Abstract

Title: Design thinking for user-centric website optimization. A case study.
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First, to find a solution to this wicked problem we adapt the process of design thinking to the context studied, i.e., to the design optimization of retail banking web sites. Second, we provide insights in how big data can aid the development of a website design that optimizes the user experience of the customers. As the creation of these user-centric websites is a never confronted task for this type of organization, a variety of methods is applied. In particular, we take advantage of state-of-the-art technologies for analyzing users` interaction with websites. More
specifically, we employ heat maps and track the clicking-behavior of users through the software tools Hotjar and Smartlook, allowing for observing the users in their native environment. Furthermore, we use the method of Digital Anthropology to complete the loop between the human-centric designs and the possibilities offered by the analysis of big data.
Design thinking for user-centric website optimization

A case study

Vella Somoza Sanchez, Frederik Andersen, Peter Schneider-Kamp, René Chester Goduscheit

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1 Introduction
Some of the wicked problems of our century surround new technology implementation at the organization. The widespread availability of the internet, the creation and use of drones for operations, and the impact of the ever-increasing feeds of data surrounding the organization are some of the problems that are part of this reality. These types of problems, new to the organization, require leadership styles that facilitate the production of solutions. Rather than to put in place previous processes, the organization is confronted with the need to ask the right questions helping to produce a solution that helps to assimilate and produce a competitive advantage out of these wicked problems (Grint 2005). The current paper is an exercise in this matter, trying to explain how to tackle a wicked problem: the optimization of websites fitting the needs and expectations of its users. The constitutive leadership approach is used as the sphere in which the current case study unfolds. We see the context studied as socially constructed by its users and constraint through the website design (Cheney et al. 2011). Therefore, observation is the best method to uncover its meanings and how users think about those designs. Design thinking (DT) fits in this framework, as the guiding tool to cluster the users’ understandings into a concrete design as well as a learning tool. Additionally, Digital anthropology (DA) is the connecting method between the big data variables available and the designs. Lastly, Human-in-the-Loop is the empirical framework through which the constitutive leadership approach operates. More specifically, in this case study we try to find which type of website design can address the needs of potential customers and, consequently, improve their user experience (UX). This wicked problem can be divided into two main sub-problems; first, how to adapt the process of DT to the context studied. And second, how the use of big data can aid developing the website design that optimizes the UX of the customers. The current study aims to find an answer to this wicked problem, focusing on a company offering a service innovation in the retail banking industry, i.e., comparison websites.
2 Theoretical Background

![Diagram of design thinking process]

**Figure 1: Theoretical framework following Beckman and Barry (2007) principles of design thinking**
Beckman and Barry (2007) establish the innovation process as a learning process to solve any type of wicked problem. Therefore this model is chosen as the framework for the DT process followed, looking to produce a suitable solution in the sense of Grint (2005); we seek for the right questions that help us select the correct design of the websites. This model that is based on four stages moves between the generation of abstractions and the use of data to form specific solutions (Beckman and Barry, 2007). The process of DT is also recorded in the ISO 9241-210:2010 (E) standard where it is theoretically described also in four stages as human-centered design activities. In this paper we use the framework of Beckman and Barry (2007) that offers richer information regarding its use and application. Additionally, we follow a constitutive leadership approach (Grint 2005), the optimal approach to solve wicked problems. Figure 1 describes the DT process carried out in the current case study based on the theoretical framework of Beckman and Barry (2007). Figure 2 shows the iterative process of design thinking formulated by Owen (1993) and described as an innovation process by Beckman and Barry (2007).

Figure 2: The innovation Process by Beckman and Barry (2007: 30).

2.1 Observation of the context studied
The first stage focuses on the observation of the context in which the user operates through ethnographic techniques. The potential of ethnography to listen and collaborate with users has been recognized by other authors such as Lüthje and Herstatt (2004), Bosch-Sijtsema and Bosch (2015), and von Hippel (1994). Beckman and Barry (2007) see this observation as an opportunity to understand how products are being used and how to make sense of this behavior. The method of observation is considered as more adequate due to the fact that brings about insights that might have been overlooked even for its actors (Beckman and Barry, 2007). As these authors propose, “understand meaning implies understanding the subconscious blueprint of a groups’ way of life” (Beckman and Barry, 2007:33).

2.2 Frameworks
The second stage moves from the concrete data recorded in the observations to a set of abstractions (ideas) based on this data seeking to explain what is important for the UX (Beckman and Barry, 2007). Beckman and Barry (2007) propose a set of steps that can help to this process. First, find concrete stories on the data. To this end, ethnographic analytic methods seem to be the most suitable. Second, these authors recommend the creation of simplifications and models to understand the structures of those stories, as for example two-by-two matrices. Finally, create timelines to observe how time influences the data collected and the models designed.

2.3 Imperatives
This stage moves onto the analytic stage of the process, trying to understand how the value proposition changes and improves after the inclusion of the new frameworks created. Beckman and Barry (2007) establish that this new value proposition contains the benefits that the new product or service carries for its potential customers.

2.4 Solutions
The last stage of the DT model, regards the concrete features that the new product or service must have to meet the new value proposition (Beckman and Barry, 2007). This phase can be further divided into three parts. The first part consists of concept generalization, where the imperatives of the value proposition are contained in concrete principles to be embodied in the design. In the second part concrete concepts are selected out of the array of concepts possible. Finally, those concepts are tested through prototypes by its potential users. Through the prototyping phase, the learning process is completed, understanding which of the concepts and understandings selected in the current value proposition are correct. Additionally, the whole process must be dynamically repeated to address the ever changing users’ needs and preferences (Cheney et al. 2011).

2.5 Design Process Workaround
Beckman and Barry (2007) finalize the description of the DT process by presenting the dangers and problems of using this framework as only a tool for rapid prototyping, forgetting its function as learning process. They see the potential of DT as a tool to understand the implications of and meanings under the success of an innovation, rather than a mere tool for innovation. Some of the dangers entail the use
of DT for express-test cycle, where the DT framework does not derive from the abstract realm (Beckman and Barry, 2007). In the other hand, the academic isolation, where the prototypes never meet the concrete dimension presents the same type of issues (Beckman and Barry, 2007). Therefore, the authors propose the ideal DT model based on an iterative process between the abstract and the concrete realms in the “Design process workaround” (Beckman and Barry, 2007: 51). This model, based on the same type of leadership of Grint (2005), is based on questions, rather than answers in order to find solutions. Some of those questions seek for disagreements, challenges, and reframing of ideas between the working team as the right path to keep on asking the right set of questions to continuously produce the current design.

2.6 Constitutive leadership
Grint (2005) explains this approach as the solution to wicked problems, where communication is at the core of the problem of leadership. It is based on the use of models to reframe taken-for-grated ideas. The reshaping tools for the constitutive model are stories, metaphors and symbols that can help to read and convey situations in new ways (Cheney et al. 2011). Grint (2005) defines wicked problems as those new, with high uncertainty lacking a right or wrong answer. The author proposes that the solution to these problems is associated with leadership; where its role is to ask questions instead of providing answers in a collaborative process between the leader and the problem’s stakeholders.

This approach is well aligned with DT where stories coming from observation can be used to construct possible solutions. Therefore we assume a constructionist understanding of the observations conducted. Also, we propose a new form of collaborative process where DT is included as a dimension on the data frame informing the analysis of big data. This way we produce suitable solutions that due to the complex nature of the problem are not linear but iterative (Cheney et al. 2011).

3 Methodology

3.1 Case selection
The case selected is the company “Intelligent Banker” in Odense. This company uses real time data in its daily operations to improve its core business: websites comparing banking products. They offer information regarding different loan possibilities for the end users, functioning as the first intermediary between the users and the credit loaners. The company operates a total of 71 webpages with financial services centered on loans. Additionally, it attends other markets such as online dating and credit card offerings. The current case study focuses only on the financial websites, with small loans as the products offered. The company operates in 7 countries; the US, Sweden, Spain, Poland, Norway, Finland, and Denmark. Where, Sweden, Denmark, Spain, and Norway are its main markets as figure 3 shows.
The company’s revenue comes from two activities; the subscriptions of users to the final loan webpages and the actual purchases of those loans. The relevance and interest of this case resides in two points: the interest of the company to create websites with a user-centric perspective, and the optimization of those websites using the big data capabilities of the company. The wicked nature of the problem makes the DT framework an ideal learning process. Additionally, the method of Digital Anthropology (from now on DA) is a suitable method to put into contact qualitative data (digital observation, anthropological data, DT) and big data analysis (Somoza Sánchez et al. 2017).

### 3.2 Human in the loop and Digital Anthropology

The method of DA aligns the use of small data (ethnographic data) with big data, for example to find lead users (Somoza Sanchez et al. 2017). This method can be of help connecting the framework of DT and the features of the (big) data collected by the company. Therefore, we want to put this method at the center of the loop in which qualitative data is the guiding force of the big data analysis. Nevertheless, at the same time, the big data analysis is what puts into motion, the collection and analysis of qualitative data. These two interdependent forces create the loop of big data analysis in which the expert (or the cluster of users with the possibility of producing experts or lead user’s opinions) is at its center. Figure 4 shows these relationships through a flow chart:
3.3 Data collection
This section establishes the design followed for collecting the data observed.
3.3.1 Qualitative data collection

The data collection of this case study is based on the collection of observations using the software tools Hotjar and Smartlook. Both of them summarized the interactions in the activity maps that can be observed on the tables of the analysis. Additionally, the software tool Smartlook allowed to select each user studied and to follow his/her activity through a video recording of the interaction. The first step of the qualitative data collection consisted on the selection the webpages focus of the observation. To this end, a first observation of the 71 webpages was carried out, concluding that there were three typical designs among them. The rest of the webpages’ designs were copies of these main three either translated to other languages. The observation was conducted over 3 of the websites of the company. The selection of websites was made taking into account the revenue produced by the site as well as the number of visits of the site per month. The objective of this selection was to attend to the three main website’s designs on those sites generating the bulk of the visits on the different sites. The variable of revenue was used as record the greatest value possible in the new value proposition for the company and the users.


For the first website, a total of 359 visits were recorded during 72 hours. These recordings where done in a timeframe of 2 weeks in chunks of 3 hours spread as to cover all the hours of the day. This was done as means to randomize the sample taken as well as to follow the timeline advice in order to produce the frameworks of the DT process in the sense of Beckman and Barry (2007). Some of the visit recorded corresponded to recurrent visitors in the 3 hours of recording, not being observed as a new record, ending therefore with a total of 339 videos of these users’ interaction. A filtered was later on conducted as to take out of the sample bots and the visits of the researches to the website during the hours of recording. Thus, the total number of observations counted a total of 162 users of desktop computers, 86 users of mobile phone devices, 2 users of tablet devices, 82 bots or inactive users and 9 visits of the researches.

A second set of observations is currently being conducted with a total of 1000 observations on the three websites during a complete week. More observations are being recorded as to produce designs not only for the mobile phone websites (as is the end result of the current case study), but as to cover all the three designs and all type of devices from which the websites can be accessed.

3.3.2 Virtual ethnography

Following the guidelines of the DT method of Beckman and Barry (2007), we use as means for analysis virtual ethnography for observation. Virtual ethnography is the observation method to study the Internet (Beckman and Barry, 2007 and Kozinets, 2013). This method is particularly adequate for two reasons. Firstly, to address users not willing to admit they are consumers of these sensitive products and second due to the fact that it is aligned with the method of Digital Anthropology (Somoza Sanchez et al. 2017). This method is used as to find relevant stories to create the DT frameworks (Beckman and Barry, 2007). For doing so, we watched the videos produced by Hotjar and Smartlook and at the same time we produced a set of notes studding the context in which the observation was produced following the
guidelines of participant observation by Bernard (2011). This was done with a double purpose; first to better understand the navigation of the websites and therefore the observations recorded in Hotjar and Smartlook. And second, as to follow the principles of DA in using all the sources of data available for a specific case (Somoza Sanchez et al. 2017).

3.3.3 Quantitative data collection
As stated before, DA combines the use of small data (ethnographic data) with big data as to find lead users. The company focus of the current case study used big data analysis in order to understand some of the characteristics of its users; for example the channels used to access the company’s websites (Google, Facebook, direct access to the website, etc.), the type of device used (Tablet, mobile phone, PC), between others. These variables are explicitly stated in Table 1.

The set of variables available through the company’s database attend to the following aspects: Data from the EPC project and fingerprint data.

The fingerprint data contains the user ID left by the users visiting the different webpages. This ID allows the company the identification of some characteristics as the location of the user, the internet browser used for visiting the webpage, the device from which the query was launched, in case that this user comes from a google campaign; the keyword that brought this user to the webpage visited, the device used to visit the webpage.

Table 1: Fingerprint data in time series available (From August 2016 to December 2017)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>website_id</td>
<td>Internal reference to the particular website</td>
</tr>
<tr>
<td>website_name</td>
<td>Textual name of the website</td>
</tr>
<tr>
<td>country_id</td>
<td>Internal reference to the particular country</td>
</tr>
<tr>
<td>country_name</td>
<td>Textual name of the country</td>
</tr>
<tr>
<td>source_channel_id</td>
<td>Internal reference to the particular marketing channel used for advertising</td>
</tr>
<tr>
<td>channel_name</td>
<td>Textual name of the marketing channel</td>
</tr>
<tr>
<td>visit_date</td>
<td>It states a visit to a website not being necessarily the first visit of this user</td>
</tr>
<tr>
<td>click_date</td>
<td>First time that the user clicks on any tag or button on the webpage</td>
</tr>
<tr>
<td>product_id</td>
<td>Internal reference to the product in the company’s database</td>
</tr>
<tr>
<td>product_name</td>
<td>Textual name of product</td>
</tr>
<tr>
<td>device_id</td>
<td>Internal reference to the device from which the request was made</td>
</tr>
<tr>
<td>device_name</td>
<td>Device from which the request was made</td>
</tr>
<tr>
<td>nr_clicks</td>
<td>Number of clicks per product</td>
</tr>
<tr>
<td>revenue</td>
<td>Total revenue per product, per day (visit date) in Danish crowns (Dkk).</td>
</tr>
</tbody>
</table>

The data from the EPC project states the relationships between those variables and how they change over time as to reflect seasonal changes learnt by the company over its time of functioning. It helps to dynamically select which products should be first on the list of offerings that the users will see on the different websites. The set of relationships is not specifically relevant for the current project and will not be displayed observing our privacy agreement with the company.
The data available was evaluated and its correlations established, arriving to a point in its analysis where feature selection was needed in order to understand those relationships. This selection proved to be inconclusive, therefore establishing the need of including the human in the loop, as to complement the circle of analysis.

4 Analysis

Beckman and Barry (2007) see the context as the physical space in which users operate, having culture, language, etc. impact on the user behavior. Nevertheless at this point, the first aspect of the wicked problem is manifested. Due to the nature of the offerings of the company (small loans, credit cards, etc.), users do not feel inclined to let others know their acquisition and therefore the collaboration with the company is scarce. Seeking to find a solution, the software tools previously presented (Hotjar and Smartlook), help to access and observe how the users interact on the context of the websites in a non-obtrusive matter.

4.1 Observation of the context studied

As Beckman and Barry (2007) state, observation is an advantageous method for understanding user’s behavior. More so in this particular case, where due to the sensitive nature of the services (small loans, credit cards, and other financial products) the consumers hide their consumption. Therefore, for companies with these types of offerings, where direct user involvement is scarce, the ethnographic method of observation is particularly interesting. The objective of this observation is to study the context in which the users move as to understand and create a framework of their behavior.

4.1.1 Desktop-based behavior

In this section, the observation focuses on the users’ behavior depending on the device used to access the websites. This information, as was stated in the methodology, is retrieved by the company through the IP’s address of the users. The way observation is carried out consist on three sets of data: scrolling behavior, clicking behavior and mouse movement tacking.

In first place, we study the scrolling behavior of the sample taken. This behavior consist on how many of the users in the sample observed scroll down to the complete bottom of the webpage or whether they stopped before. Table 2 shows in the heat map the warmer colors (red and yellow) the parts of the website with the highest affluence of users and it changes towards the cold colors (green and finally blue) to show less activity. As table 2 show, only 45% of the visitors go to the complete bottom of the site. Therefore, the information displayed on the bottom is not seen by some of the users, even though it could be regarded as important since it contains the terms of the refund policy.
Second, the clicking behavior of the users in the website is taken into account. This variable focuses on where the users click on the website. Table 3 shows this behavior. It can be observed a correlation in the same sense of table 2; users click more at the top of the page, decreasing their activity once they need to keep on scrolling. Nevertheless, this observation brings about a new dimension; the larger the icons representing the different products, it can be observed an increased amount of clicks. Therefore, the size of the logos is an aspect to be taken into account for the redesign of the sites. This implication is aligned with the design principles theory, that states that elements highly saturated attract higher attention (Landa 2011). Furthermore, table 3 and 4 shows how other parameters of the offerings are not as important for the users as the logos. The relevance of this behavior resides in the fact that the logos can be used as the guiding force of the sites.
The third element observed regards the tracking of the mouse movement. This variable studies where people moved the cursor of the mouse. Table 3 shows a brighter shade of blue in those parts where the mouse stood more often.

Taking into account the fact that 44.4% (80 out of 180) of users observed come from Google searches, the strongest blue circle on table 3 shows the point where the cursor comes to be once the link to the webpage is accessed, not implicating any extra movement from the user. The rest of the observation follows the same correlations presented before; users’ attention is fleeting and the mayor part of the mouse activity happens at the top of the site and in the first two products offered. Additionally, it can be observed that the text of the products is consistently read by some of the users using the cursor as guide to follow the text; although, the activity decreases along with their scrolling.

### Table 3: Clicking behavior for desktop computers

<table>
<thead>
<tr>
<th>Top of the website</th>
<th>Middle part of the website</th>
<th>Bottom of the website</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="Image of desktop clicking behavior at the top of the website" /></td>
<td><img src="image2.png" alt="Image of desktop clicking behavior in the middle part of the website" /></td>
<td><img src="image3.png" alt="Image of desktop clicking behavior at the bottom of the website" /></td>
</tr>
</tbody>
</table>

!
Summarizing the behavior observed through the observations, it can be perceived that the users accessing the sites through desktop computers pay attention mainly to the top of the site and to the products with larger and most saturated icons. They do not scroll enough as to read the terms of refund, or any other text on the bottom. Some of them enter but do not engage in any other activity on the webpage, therefore missing the content that they were looking for. And finally, some of them use the mouse as a help to read the text of the products mainly from the top of the site.

Through these DT “stories” in the sense of Beckman and Barry (2007) the observations are used as to try to understand why some users decide not to engage on the site and what elements are missing. The data recorded shows that interaction means higher probability of clicking on a product. Nevertheless, increased rate of interaction does not imply higher probability of conversion (clicking on a product). This information is interpreted as an increased interest from these users and therefore it will help as to frame the users’ behavior in figure 5 in the framing section.

### Table 4: Mouse movement behavior for desktop computers

<table>
<thead>
<tr>
<th>Top of the website</th>
<th>Middle part of the website</th>
<th>Bottom of the website</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="Image" /></td>
<td><img src="image2.png" alt="Image" /></td>
<td><img src="image3.png" alt="Image" /></td>
</tr>
</tbody>
</table>
4.1.2 Mobile phone-based behavior

Table 5: Scrolling behavior for mobile phone devices

<table>
<thead>
<tr>
<th>View by 100% of the visitors</th>
<th>View by 70% of the visitors</th>
<th>View by 25% of the visitors</th>
</tr>
</thead>
<tbody>
<tr>
<td>7.000 - 75.000KR</td>
<td>21 ÅR</td>
<td>12 MÅNEDER</td>
</tr>
<tr>
<td>1.500 - 15.000KR</td>
<td>23 ÅR</td>
<td>12 MÅNEDER</td>
</tr>
<tr>
<td>5.000 - 40.000KR</td>
<td>23 ÅR</td>
<td>15 ÅR</td>
</tr>
<tr>
<td>1.500 - 15.000KR</td>
<td>23 ÅR</td>
<td></td>
</tr>
<tr>
<td>5.000 - 10.000KR</td>
<td>20 ÅR</td>
<td>10 MÅNEDER</td>
</tr>
<tr>
<td>1.500 - 15.000KR</td>
<td>23 ÅR</td>
<td>90 MÅNEDER</td>
</tr>
<tr>
<td>5.000 - 20.000KR</td>
<td>20 ÅR</td>
<td>100 MÅNEDER</td>
</tr>
<tr>
<td>5.000 - 20.000KR</td>
<td>20 ÅR</td>
<td>3 MÅNEDER</td>
</tr>
</tbody>
</table>

The scrolling behavior is aligned with the desktop device. Nevertheless these users scroll less; only 25% of all the users observed scrolled to the complete bottom of the mobile phone sites and therefore read the refund terms.

The clicking (tapping) behavior shows that the users are right handed and they use their thump to scroll and tap on the sites. The behavior observed for the desktop device is also applicable for the mobile phone users; the more saturated and larger icons attract the attention of the users and a few of them use their finger to read the texts. This can be observed in tables 6 and 7.
Table 6: Clicking behavior for mobile phone devices

<table>
<thead>
<tr>
<th>Top of the website</th>
<th>Middle part of the website</th>
<th>Bottom of the website</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="Image" /></td>
<td><img src="image2.png" alt="Image" /></td>
<td><img src="image3.png" alt="Image" /></td>
</tr>
</tbody>
</table>

Table 7: Finger movement behavior for mobile phone devices

<table>
<thead>
<tr>
<th>Top of the website</th>
<th>Middle part of the website</th>
<th>Bottom of the website</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image4.png" alt="Image" /></td>
<td><img src="image5.png" alt="Image" /></td>
<td><img src="image6.png" alt="Image" /></td>
</tr>
</tbody>
</table>
4.2 Frameworks and Imperatives
This section establishes the framework for the case study and the concrete solutions that were produced as to implement the analytic changes.

The framework created for this case study is gathered in figure X. It was produced following the advices of Beckman and Barry (2007). First, concrete stories based on the observations were collected. Second, they were collected into a two-by-two matrix in figure X. Third, the time influence of this framework will be integrated, through the method of DA, into the data frame of the big data analysis as to be able to make changes and produce new abstractions based on seasonality.

<table>
<thead>
<tr>
<th>Device/Channel</th>
<th>Google</th>
<th>“STUDENTS”</th>
<th>Facebook</th>
<th>“WINDOWSHOPPER”</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobile</td>
<td>• Options • Comparison</td>
<td>• Attention • Search function • Simple design</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Desktop</td>
<td>• Users are older due to newsletter subscription. • Recommendation &gt; Search function • Trustworthy</td>
<td>• Attention • Search function</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 5: Framework for the Intelligent Banker case

Figure 5 collects the stories regarding new users. The users entering the sites through direct access, not using google or social media, where considered as recurrent customers and therefore where not recorded in figure 5. We consider them as recurrent due to the complexity of the names of the websites that are not easily remembered. Figure 5 shows two types of users’ profiles or “personas” based on the triangulation of the device and the channel used for their website visit. The “students” profile regards to those users who were experts on these types of products and expend longer time on the sites. Those using a desktop device usually subscribed to the newsletter and were considered older to the fact that they were using the cursor to go over the text of the different products. This segment of users required an image of trustworthiness in order to click on the products since they expend longer time examining the content of the websites. A recommendation system, were several products can be compared, can deliver an image of trustworthiness and serve the needs of these users that often clicked back and forth between different products.
The mobile phone users had similar interests, requiring a different way to establish the comparisons, still in a simple interface. The expert evaluation and a set of questionnaires spread over the newsletter system revealed the fact that people accessing the mobile sites were younger and with a lower average level of education. Nevertheless they were more used to complex online functions and tools that they used often. Therefore, the recommendation system was also implemented on the mobile sites, based on designs familiar to the users. Those designs consisted on the possibility of clicking in several products and accessing this way to a comparative of the clicked products. See figure 7 for an example of this design.

The “window-shoppers” profile corresponds to those users connecting to the sites through social media channels; specifically from Facebook campaigns or ads. These users did not expend much time on the sites and left before clicking in any product and not even scrolling. This behavior can be interpreted as a lack of interest on the websites. Therefore, one of the main objectives of the design focuses on dragging attention instead of on implementing a recommendation system. This design addressing these user needs should explain the process in a simple way allowing the users to envision the process in a glimpse. Following this principle of simplicity, a way of offering the best experience was considered to be the use of a search function. If the users where exposed to a recommendation system, they would lose interests and therefore leave the webpage. Therefore, a search function will have a simple design and enable at the same time to access directly specific information without distractions. Figure 8 contains the final design for the “window-shoppers” profile.

4.3 Solutions
The last stage of the DT model embodies the features selected in the previous section. Therefore we present the final designs currently going through A/B testing. The following figures represent the selection of the generalizations made embodying the new features of the value proposition. In this sense, the “students” are presented a recommendation system to guide their decision and the “window-shoppers” are given a simple model of the process and a clickable search function.

Currently, these design prototypes are being tested. It is expected that the results of the testing process reveals which concepts and understandings are correct, opening the possibility on new testing. Furthermore, a new collection of observations is being made and analyzed as to be able to test design for the desktop prototypes. The decision of beginning with the mobile phone prototypes is based on the fact that the bulk of visits and revenue comes from the desktop device, being the possibility of failure too expensive for the company. It can be therefore considered, that the designs follow a process workaround where the results learned in this case study will serve the learning process for the desktop website designs. Following the advices of Beckman and Barry (2007), the questions, disagreements, and challenges of the current designs will be used to reframe the ideas presented in this paper in an attempt to find the right questions to optimize the designs.
Figure 6: Prototype solution for the “students” profile
Figure 7: Prototype solution for the “students” profile; Comparison function.
Figure 8: Prototype solution for the widow-shoppers profile; a simple design seeking to drag attention.
Figure 9: Prototype solution for the widow-shoppers profile; the search function opens once the blue button is clicked.
4.4 DA, DT and big data

Once the process of design thinking is concluded, the next step consists of its inclusion into the big data analysis. Table 1 showed the variables that the company had available on the fingerprint data. The EPC project contains the relationships learnt by the company overtime in regards to those variables. We propose the inclusion of the relationships learnt through the DT process as another dimension of the data frame used for the big data analysis. Therefore, the website that will be showed to the user will be selected through a data frame that will select the design depending on not just the channel and device contained on the IP information of the user, but also on their clicking, scrolling and pointer behavior as well as the rest of relationships on the EPC project. This possibility brings about the possibility of the optimization of other dimensions; as the website designs depending on the country from which the users access the sites, the company’s revenue per product; as the observation showed the first products are more popular, etc. The connections learnt through the process of DT can be then used to optimize the rest of dimensions operating in the company’s database.

5 Discussion

This paper contributes to link the literature of DT with an empirical case as so open its application for website optimization through the use of big data. To this purpose, the method of DA comes in hand as to connect anthropological behavior with UX and data analysis. The case study shows that the in order to optimize the webpages’ design, the relevance resides in understanding the user’s behavior on the webpages. This way, the designs can be created as to solve the issues that the users may be confronting in their interactions therefore improving their UX. The use of other variables as the channels or the devices used to access the webpages is at the service of this understanding, being therefore the element that optimizes the UX the redesign of the sites seeking fit the user’s behavior.

Following the ideas of Beckman and Barry (2007), we have acknowledged that the process of design thinking is a continuous one not being finished with the prototypes presented or the relationships established. This continuous learning process can help to refine the websites. Using the software tools proposed in this paper, more data can be collected, framed and embodied into prototypes improving not just the designs but also the company’s knowledge about their customers. The improvement of the UX will grow with the knowledge of the user’s behavior. Furthermore, the optimal tool for doing so is the framework on DT.

Another aspect worth mentioning relates to the generalization of this study to other companies whose offerings are also sensitive products. This study offers a way for website optimization based on improved UX. The process proposed in this paper follows a “design process workaround”, collecting more observations as to reframe the personas ideated in the framework to be able to make different adaptations for the websites. This model is based on a constitutive way of leadership seeking to answer a wicked problem through the constant motion between the DT framework and the big datasets. Therefore we conclude that DA is a dynamic method, as are DT and BD analysis offering solutions that bring about more questions.
5.1 Limitations

The size of the sample studied are limited and we are working on recollecting data as to improve the insights and the conclusions presented in this document. Nevertheless this fact is observed by the theoretical framework of DT, showing that even with rapid prototyping, improvements of the website design are already happening.

One of the mayor limitations of this study regards the software tools Smarlook, that does not allow to record the videos of each user’s observation externally and deletes the data after one month of its creation. Therefore the opportunities of reproducibility of this study regard a very short period of time. Nevertheless the software allows the storage of the heat maps showed on the figures of the analysis’ tables summarizing the observations of the users.

6 References


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