success, the 7 identified causes for change failure commented in the literature (section 6.2 of this chapter) were considered before starting the transformation planning.

According to the first listed failure cause (not following an organizational change procedure), the earliest decision of the planning was to follow an organizational change model process.

The initial consideration was to use Lewin's 3 step framework due to its simplicity (Lewin, 1951). However, finding a practical guide on how to apply the model (i.e. knowing exactly what to do) was not possible. Consequently, the team decided to go for a more business-oriented model and, if possible, based on Lewin's principles. As previously discussed, there is a wide variety of organizational change models based on Lewin's unfreeze-move-freeze model (Elrod and Tippett, 2002). Therefore, new selection criteria for the model were added. These new criteria required the model to be top-down (according to the nature of the project), to be valid for small project scopes (because this change was only affecting the website-related departments instead of the entire organization) and to have special focus on team involvement and communication (taking into consideration the list of failure causes). With all of this in mind the chosen framework was

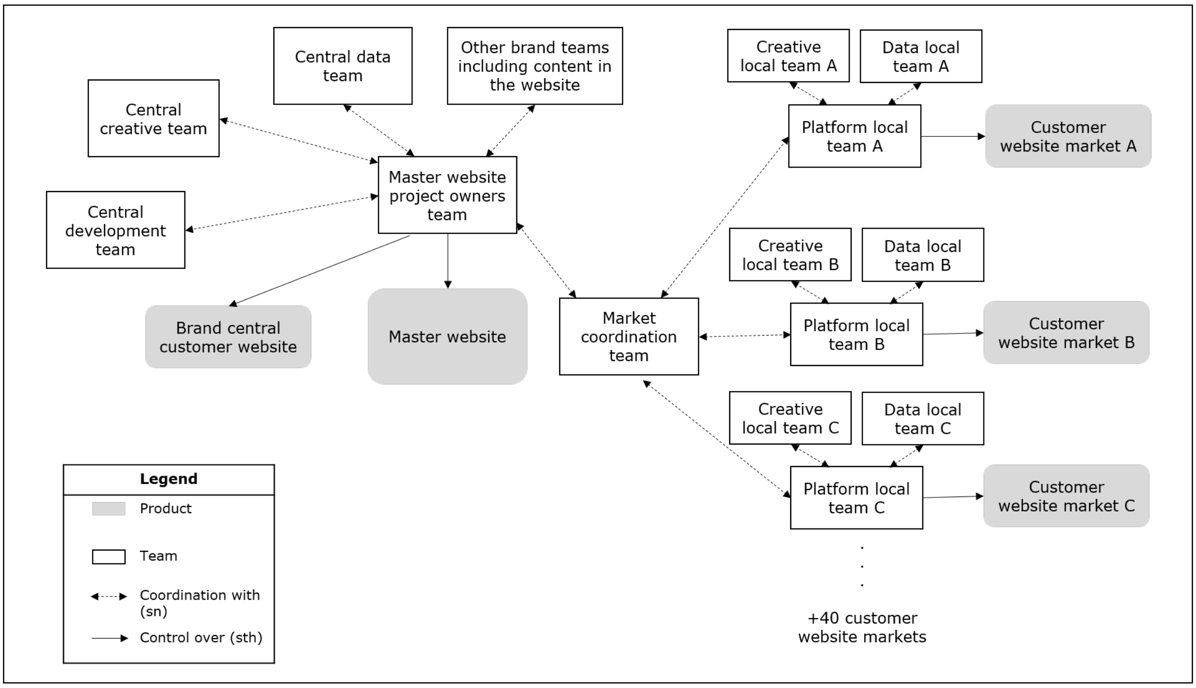

FIGURE 6.2. Approximate diagram of the organization sub-teams involved in the organizational change of the case study. Figure published in Esteller-Cucala et al. (2020b)

Kotter's eight-stage model (Kotter and Rathgeber, 2005; Kotter, 1996).

After selecting the framework, the team strictly followed Kotter and Rathgeber's eight steps described in the model. In summary, the organizational change performed in this project followed the following order/steps::

Step 1. Establish a sense of urgency: In order to convince the team of the need of change, three main arguments were used:

a. Website experimentation is already implemented in other companies

b. Intuition or expertise-driven decisions are one of the main causes of discussion between teams

c. Website experimentation includes the user in the decision making

Step 2. Form a powerful guiding coalition: Direct management created and supported a group that included members from project-owners, creative and data central teams.

Step 3. Create a vision: The shared vision created aimed to (1) base the decisions on users' data, (2) improve collaboration between teams and (3) reflect transparency in the decision making.

Step 4. Communicate the vision: In order to effectively communicate the vision, different actions were made:

a. Documentation and training was made accessible to all involved teams.

b. The guiding team actively communicated their willingness to train, support and solve questions.

Step 5. Empower others to act on the vision: Non-technical training manuals and templates were created including guidance for hypothesis generation, test planning, interpretation of the obtained results and definition of the most common vocabulary. Also, the processes were designed considering the autonomy of local teams and the testing tool access was shared to all teams who required it.

Step 6. Plan for and create short term wins: During the second month of the project the guiding team leaded the creation of some experiments. The results obtained were extensively shared and explained.

Step 7. Consolidate improvements and produce more change: In order to consolidate improvements and follow with the change motivation, three main actions were taken:

a. The first experiments were reproduced in other markets

b. Website developments were based on test results only

c. A fortnightly global communication was scheduled to share experiments generated and their results

Step 8. Institutionalize new approaches: At the end of this project, the team was working on the follow-up strategy.

6.5 Results and discussion

Once the framework model was selected and accepted (Kotter and Rathgeber's eight steps model), different risks were predicted to affect each of the steps based on the literature (see 7 most commented failure factors in section 6.2 of this chapter).

After reviewing the information from the different sources commented, we present the results obtained, for each of the 8 steps followed. For each of the steps, the predicted risks, the action taken by the team in order to minimize each risk and the finally in fact detected risks are described:

Step 0. Before starting the first step:

Predicted risks and mitigation actions planned

- Not following an organizational change procedure (Appelbaum et al., 2017). To mitigate this risk, the team decided to select and follow Kotter's eight-stage model (Kotter, 1996).
- Insufficient organizational readiness for change. The structural complexity of teams, the internationally scattered locations, the linguistic barrier and the different skilled roles involved in the project were seen as barriers for the readiness for change (Aslam et al., 2018; Imran et al., 2016; Jacobides et al., 2015). However, the team considered that those factors were rooted in the organization and no mitigation actions were taken for this risk.

Step 1. Establish a sense of urgency:

Predicted risks and mitigation actions planned

- Lack of sense of urgency. Some teams were already experimenting in their local websites, whilst other teams were established in the old decision-making culture, therefore, the actual risk was not the complete lack but the disparity of sense of urgency (Aslam et al., 2018). This risk is considered to be especially relevant for digital transformations (Kohnke, 2016). In order to mitigate the risk and equalize the differences between teams' motivation, the initiative was presented to all the teams in an event where they were all physically together (instead of individualized and online communications), and hence promoting communication and connection between teams from different countries.

Detected risks

- Despite the prediction, no notifiable risks were detected at this stage of the project.

Step 2. Form a powerful guiding coalition:

Predicted risks and mitigation actions planned

- Insufficient organizational readiness for change. The vertical structure of the organization was considered a potential risk for the collaboration of the different members of the guiding coalition (Kotter, 2006; Vakola and Wilson, 2004).However, the team considered that there was no need for mitigation actions.
- Insufficient management support and involvement. Even if the management stood behind the project and the guiding coalition, local teams needed to perceive this support in order to follow the guiding coalition (Appelbaum et al., 2017; Attaran, 2000). In order to minimize this risk, both the project and the guiding coalition were introduced by managers who also led the 'kick-off' meeting.

Detected risks

- At this stage of the project, no risks were detected to have any effect (neither the predicted nor unexpected ones).

Step 3. Create a vision:

Predicted risks and mitigation actions planned

- Failure to cope with resistance to change. The vision may generate negative responses if perceived by the team as too complex, vaguely defined or not aligned with the general company vision (Appelbaum et al., 2017; Kotter, 2006). However, apart from trying to define a clear vision aligned with the company, no actions were taken to mitigate this risk.

Detected risks

- No risks were detected at this stage as the vision and the proposal was welcomed among most teams' members.

Step 4. Communicate the vision:

Predicted risks and mitigation actions planned

- Not filling the knowledge gap. Both the lack of experimentation skills and the individual perception of this knowledge gap are some of the main risks to be considered in digital transformations (Kohnke, 2016; Martin et al., 2005a). According to this risk, the communication initiatives were carefully selected and planned by the team in order to make understand and share the vision behind the change initiative.
- Lack of or ineffective communication. In order to mobilize the organization for the change, encourage feedback and make the involved teams feel that they are an active part of the change, special communication efforts are needed (Appelbaum et al., 2017; Brisson-Banks, 2010; Kohnke, 2016; Kotter, 2006). In order to mitigate this risk, the guiding team focused on the open by-directional communication with all the teams involved.

Detected risks

- Even though the communication efforts were perceived as positive by most of the involved employees, the first signals of resistance to change were detected at this stage.

Step 5. Empower others to act on the vision:

Predicted risks and mitigation actions planned

- Not filling the knowledge gap. Teams not feeling prepared to start experimenting by themselves was one of the main risks (Wong et al., 2005). In order to mitigate this risk, specific documentation was generated and distributed to all involved teams. Moreover, all processes were adapted to different skills and autonomy levels.
- Failure to cope with resistance to change. Testing ideas by experimentation instead of making decisions based on intuition of previous experiences can generate psychological insecurity within employees as their ideas could then be proven wrong (Fabijan et al., 2018b). In order to mitigate this risk, the communication was focused on the benefit of testing and descanting ideas that might cause a bad user experience compared to implementing them based on intuition without previous testing.

Detected risks

- Because of the lack of experience on website experimentation and the fear of failure, some teams proposed only tests based on small changes and visible for a small number visitors. Those experiments ended up as 'inconclusive' given the small number of visitors and the almost negligible changes, this had a lowering effect on the motivation.

Step 6. Plan for and create short term wins:

Predicted risks and mitigation actions planned

- Lack of sense of urgency (motivation). Short-term wins are important for the success of the change initiative, however, they do not have less individual impact than the whole transformation process (Kotter, 2006). Consequently, short-term wins entail the risk of not copping with the expectations generated with the vision producing reduction in motivation (Martin et al., 2005a; Ouedraogo and Ouakouak, 2018; Venugopal and Suryaprakasa Rao, 2011). This risk was mitigated by intensifying communication efforts.
- Lack of or ineffective communication. Along with the previous risk, both over-communication and under-communication of the short-term wins can have a negative impact on the team motivation (Appelbaum et al., 2017; Martin et al., 2005a; Vakola and Wilson, 2004). In order to mitigate both risks, the decision was to extensively communicate all short-term wins.

Detected risks

- Once the first short-term wins were presented, part of the management considered it an indication of the project being finished or under control and so they involvement started to decrease. This risk had not been predicted based on the literature, but it was detected during the project observation and the interviews. However, this was not detected to have an impact on employees' motivation at this stage of the process.

Step 7. Consolidate improvements and produce more change:

Predicted risks and mitigation actions planned

- Not filling the knowledge gap. At this stage of the organization change, if the knowledge gap has not been closed, teams might not be self-sufficient to keep the transformation once the process ends (Wong et al., 2005). In order to mitigate this risk, the guiding coalition kept communicating, supporting and training the teams involved.
- Lack of or ineffective communication. At this step of the process there is a need for the guiding coalition to communicate acknowledging the accomplishments gotten so far without suggesting that the process is over, as it could reduce the motivation (Kotter, 2006). In order to mitigate this risk the guiding coalition started a new fortnightly communication of experiments planned, active and finished, including all results obtained. This communication was shown to have a positive impact, as it motivated local markets to start adopting the new decision-making model.
- Failure to cope with resistance to change. At this stage of the process, passive or covert resistance to change can have a determinant impact on the final result of the transformation effort (Attaran, 2000; Bovey and Hede, 2001; Imran et al., 2016). No mitigation actions were performed in this case.

Detected risks

- Not filling the knowledge gap. As predicted, the notable difference between totally autonomous teams and the ones still needing notable support to perform experiments in their websites represented a risk for the success of the transformation. At this point, the excess of non-autonomous teams was at risk of collapsing the guiding coalition, as they were not able to give support to every team requiring assistance. Moreover, the initiative was not expanding as expected to new local teams.
- Failure to cope with resistance to change. As predicted, this risk started to have an impact on the change result. At the time of this step of the process the organization faced a peak of work (not related with the initiative) affecting all the websites' management teams. The local teams already engaged with the new decision-making process continued experimenting. However, some of the local teams that had previously shown passive acceptance of the transformation started trying to go back to intuition/experience driven decision-making model, and hence discarding experimentation.

Step 8. Institutionalize new approaches: At the end of this project, this was an ongoing step planning to be mid- or long-term. Therefore, not there were no risks predicted or detected yet.

Table 6.1 presents a summary of the results obtained, including the predicted, mitigated and actually detected failure factors in each step of the followed process.

Table 6.1: Summary of failure factors predicted, mitigated and detected as risks for the organizational change in each step of the change process

Failure factor	Step 0	Step 1	Step 2	Step 3	Step 4	Step 5	Step 6	Step 7	General
1. Lack of change framework	PM								
2. Knowledge gap					PM	PM		PM-D	D
3. Resistance to change				P	D	PM		P-D	
4. Lack of sense of urgency		PM				D	PM		
5. Insufficient readiness	P		P						
6. Insufficient management support			PM				D		
7. Lack of communication					PM		PM	PM	D

P = Predicted as risk; PM = Predicted and Mitigation actions applied; D = Detected as an actual risk

Additionally, other non-predicted risks for the success of the organizational change initiative were also detected but not specifically related to any particular step of the process.

On the one hand, even if the risks 'ineffective communication' and 'not filling the knowledge gap' were thoughtfully worked on during the whole process, it was not enough to cope with the communication and training needs of all the team-members involved. In order to engage as many local teams as possible in the initiative, and paying special attention to the less autonomous ones, the communication and training provided was as simplified as possible. This was found to be too simplistic to be relevant for the most advanced local teams, which were engaged with the vision of the transformation but ended up being unattached to the process and to the guiding coalition.

On the other hand, some other risks not so extensively commented in the literature were detected. In first place, it was not possible to track the results of the organizational change because there were not objective performance indicators defined. This risk is related to losing management support and team members motivation (Fui-Hoon Nah et al., 2001; Soja, 2016). In second place, there were not anchoring points provided during the process (Appelbaum et al., 2018; Kotter, 2006), therefore, the sudden risks detected during the 7th step of the process presented a risk for the global success of the change effort. In third place, because of the focus on the transformation itself (process followed, risks predicted, mitigation actions, etc.), the vision of the process was sometimes lost and this could have caused a decrease of motivation within the teams (Ouedraogo and Ouakouak, 2018). Finally, some resistance to change was difficult to detect as some teams were using the new procedures to cover their old practices. This is, experiments were designed to obtain the desired results in order to validate their pre-made decisions based on intuition.

Finally, as seen by our results, even if some of the failure factors from the literature were detected as risks for the transformation, they only had a moderate negative effect on the change result. This could possibly be due to the awareness about these risks beforehand. Moreover, some authors agree that not only following an organizational change procedure, but also planning ahead and considering all potential risks (and their mitigation actions) might have a positive impact on the final results (Hamdi and Abouabdellah, 2018). Moreover, no mitigation actions were taken to each of the risks predicted and this did not seem to have a detectable effect on the process. According to the literature, a possible answer to this is the interrelated effects between the different failure factors, where ones can moderate the effect of the others' (Aslam et al., 2018; Ouedraogo and Ouakouak, 2018). However, the exact effect that some factors have on the others or even if this effect is positive or negative has not been clarified yet.

According to the literature, all the seven studied factors were common risk factors in organizational change processes and most of them were actually detected during the project. Nevertheless, none of them were detected until the second half of the process (measured in steps). This could be due to the lack of ability to diagnose those risks, meaning that the risk could be present in earlier steps of the process but remain undetected (Long et al., 2018). The inability to detect risks in the early stages of the process could be a risk for the transformation itself. Moreover, even if the company was aware of the risks obtained from the literature, there was not conclusive information on how to detect them or on how to mitigate them.

For these reasons, we suggest that future research could address not only the failure factors or risks for the transformation processes as independent factors but also the interconnections and cross-effects between them. Furthermore, more research is needed in order to know how to detect those failure factors and how to manage them so as to minimize their negative effects. Finally, we identified a notable unbalance between failure and success factors analyzed in the literature, and this could also be addressed by future research as they could potentially be used to boost the success chances of organizational changes or even lower the negative effects of some of the failure factors.

Finally, an organizational change process is highly context dependent, being affected not only by the specific organization or the teams involved, but also by the specific time and other projects affecting to the same team members (Imran et al., 2016; Jansson, 2013). Therefore, the results obtained in this research are limited to the specific case study and generalizations can only be made cautiously.

In conclusion, given the case study presented in this chapter we can use it to answer the research question of this study:

RQ: Which are the potential factors that may affect the success of an organizational change in a company from the automotive sector?

Answer: Based on the literature, there are several factors that can affect (positively or negatively) the result of an organizational change. Among them, there is a list of seven failure factors that have been given special attention in the literature (not following an organizational change procedure, not filling the knowledge gap, failing to cope with resistance to change, lack of sense of urgency, insufficient organizational readiness for change, insufficient management support and involvement and lack of or ineffective communication). However, an organizational change is a highly context-specific process (i.e. can be affected by the company, the team, the change itself, the timing, etc.). Therefore, even if it is important to have a list of potential factors affecting the organizational change, it is critical to study and plan the process for each independent case.

6.6 Conclusions

In order to include personalization in a website, the organization needs to be digital and reliant on users' data. In addition, data-driven decision-making is a growing trend and lots of companies are already adopting it. However, the organizational transformation needed is not always manageable and it remains hard for traditional corporations to integrate data in their day-to-day culture. Moreover, traditional companies from the automotive sector have been distinguished as not moving fast enough towards digitalization.

In this study, we identified the potential problems that may arise during the organizational change (from traditional to data-driven decision-making model) in a real organization from the automotive sector once the team knows beforehand the most commented failure factors in the literature. By doing so, this study contributes both to theoretical and practical research in the field by offering a vision of how organizations address this kind of digital transformations in practice.

On the one hand, this study shows organizational change failure factors extensively studied that might not represent a high risk once the company is aware of them and, in some cases, tries to mitigate them. In the present chapter, a literature review on organizational change has been presented. With it, the most commented causes for organizational change failure by researchers have been discussed (not following an organizational change procedure, not filling the knowledge gap, failing to cope with resistance to change, lack of sense of urgency, insufficient organizational readiness for change, insufficient management support and involvement and lack of or ineffective communication). The case study has been analyzed with special attention on these risks. However, not all of the commented factors had a noticeable effect on the process.

On the other hand, the study also shows how some of the failure factors, even being predicted to appear, were not detected until the final stages of the process. Although the company intended to have a solid plan for the organizational transformation, they found it difficult to predict the specific risks of each step of the process and to plan mitigation actions. There is no shortage of literature on success and failure causes of organizational change but mapping them in a real change process is not an easy task for practitioners.

Finally, as a case study research approach, the main limitation of this paper is the inability to offer a generalized picture of the phenomenon. Furthermore, given the high contextual dependence of organizational transformations, the result of this study cannot be taken as a closed final conclusion for different cases. Therefore, in order to validate the results obtained in this case, and to further explain the potential problems that may threaten the success of organizational change initiatives, future work could be replicated in similar case companies (digitalization within traditional industrial companies).

In conclusion, this study adds to the existing literature and points up the need for further research in the area of organizational change.

Chapter 7

Final discussion and conclusions

Personalization, and especially website personalization, are completely integrated practices in some big technology companies (Kardan and Roshanzamir, 2012). Accordingly, customers no longer see website personalization as an advantage but as an expected commodity (Boudet, Julien; Gregg, Brian; Rathje, Kathryn; Stein, Eli, Vollhardt, 2019; Harvard Business Review Analytic Services, 2018; Goldenberg et al., 2021; Fenech, Céline; Perkins, 2015; SmartFocust, 2014). As a consequence, despite the fact that website personalization is conceptually and technically complex, in the last few years, the interest in implementing it has spread to companies from almost any sector (Accenture Interactive, 2018; Christian Thomson, 2019; Gregg et al., 2016). However, this expansion to other sectors has become more challenging than anticipated (Kardan and Roshanzamir, 2012; Tuzhilin, 2009). And, some authors already predict that, as a result of the frustration driven from not being able to effectively implement website personalization, these efforts will be massively abandoned by most companies (Gartner, 2019; Kaneko et al., 2018b).

In conclusion, there is a research gap in addressing how website personalization can be expanded from the big tech organization to companies from other sectors. In order to help fill this gap, we present a research which aims at studying the implementation of website personalization in a company of the automotive industry, as this type of company exemplifies a business with long industrial tradition previous to the era of digitalization.

Aiming to obtain a global vision of the problem, we have divided our research into four main studies, each of which represents a fundamental component in the adoption of website personalization in the organization. In this section, we summarize the main discussion, contributions and limitations of each of the presented studies in this research.

A broader concept of personalization

In first place, in order to adopt website personalization initiatives, companies need to understand what personalization really means. Since the beginning of the topic, personalization has attracted the attention of a diversified group of fields and it has been addressed from a variety of viewpoints (Fan and Poole, 2006). Consequently, the concept of personalization is used to cover a wide range of ideas meaning something different to each research field and there is no basis of knowledge for mutual understanding among fields (Blasco-Arcas et al., 2014; Riecken, 2000). Moreover, given that each area of investigation had a different research agenda and assumptions, some key aspects of personalization have been overlooked (Kwon et al., 2010). Additionally, this is not only affecting the research development of the topic but also its implementation in the industry (Tuzhilin, 2009; Sunikka and Bragge, 2012). Therefore, a cross-domain understanding of the personalization concept is needed (Vesanen and Raulas, 2006). With the presented framework we aimed to fill this gap.

In order to fill this gap, a cross-field review of the literature. As a result, a personalization framework has been presented. The novel personalization framework introduced in this study presents the concept of personalization not as a unique closed term, but as a versatile idea conformed by the variation of seven dimensions. As discussed in chapter 3 (*A broader concept of personalization*), the framework presented is consistent with both previous personalization frameworks and classifications from different research fields. Additionally, in accordance with the presented framework, we propose a general definition for the term personalization. Moreover, we present the definitions of some of the most used terms within the personalization topic.

As commented in chapter 3, the main contribution of this research is the proposal of a research framework applicable to different research fields.

The presented framework and resulting definitions (both for personalization and other personalization-related terms) do not have the objective to be established as a standard. Instead, it aims to be a tool for mutual understanding on the topic of personalization across research fields. This contribution to the mutual understanding from the different fields represents a gain in the transversal visibility of personalization and its now field-isolated advances, which may also help easing the cross-field identification of research gaps yet to be solved (Arora et al., 2008; Riecken, 2000)..

The final contribution of this personalization framework is related to the evaluation of personalization. As previously discussed, trying to measure personalization effects considering it as a whole regardless of the specific personalization strategy used (i.e. evaluating 'personalization' vs 'no-personalization') drives to inconsistent results Kalaignanam et al. (2018); Thirumalai and Sinha (2013). Therefore, in measuring personalization effects, each dimension needs to be considered and evaluated separately, and the specific set of dimension options effective for a specific case will not necessarily be valid for other scenarios (Kwon and Kim, 2012; Tuzhilin, 2009). The proposed framework identifies the different dimensions compressing personalization, therefore, easing the measurement of personalization effectiveness when considering the dimensions independently.

Finding persons: audience segmentations

In second place, once the concept of personalization has been analyzed and a description of the term *personalization* has been provided. In order to apply website personalization, the second fundamental need is to know what users want (Kramer et al., 2000).

In order to understand the users' needs and preferences, both scholars and organizations have historically used market segmentation (Florez-Lopez and Ramon-Jeronimo, 2009; Hassan and Craft, 2003; Lieberman, 2016; Prashar et al., 2016; Smith, 1956). Consequently, one of the bases of website personalization is website audience segmentation (Fan and Poole, 2006; Mobasher et al., 2000; Simkin, 2005; Slaninová et al., 2010). However, website segmentation is highly context dependent and, unfortunately, some companies still fail at considering the context of their segmentation activities which might result in time, efforts and business opportunity losses (Bijmolt et al., 2010; Webber, 2011).

Accordingly, the second study of this research, presented in chapter 4 (*Finding persons: audience segmentations*), focuses on website audience segmentation. The presented research includes an analysis of different segmentation criteria assessing their effectiveness to be both informative of the users preferences and to be used for website personalization. Moreover, within this research, we presented a new variable based on two segmentation criteria highly recommended in the literature (the RFM model and the 'Customer Journey'), and we further assess its potential to be used in web personalization.

The results show that, for the given website, none of the tested segmentation criteria is informative enough to be used for the personalization strategy selected by the company (i.e. system-driven personalization able to forecast the preferred website section for the user at any given time of the navigation without explicitly asking it to the user). However, some conclusions can still be drawn from the analysis performed. Namely, first the dataset extracted from the website presented poor data quality, moreover, a potential error in the visitor identification has emerged from the analysis of the data. Therefore a complete assessment on the data gathering system should be performed. Second, the nature and volume of the data currently tracked in the website might not be informative enough about the users' preferences to forecast their preferred sections. Therefore, as not all the personalization strategies are effective or valid for different organization (Tuzhilin, 2009), a proper reevaluation of the personalization strategy should be done considering not only business objectives (i.e. identify the preferred user section) but also the users' needs and the possibility of including specific data depending on the personalization strategy selected. For example, if the website traffic (i.e. number of visitors and visits) is not large enough to implement a specific personalization strategy (i.e. identify user's preferred car) and there is not other available data usable for this purpose, another personalization strategy should be selected.

The presented research sheds light on the real state of website audiences segmentation in traditionally industrial companies. Eventhough the study is based only in one company and therefore conclusions can not be generalized, some of the challenges found in this organization are potentially present in similar companies (such as the website traffic volume). Therefore, further research could be addressed to assess the real current state of website audience segmentation in companies other than big techs.

Dos and don'ts in the evaluation of personalization

In third place, before implementing any real change in the website, it is essential to evaluate the effects these changes might have. As described in chapter 5 (*Dos and don'ts in the evaluation of personalization*), one of the obstacles for the extension of personalization effort in the industry, is the organizations' lack of confidence in their ability to capture the effect of implementing website personalization (Forbes, 2019; Kaptein et al., 2015; Kwon et al., 2010; International, Researchscape (Evergage, 2018; Vesanen, 2007). Given this need to understand how to evaluate personalization, authors have proposed different solutions.

On the one hand, the most extended method to evaluate website personalization are randomized control trials, also known as online controlled experiments or A/B tests) (Amatriain and Basilico, 2012b; Dmitriev et al., 2016; Govind, 2017; Letham et al., 2018). However, even if this method is considered simple, is substantially well-documented and is a common practice in website evaluation, some traditionally industrial companies face some difficulties when applying it (Amatriain and Basilico, 2012b; Bakshy et al., 2014; Dmitriev et al., 2017; Knijnenburg, 2012; Mattos et al., 2020) As a consequence of this lack of fluency in the application of A/B testing, authors report that some critical experimentation errors are commonly made when performing those tests (Dahl and Mumford, 2015; Dmitriev et al., 2017; Kohavi et al., 2014; Kotapalli, 2020). Subsequently, the incorrect implementation or analysis of A/B tests has led some organizations to the conclusion that online controlled experimentation is not an effective practice (SiteSpect, 2018).

On the other hand, even if A/B tests are the most recommended website evaluation method, they can not always be performed (Salimkumar et al., 2021). In these cases, other techniques, such as causal inference, can be used to estimate the effect of new features in the website (Goldenberg et al., 2021; Govind, 2017; Adam Kinney, 2019). However, given its complexity and its applicability, causal inference is relatively unexplored in marketing contexts (Adam Kinney, 2019).

In this study (*Dos and don'ts in the evaluation of personalization*), the two mentioned methods to evaluate website performance (i.e. A/B testing and causal) have been examined. Regarding A/B testing after an analysis of both academic and industrial literature, a guideline to implement testing on the website has been presented. These guidelines consist of three main steps. Namely, (1) pre-experiment conceptualization, (2) experiment design and execution and (3) post-experiment analysis and learning. Moreover, based on a set of interviews conducted to companies of the automotive sector and, then, extended to companies from other sectors, the presence of some critical experimentation errors has been assessed. Moreover, the limitations of this research have been identified and described. Namely, this research is focused on a specific type of companies (traditionally industrial companies), this, together with the sample size utilized make the results of this study not being generalizable for companies from other sectors.

Additionally, regarding causal inferences, in order to offer a clear vision of the methodology a practical case of the implementation of these methods has been described. The presented causal inference method applied case was by no means a representation of the extensive and complex causal inference field. However, given the lack of literature on this topic applied in the marketing field, this study can serve as an example of how to evaluate website performance in a case where an online controlled experiment is not feasible.

Organization readiness for personalization strategies

Finally, in order to include personalization in a website, the organization needs to be digital, user-centric and data-driven (Forbes, 2019; Harvard Business Review Analytic Services, 2018; McKinsey&Company, 2018). However, integrating data in the daily culture of the company is not easy and the organizational transformation needed is not always manageable (BVACCEL, 2020; Germanakos et al., 2021; Lazarova, 2020; Serrano-Cobos, 2016). Moreover, digital transformations result especially challenging for companies from the automotive sector (Genzlinger et al., 2020; Jacobides et al., 2015).

In the forth study of this research, included in chapter 6 (*Organization readiness for personalization strategies*), we present a case study of an organizational transformation (from traditional to data-driven decision-making model) performed in an real organization from the automotive sector. First a literature review on organizational change has been presented with special focus on the seven most commonly committed causes for transformation failure. These being, not following an organizational change procedure, not filling the knowledge gap, failing to cope with resistance to change, lack of sense of urgency, insufficient organizational readiness for change, insufficient management support and involvement and lack of or ineffective communication. Second, a case study has been analyzed with special attention on these risks. By doing so, this study contributes both to theoretical and practical research in the field by offering a vision how digital transformations are addressed by organizations.

However, as a case study research approach, the main limitation of this paper is the inability to offer a generalized picture of the phenomenon. Furthermore, given the high contextual dependence of organizational transformations, the result of this study cannot be taken as a closed final conclusion for different cases. Therefore, in order to validate the results obtained in this case, and to further explain the potential problems that may threaten the success of organizational change initiatives, future work could be replicated in similar case companies (digitalization within traditional industrial companies).

After summarizing the main discussion, contributions and limitations of each of the presented studies in this research we summarize the main findings related to each research question.

RQ1: What is personalization?

Answer 1: Personalization is any process or action that changes or adapts any part of the provider's marketing mix based on certain knowledge to increase the personal relevance to an individual or group of individuals.

RQ 2: Which users' segmentation criteria can we use that are informative enough in the implementation of website personalization?

Answer 2: None of the evaluated users' segmentation criteria has been proven effective to be usable for the personalization strategy selected by the company (i.e. system-driven personalization able to forecast the preferred website section for the user at any given time of the navigation without explicitly asking it to the user). However, the poor data quality, the nature of the data currently tracked in the website and possible errors in the visitor identification have been identified as possible causes of the obtained results. Therefore, the research could drive different results after addressing these issues.

RQ 3: How can we evaluate website personalization?

Answer 3: The nowadays most commonly applied website evaluation method is A/B testing. However, despite its simple conceptualization, some common mistakes that organization make when performing these type of tests. Some of those experimentation errors are critical for the validity of the test, therefor their knowledge and understanding are fundamental when performing A/B testing. Moreover, given that there are some specific cases where online controlled experiments can not be used, causal inference should also be considered as a usable website evaluation method.

RQ 4: Which are the potential factors that may affect the success of an organizational change in a company from the automotive sector?

Answer 4: Based on the literature, there are several factors that can affect (positively or negatively) the result of an organizational change. Among them, there is a list of seven failure factors that have been given special attention in the literature (not following an organizational change procedure, not filling the knowledge gap, failing to cope with resistance to change, lack of sense of urgency, insufficient organizational readiness for change, insufficient management support and involvement and lack of or ineffective communication). However, an organizational change is a highly context-specific process (i.e. can be affected by the company, the team, the change itself, the timing, etc.). Therefore, even if it is important to have a list of potential factors affecting the organizational change, it is critical to study and plan the process for each independent case.

With it we can now answer the main research question of this thesis:

RQ: Which considerations should be taken into account when designing an automatically personalized website in the automotive sector?

Answer: Personalization is a broad topic and depending on the context, it is not always recommended. In order to implement website personalization a company from the automotive sector might have several considerations:

- First, before starting to personalize a company from any sector should first understand what personalization is and what kind of personalization strategies are feasible given their specific context. Moreover, even if website personalization is understood, technically possible and a personalization strategy has been selected, the organization should consider why to personalize (i.e. what is the benefit that a given personalization is going to offer to the user or do the user wants the personalization that is being planned).
- Second, in order to personalize the company should assess its capacity to understand its users and their preferences. From the technical viewpoint, the company should be able to track sufficient data from the website or include additional data sources. From the company viewpoint the company should be able to manage these data sources in order to extract valuable information. However, regarding the user, the data used to personalize should be in line with the user-organization relationship. The user can consider valuable or concerning the use of different data to personalize depending on the perceived relationship with the organization. From the resulting data, the company needs to be able to extract useful audience segments. This is, groups of users with homogeneous preferences or characteristics and different enough from the users of other groups.
- Third, the company needs to be fluent in evaluating the impact of website modifications. To this effect, it is critical to have a clear vision of which are the expected benefits of any modification included in the website. With it, identify which metrics are usable to measure these potential benefits. And finally, to select and use an evaluation methodology (e.g. A/B testing or causal inference) considering its potential pitfalls.
- Fourth, after considering and planning all the previous considerations, the company might find that the current organizational structure is not suitable for automatic website personalization. In this case, an organizational transformation needs to be planned and performed.

In this research we have studied each of the presented considerations for a company to implement website personalization. By doing so, this research sheds light on the real state of website personalization in companies of the automotive sectors. With it, the main conclusion of this research is that there is currently available technology in the market that companies can use in order to implement website personalization. Therefore companies across sectors can already implement it. However, current lack of understanding of the fundamental bases of personalization, website segmentation and website evaluation might be the main cause for ineffective implementation of website personalization. Moreover, in the SEAT case, even if personalization could be applied effectively, the current organizational structure might prevent the company to be able to implement truly automated website personalization without a previous organizational transformation.

Given the context dependency of the problem tackled in this research, it has been focused in a single company of a single specific sector (i.e. automotive sector). Therefore, the main limitation of this study is the inability to produce generalizable results across sectors. However, given the challenges encountered for the companies in the automotive sector to implement website personalization and the industrial interest on implementing personalization across many other sectors, further research is needed in order to address the current situation of website personalization.

In summary, the main contributions of this thesis include a novel framework for the conceptualization of personalization, the identification of several critical problems to perform website audience segmentation and the proposal of novel segmentation variable, an assessment of the current state of website evaluation (including a guideline to perform A/B test and the identification of some critical pitfalls when performing it) and an evaluation ability to perform the organizational change needed to effectively implement website personalization (including a list of the seven most common failure factors and some actions taken by the company to avoid them).

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