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Growth Hacking, Digital Marketing and Startup Metrics

- A Data Driven Approach

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Abstract

The main goal of the work project is to discuss the importance of analytics and data driven decisions in startup companies, since they are frequently presented as neglected components within startups. In order to understand their benefits for startups several tools were used: literature review, questionnaires, interviews and a Startup Company as a case study. This Startup allowed this work project to focus on analytics and metrics, more precisely on those related with marketing area. Therefore, this work was conducted to propose several suggestions that will allow startups to grow in terms of revenues and users without jeopardizing sustainable growth.

Keywords: Analytics; Data Driven Decisions; Growth Hacking; Metrics.

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1. Introduction

It has to be acknowledged that Portugal, and more specifically the city of Lisbon, has become a major player in the European entrepreneurial ecosystem. The international recognition has not longed to appear, and Lisbon has not only won the European Entrepreneurial Region of the Year Award as it was announced to be the new host of the biggest event of technology, innovation and entrepreneurship of Europe (Websummit) for the upcoming three years (2016, 2017 and 2018).

A phenomenon of such magnitude, and at the same time so recent, usually emerges as an opportunity to develop further research. So, to which areas is entrepreneurship not giving yet its deserved attention? One of the possible answers to this question is on the basis of this work project: Analytics and Data Driven Decisions. If Business Intelligence plays a major role in many businesses, and it is even the foundation of many others, why should not startup companies also take the most out of it as well? Croll and Yoskovitz (2013, p. 3) tackle this question in a very interesting way: "…Lying may even be a prerequisite for succeeding as an entrepreneur… you need to live in a semi-delusional state just to survive the inevitable rollercoaster ride of running your startup… Analytics is the necessary counterweight to lying, the yin to the yang of hyperbole… Data-driven learning is the cornerstone of success in startups." To further understand the relevance of this question and its potential benefits for startup companies, several tools were used in this work project including: Literature review; Questionnaires to startups of four different continents; interviews to startup incubators and to business angels and venture capital companies; and finally MyGon, that was used as a case study. More specifically, and also due to the availability of data at MyGon, the case study was particularly focused in analytics and metrics that were related to marketing. A set of marketing channels and different customers and transactions were analyzed in order to ultimately propose suggestions that may generate either more revenues/users with the same marketing expenditures; or the same revenues and user acquisition with fewer costs, thus contributing to a sustainable growth of the company. Hence the whole work project will also give a special relevance to data driven decisions associated with marketing, in comparison to other functional areas of a company.

2.1. Data Driven Decision Making – General Decisions

Data is everywhere and it is generated by almost everything that exists. For businesses to take the most out of it, they need to fully understand what data truly is and in which ways they can and should use it. According to the BusinessDictionary.com (n.d., par. 1), data is "Information in raw or unorganized form (such as alphabets, numbers, or symbols) that refers to, or represent, conditions, ideas, or objects. Data is limitless and presents everywhere in the universe." If organizations want data to be a contributor to business improvement, they must be able to cope with two challenges that are inherent to the characteristics of data: unorganized and limitless. Hence, they need to structure and organize it, transforming it into information and into useful knowledge in order to decision-makers act upon it. However, if data can be infinite, it is virtually impossible to process it all and that is why it is important to also know which data should be analyzed. As Harris' (2012, p. 2) slideshow proposes "…begin by understanding the decision criteria before evaluating the data requirements… Many organizations don't begin with the decision in mind, but instead begin with the data in mind, turning data management into data mountaineering…". This means that data and analytics should be means to achieve a pre-determined objective and not an end by itself.

Before understanding which data is relevant to analyze in order to take certain decisions, it is important to know which functional areas of a company may need to be improved, as well as which decisions may need to be taken. Since data is generated everywhere, it is not surprisingly that every single area of a company may take advantage of it. Power (2008, p. 149) points out that "data… helps managers gain insights into organization processes, customer activities, employee performance and organization-wide performance metrics" while Frick (2014, par. 3) evidences that "Companies are vacuuming up data to make better decisions about everything from product development and advertising to hiring".

When thinking about a startup company, things may be a little bit different, since these organizations usually have fewer and limited resources. In this sense, it is of utmost importance to understand which areas are keys to improve, via which decisions and which data may be used to base such decisions. In addition, it is also crucial for organizations to ensure that they have the right systems and mechanisms in place to gather significant and reliable data out of their operations.

2.2. Startup's Purpose: Marketing and Growth

This chapter pretends to disclose what is the purpose of a startup organization, and hence to identify where and how data analytics can be used to help this type of organization achieve its goals. The definition that appears more often when searching for it is that given by Blank (cit. in Marsh, 2013, par. 11) (Silicon Valley Guru): "A startup is a temporary organization designed to search for a repeatable and scalable business model." Blank (cit. in Marsh, 2013, par. 6) also points out that "In a startup… what matters is having forward momentum and a tight fact-based data/metrics feedback loop to help you quickly recognize and reverse any incorrect decisions. That's why startups are agile". Another important aspect of startups' management nowadays is the widespread lean startup philosophy. Ries (cit. in Ford, 2014) proposes that startups must focus in assessing the specific demands of consumers and how to meet them using the least amount of resources possible. For this to happen there must be some metrics that each startup must track and try to improve, otherwise they cannot move away from the light perception and the common sense. These metrics are those known as actionable metrics, in the sense that the acquaintance of them may force decision makers to act and change the course of actions (Croll & Yoskovitz, 2013). Since as it is perceived in this chapter, it is important to add that it is quite accepted that startup goals are mostly linked with improving the product-market fit and in taking advantage (mainly economical) of that. Therefore, the metrics in which startups must focus and the data that startups must "dig" must be intrinsically linked with these same goals. Consequently, that is why the metrics that can be of most usefulness for a startup are precisely those linked to marketing. Hence, the next chapter explores how characteristic can be the marketing practices in these ventures and which metrics are more appropriate and valuable to explore.

3.1. Startups' Marketing is equal to Growth hacking

Marketing practices in startups, as many other functional areas of a company, are different from marketing practices in large companies. Not only there is a big contrast in terms of resources' availability (budget, people, technology, etc.) as they have different goals due to their nature, years of life and uncertainty faced. For example, a startup company can hardly be as worried as a large company with brand recognition/awareness. So what is so distinctive about marketing in startups? It is the fact that they have fewer resources, which means that they must get much more creative, but also, and specially, the fact that their main goal is growth. Elis (2010), who helped several internet companies to achieve tremendous growth, understood this difference and, in 2010, came up with a term to define this so characteristic type of marketing: "growth hacking". In his own words, "a growth hacker is someone whose true north is growth" (Elis, 2010, par. 5).

Hence, this chapter pretends to develop more on this term and into how data and analytics are linked to it. In this sense, it is also important to emphasize the definition proposed for this buzz word by Mettetal (2013, par. 1) "A growth hacker finds a strategy within the parameters of a scalable and repeatable method for growth, driven by product and inspired by data. Growth hacking's goal are based in marketing but driven by product instincts… Growth is never instantaneous… It is a mindset at which you approach problems.". Another two authors (Patel & Taylor, n.d.) also add a significant contribution, namely by helping to structure the growth hacking process. According to their book, *The Definitive Guide to Growth Hacking*, there are six steps which make up this whole process: 1. To Define Actionable Goals; 2. Implement Analytics to Track These Goals; 3. Leveraging the Existing Strengths of the Company; 4. Execute the Experiment; 5. Optimize the Experiment and 6. Repeat.

Growth hacking, namely its techniques and processes, is used in five different levels according to McClure's (2007) AARRR metrics, which introduces the notion of growth hacking funnel. The metrics that are tracked along this funnel are those that allow startups to analyze the success of their actions and to iterate quickly. The next chapter develops more accurately this funnel and metrics.

3.2. Startups' Marketing ROI equals to AARRR Metrics / Growth Hacking Funnel

The AARRR metrics are used in startup companies in order to improve the product's marketing and management. According to McClure (2007), the customer's lifecycle must fulfill five different steps to be successful, which are:

- Acquisition: which is related to the diversity of channels that allows users to go into the website of the company (blogs, email, social networks, TV, etc.);
- Activation: that refers to the enjoyment that users feel when they visit the website for the first time. Such feeling may be related to the homepage itself or even to product features;
- Retention: when users go back to the website several times;
- Referral: it occurs when users like the product enough to refer to others;
- Revenue: when users conduct some monetization behaviors, namely through ads, lead gens or subscriptions. This is definitely a crucial metric given the fact that, by measuring and tracking the lifetime value of a customer, a startup company is able to also understand how much it can spend to acquire those same customers while remaining profitable.

In fact, McClure (2007) also presents a chart that demonstrates how such steps allows the company to grow, namely by concluding that, the further the steps go, the higher is the estimated values to the company itself. Nonetheless, he also argues that there are four types of metrics and measurement: qualitative, quantitative, comparative and competitive. The qualitative metrics is used in usability testing and in session monitoring. Thus, it is used to watch what users do in the website and to solve the arising problems related to the percentage of users that visit it. The quantitative metrics are used to analyze traffic and the user's engagement, reporting what users do, tracking the usage and converting the percentages of the users. The comparative metrics are used to compare what users do in different scenarios as well as to conclude which copy/graphics/UI are most effective. Finally, the competitive metrics are used to monitor and track possible competitors, thus tracking the competitor's activity as well as comparing the channels, traffic and user satisfaction in both the competitor's and the company's websites.

It is essential that the startup company proceeds to a measurement of all of its components, namely the audience segment, the channel source, the campaign theme/brand promise, the landing page and the copy and graphics.

Regarding the concept of growth hacking funnel, it is important to establish that funnels are essential guidelines to control things that are difficult to control. In fact, Patel and Taylor (n.d.) argue that, if you are building a product, then you have to guide people towards a specific goal. However, the problem that arises from this is related to the fact that people are unpredictable. So, "If you are going to get people to do what you wish, en masse, then you must employ a funnel." (Patel & Taylor, n.d., p. 3).

Finally, Patel and Taylor (n.d.) also suggest that startup companies must place their energy into places where they have the weakest ratios, as well as to grow some in order to find a product-market fit, thus not merely focusing on growth exclusively.

3.3. Conditions to have a Data-Driven Strategy

In order to startups start taking data analysis as a key element in the decision making process there are a number of things that they must do. First of all, startups must ensure that they keep a proper track of the data produced be the company's operations and customers' interactions with the company, otherwise there will not exist anything to analyze at all. A free but yet powerful tool for this effect is the google analytics software (in fact this work project relies a lot on data stored by this tool).

Secondly, it is important for startups to have CRM approach to the customers' database, especially in this stage where the company is still tuning its business model and improving product-market fit. It is essential that the startups learn how to separate their customers in different groups in accordance with their preferences, behaviors and value to the company. If a company does not do this, not only cannot know in which customers should focus on, but it can also only have a blurry and partial picture of its company's reality. Gupta and Lehmann (2003) and Reinartz and Kumar (2003) advocate that research suggests that the most important issue is not customer loyalty or customer retention but profitable customer retention and profitable customer portfolio management. Thirdly, it is also necessary that startups possess resources with time availability and sufficient technical expertise to analyze the data and to process it, in order to extract valuable knowledge from the information "hiden" in the data. Gupta and Lehmann (2003) and Reinartz and Kumar (2003) also said that research also indicates that, by using relatively unsophisticated analysis, startups can make a difference to their CRM performance. Finally, it is important that the upper management is capable of acting in accordance with evidences brought by data. As someone has pointed out back in the days, a straightforward analysis of the value of the customer can lead to a change in customer management strategies (Ryals, 2005).

Relatively to the questionnaire for this work project (Appendix 1), which was applied to 40 startups from different countries, the main constraint to consider data analysis as a major decision criteria was the reliability of the data collected (56% of startups surveyed referred to this problem), even though they have not pointed out too much that they do not have the means to collect data (19% of respondents only). Another two problems identified in the survey were the lack of resources (time, money, proper software or others) to analyze the data that their startups produce (31% respondents) and a lack of a CRM strategy (32% of respondents).

4.1. Introduction to Mygon's Decisions and Data Challenges

MyGon is a local guide with deals and last minute discounts provided near its users. The company's main difference in comparison to other solutions in the market is related to the fact that it does not issue vouchers, which means that its users are not required to pay anything online (the users pay directly to the merchant, which in its turn pays MyGon the due commission). The company's most known and largest direct competitor is Groupon, even though there are others, such as "Goodlife" or "LetsBonus".

MyGon has offers in different types of products and services, such as Restaurants, Spas, mechanical repairs and many others. In addition, there are many channels which are responsible for driving users and customers to the website or app. This means that MyGon is composed by a heterogeneous group of customers, who respond to different stimulus, can be found in diverse and multivariate channels and present different behaviors, preferences and value to the company. Despite being a challenge, such heterogeneous group can be considered as presenting an unique opportunity, namely that related to the understanding of how can the company enhance and optimize marketing spending's and efforts, as well as gain more value from current and future customers. In order to pursue this, some analyses were conducted. These analyses can be spilt in two main ones, while the others are complementary to the previous ones. Despite the fact that the two analyses are similar and based on the same or very similar metrics, what changes in both is the data availability and the way in which a customer is considered in each analysis. In the first one (1st analysis hereafter), MyGon's client database was segmented and customers were grouped based on their behaviors, preferences and attitudes towards the company, while in the second (2nd analysis hereafter) customers were grouped based on the marketing channel responsible for acquiring them.

To select the adequate metrics for the analyses there were two points which played a major role: the availability and reliability of the different types of data; and McClure's (2007) AARRR startup metrics and growth hacking process. Therefore, the metrics chosen to illustrate the potential and the value of each type of customers and marketing channels were the ones that can be found in Appendix 2. The next question is: Of what is worth to MyGon these analyses and the exploration of these metrics?

- In the 1st analysis, these metrics can give a deeper understanding about the company's customers. It also refers to what drives them to MyGon and which are the differences between different groups of customers. Furthermore, it allows MyGon to identify the value of different groups of customers, and hence in which groups of customers it should focus more and those that may probably not be worth for the company to acquire and develop relations with. Finally, it allows to breakdown this analysis in different parts, which are responsible for the value that a group of customers generates. This is, it can tell the company if a group of customers is performing greatly or poorly in terms of acquisition/activation, retention, revenue and referral; instead of just demonstrating the perception of an overall assessment. Thus, it allows MyGon to know in which part of the "funnel" it should place its efforts, as well as for each group of customers.

- The 2^{nd} analysis provides the company with insights on the effectiveness and value generated by their channels. It lets the company know on the one hand, how much are they spending in acquisition and retention with a customer and, on the other hand, what value does it generate to them. Once again, and thanks to this analysis, all the channels can be compared, not only in an overall perspective, but in all of the "funnel" dimensions. The numbers of this analysis may make the company slow down the marketing spending in some channels over others. It may also let the company know what part of the funnel may be hampering the optimization of a determinate marketing channel.

To conduct such an analysis, historical data from diverse Mygon's operations was used. On one hand, all the mechanisms and software that are responsible for recording, gathering and storing data in MyGon's databases, and which were set prior to this work project, are the foundations that make these analyses possible. On the other hand, they are also what set the boundaries and limitations of the analysis, where in some cases the available data is not as good or sufficient as desired. For example, a user can do her first transaction by the time she registers or only days/months afterwards. However, the mechanisms in place to record users' registration data are delivering poor results since the data is inaccurate and incomplete. On the other hand, transactional data is much more comprehensive and reliable, so the criteria used to consider that a user was acquired is the date when she did her first valid transaction. As a consequence, there is no way to separate acquisition metrics from activation metrics in these analyses, since the two "AAs" from "AARRR" metrics are combined in just one. This historical data was gathered through mainly three sources:

- Internal (Back Office): These sets of data contain information on every transaction; campaign and user; Dates, values charged, categories and subcategories, transaction statuses (necessary to separate valid from invalid transactions and to understand the cancellations patterns). Note that each transaction is associated with a user and with a campaign. In addition, also the number of reviews, recommendations and points used per user are based on Back Office's data.

- Google Analytics: This tool also provides a lot of valuable data suitable for analysis. Nevertheless, it was mostly used only to understand from which source users were coming at each time they were purchasing in the website/app.
- Advertisement Channels: Here it is mostly included the reports from Facebook ads' manager. This report provides essential data to understand metrics such as CPM, CTR, CPC, Conversion Rate and Cost per Conversion. Google ads' data was also available, though due to the inclusion of the keyword "Mygon" some statistics became distorted. Data from newsletter, Bownty, Forretas or Wone is limited to the amount of money spent. Most of these types of data are used only for auxiliary analyses. Nevertheless, they provide potential valuable insights, even if they fall out of scope of this work project.

Other limitations/difficulties and their respective solutions/turnaround include:

- The record of sources (channels) of transactions is done differently by google analytics and internal software and they do not match as much as it is desirable. In addition, they lack source recording for some transactions. There are less flaws in analytics data (Appendix 3) and therefore priority was given to it. Internal data on source keeping was only used when analytics data was lacking an entry.
- Facebook CPC transactions (transactions that occurred via a payed ad on Facebook) are considerably less in accordance with google analytics numbers vs Facebook reports'

numbers (due to the way Facebook is set to track a conversion and also Facebook does not recognize an invalid transaction).Once again, priority was given to google analytics.

- With exception of Facebook CPC and Newsletter sources, it is not possible to totally know what was spent in acquisition and what was spent in retention. For every other paid channel, the division was made accounting only for the number of transactions (Example in Appendix 4) In Facebook it is possible to separate the ad targets between current and prospect customers, and hence Facebook reports' data was used to make this division (a conversion from a prospect client is on average 4 times more expensive than from a current customer) (Appendix 5 and 6). Regarding the newsletter, there is a cost per email sent, and knowing within the database who is a current customer and who is only an user makes this distinction possible as well.
- The churn rate used for estimating a lifetime value considered a customer to churn if it stays one year without making a valid transaction (such as Groupon states in his reports and accounts of 2014). This is a problem and a limitation because, in fact, what is being calculated is the last years' churn (someone who joined as a customer in the last 365 days will never have the chance to effectively churn). This may not be a critical issue for big and stable companies such as Groupon, though for Mygon, as a startup with considerable growth and modifications from one year to another, may mean that the churn rate will be overestimated (today's users will churn less than users from one year ago). It is even a bigger problem when acknowledging that some marketing channels have only about one year of existence in MyGon. In order to have some results for an estimated LTV, in the 2nd analysis the definition of churn was "shrunken" and the timespan reduced to 6 months without a valid transaction. Unfortunately this has as a consequence the underestimation of

the lifetime of a group of customers and their LTV. Another measure used to turnaround this issue was to calculate an historical LTV as well. This concept is further developed in the next chapter.

To finish, it is also important to mention that an historical analysis has its limitations. The first one is that reality changes quickly, especially in the context of a startup, and hence all analysis should be up to date. MyGon is currently implementing a solution that provides an automatic analysis of some of the metrics presented in this work project, for both present and future data. Another limitation of an historical analysis has to do with the impossibility of testing new things. Recommendations will be made based exclusively on past performance and valuable tools such as A/B testing, control groups and others cannot be implemented in such a timing that could make them suitable of being analyzed in this work project.

4.2. MyGon's Data Analysis

This chapter tackles the methodology and results found for the 1st and 2nd analyses. It also refers to complementary analyses when useful. In the 1st analysis, the first thing that was needed to do was to segment the clients' database. This segmentation contemplates the number of valid transactions a user has, its cancellation patterns, their sub-categories of preference and also the preferred categories. Having this into consideration, thirteen different groups of customers were created in a total of 48939 customers as shown in appendices 7 and 8. In the 2nd analysis the segmentation, instead of being done based on users' transactions patterns, it just simply takes into account from which channel did a user complete her first valid transaction to divide the customers' database.

The next step has to do with the calculating of CAC and of the cost of retention per group of customers. As previously said in page 13 each marketing channel's monthly budget is allocated to retention or acquisition based on the number of transactions of new users vs the number of transactions of existing customers. For Facebook and Neswletter, there is also an extra consideration to do the split, despite the number of transactions. An example will follow helping to better understand the used methodology to calculate the CAC and cost of retention, but first it is useful to get in touch with the definition of cohort, since it plays an important role in the analysis. As per the website Cohortanalysis.com (n.d., par. 1) “A Cohort is a Group of people who share a common characteristic over a certain period of time…For example… all students graduated in 2010” (Appendix 10 is an example of the importance of cohort analysis).

Having this covered, it is time to move to an example that is a simplified version of what was done for this work project, however not losing any key insights in relation to the underlying analyses that sustain this thesis. Consider that this company (from now on “MyExp”), has two types of customers (“A Lovers” and “B Addicted”) and that has two channels that are responsible to drive traffic to their website (Channel 1, which is a paid channel and Channel 2, which represents users coming directly to the website and hence free of advertising costs). Customers can do two types of transactions (“Acquisition transactions” meaning that it is their first transaction with the company and “Retention transactions” that stand for the 2nd and subsequent transactions of a customer with MyExp). Consider also that in what respects to channel 1, it is two times easier (or 2 times cheaper in terms of advertising €) to close a transaction with an existing customer (a “retention transaction”) when compared with closing a transaction with a prospect client (an “acquisition transaction”). This means that, for example, if 12 € were spent in advertising in month 1 and those 12 € generated 2 “retention transactions” and 2 “acquisition transactions” then instead of allocating 50/50 to acquisition and retention, 8 € out of those 12 will be allocated to acquisition and 4 € to retention. For the purpose of this example a time-span of 4 months was considered and transactions occurred like shown in Appendix 10.1.

The monthly spending in advertising in channel 1 was of € 100 in month 1; € 250 in month 2; € 350 in month 3 and € 450 in month 4, while in channel 2, since it is a direct channel, there is obviously no advertisement expenses to register. Having this, it is possible now to breakdown the advertisement spending into "acquisition" and "retention" and also to know the cost per "acquisition transaction" and per "retention transaction" (as in appendix 10.2).

In month 4 occurred 40 "acquisition transactions" and 25 "retention transactions" via channel 1, and € 450 were spent in total with this channel. This means that € 343 out of this € 450 must be allocated to Acquisition ((450* (40*2)) / ((40*2)+(25*1))) and € 107 to Retention ((450* (25*1)) / ((40*2)+(25*1))). As a consequence, this also means that each "acquisition transaction" in month 4 had a cost of € 8,6 (343/45) and each "retention transaction" costed, in advertisement, € 4,3 (107 / 25).

Reaching here, calculating the average cost of acquisition per segment of customers is now just one step ahead. There are two ways in which CAC can be presented at this point: Month by month, so that it is possible to understand the evolution, or for the whole period as demonstrated in appendix 10.3. The results in the example are the ones shown in appendix 10.4.

Finally, it comes the time to present the calculations and the results for the cost of acquisition per segment, which is also the final step of this example. Although here things are a bit trickier than for calculating CAC, it is here that the notion of cohort gets its relevance as well. A customer can only be acquired once and it will be acquired evidently in its first month as a customer, however a customer can be retained throughout a long period of time. If cost of retention was to be calculated in the same way as CAC, then the fact that customers tend to make less transactions as they get more mature clients will always contribute to a lower average cost of retention per customer in general. Hence, this would be distorting the real customer retention effectiveness of MyExp, leading to believe that they are being able to retain clients at a lower cost. Though, what is happening in fact is that their customers are not only making fewer "retention transactions", but also paying less (coming from channel 1) "retention transactions" due to the circumstance that the customers' base is on average more mature. Appendix 10.5 evidences this pretty well, especially for "A Lovers" customers. The cost of retention calculated in the "wrong" way shows a decrease from €0,60 per customer in month 1 to € 0,48€ which would be a positive thing for the company. However, a cohort analysis shows different conclusions, since it evidences that customers acquired in month 1 needed the same retention spending in the 1st month as those clients acquired in month 4, for example.

To finish MyExp example case, there is one extra point in what relates to the cost of retention, which is, in fact, of utmost importance for the real analysis carried forward in this work project: How to calculate the whole period average cost of retention? The formula in appendix 10.6 shows how to solve this issue and the appendix 10.7 shows the results in the example.

Having completed the example, it is time to understand what changes from this example to the real analysis for this work project. Besides the results, of course, what changes is that instead of one paid channel there are five (i.e. Newsletter; Facebook CPC; Forretas; Google CPC and Wone) and instead of one non paid channel there are also five non paid channels (Direct; Facebook Organic; Search Engine; Without Source and Referral). In addition, the segmentations' criteria (or types of clients) are different. In the first analysis, the types of clients are those in Appendix 7, and in the second the existing types of clients correspond to the five paid channels (Newsletter; Facebook CPC; Forretas; Google CPC and Wone). Finally, the period of the analysis is, for the 1st analysis from January of 2014 to October of 2015, and also only from January 2015 to October 2015; whereas in the 2nd analysis the periods in analysis are from January of 2015 to October of 2015 and also from April of 2015 to October of 2015.

In the real analyses, the cost of retention that will be privileged will be the global one as explained in the last part of the example. The reason for this is that there are several metrics of several parts of the "funnel" being calculated for a considerable diverse group of customers, and the main purpose is to have the metrics calculated in an easiest way to integrate between each other. Besides, when calculating the LTV, it is mandatory to have a cost of retention that matches the same period in order to find the Net LTV (which in this case study is considered to be the LTV minus the CAC minus the Cost of Retention).

It is now time to explain the methodology used for calculating the LTV of the various groups of customers for both analyses. First of all, it is important to clarify why the LTV was calculated in two different ways: An estimated LTV and an historical LTV. The estimated LTV, if calculated in an one hundred percent accurate way, would be the "holy grail" of the metrics. If any company could know for sure which value each type of customer yields, then it could adjust all its actions to spend marginally in acquisition and retention up until the same amount that any group of customers has for the company. However, it is virtually impossible to get this value sharp, since it is reliant on values that are difficult to know for sure, such as the value yield from customers referred from other customers; it is dependent on a large historical database with enough statistical significance; relies on assumptions that the macro economical scene and even the environment in which the company is inserted remains more or less stable, and some others. In addition, for a startup company is particularly difficult to have such a complex model that can handle this metric with most of the accuracies. Specifically in MyGon case, there are some additional constraints related with calculating the churn rate (already mentioned in chapter 4.1). As said before, one of the solutions found for the problem posed by an estimated LTV was to calculate an historical LTV and have both complementing each other and understand whether they lead to the same conclusions or not. Nevertheless, what is this historical LTV, how is it calculated and which are its pros and cons when compared with the estimated LTV?

The historical LTV is, in fact, the average revenue generated by a user from any group of customers for a given period of time calculated based on historical data for that same period. It is calculated in a similar way as the global cost of retention. However, instead of being based on the total spending in retention it is based on total revenue generated (sum of total value charged for all valid transactions). The formula that gives the historical LTV can be found in appendix 11.

In the real analyses, the period is not from month 1 to month n, but instead the exactly same periods as those for which cost of retention and cost of acquisition were calculated as well.

The historical LTV "loses" against the estimated LTV, since it does not make projections for the future and does not achieve the real LTV value. However, it "wins" in reliability since it is based on things that happen indeed (they are factual results and not projections or forecasts). In addition, to make up for the lack of "not having a glimpse into the future" with the historical LTV, additional metrics were computed that are complementary to the historical LTV and allow a good understanding of what to expect in terms of revenue from a group of customers in the future. Those metrics are: "Percentage of Revenue not in 1st Month" (many of MyGon users generate most of their value in the 1^{st} month); "Revenue in last 3 Months"; "Ration of Revenue in Last 3 months in relation to Revenue in 1st month". Nevertheless, how can these metrics reveal the future pattern of revenue for a group of customers? For example, in the 2^{nd} analysis the group of customers acquired via "Facebook CPC" generated an average revenue (historical LTV) from October 2014 to October 2015 of € 7,69, though the first month of life of these users account for 78% of this value, and the revenue in the total of the last 3 months represents just 4 % of the revenue obtained in the 1^{st} month. One can draw as a conclusion that the € 7,69 will not grow exponentially (far from that) up until the end of the lifetime of this group of customers with the company. It is fair to assume that the real LTV of these customers will hardly reach € 9,00 for example (they are already "dying" as customers within the company). Nonetheless, for groups of customers whom are still "very healthy" at the end of the period in analysis for which a historical LTV is being calculated, the estimated LTV gives a better picture of their value for the company when compared with the historical LTV. For these type of groups of customers it is better to understand their expected lifetime with the company, because metrics such as “Revenue in last 3 Months” will only tell that it is reasonable to assume that a good flow of revenue will continue, but makes it hard to understand for how long.

The estimated LTV for each group of customers was calculated as in appendix 12.

To finish this chapter, a brief overview to the metrics related with referrals (customers brought to MyGon by other happy customers), Cancellation patterns, Reviews of users (users can give feedback in the website/app on a sale that goes from 1 to 5. This is important for two reasons: The more feedback users give, the better overall product MyGon gets because potential customers trust in other customers’ feedback; the higher the reviews’ score the more satisfied and engaged with the product users are, and thus are more valuable to MyGon); Points used (users receive points for each valid transaction they make and for recommending other users. It is not too easy to have enough points to be able to claim a prize and hence the more points used, a group of customers has the more “super” users that group of customers has. In addition, it also helps to boost and measure the retention effectiveness of MyGon).

The full results of both 1st and 2nd analysis can be found in appendices 13 and 14.

4.3. Conclusions and Recommendations to implement in Mygon

The main recommendation of this work project is for MyGon to focus on their Sushi Lovers Customers’. The conclusions taken from the analysis of the data are pretty straightforward. They have by far the highest estimated LTV (€ 128,16 vs. € 42,22 by the group of customers with the 2nd highest LTV - Saude Lovers – and vs a general average of € 10,27) and their estimated net LTV is 4 times bigger than the 2nd best (Restaurantes Lovers) and 17,5 bigger than the general average. Their predicted lifetime with the company is of 8,6 years and their churn rate does not stop to decrease month by month (as of September of 2015 when comparing with September of 2014 this group’s yearly churn was of only 6,4% - this would mean an estimated LTV per sushi lover customer of € 219,38 if solely based on September’s data instead of the average of all months of 2015). In addition, the historical LTV leads to the same inferences, since for the period based on data from January of 2014 to October of 2015 Sushi Lovers LTV is bigger than all others groups’ LTVs and Sushi Lovers complementary metrics results totally offset the other groups: Only 13% of the revenue occurred in the first month of life; each customer is generating an average of 83,3 cents per month in the last 3 months and the ratio of revenue in the last 3 months vs revenue in the 1st month is by far the largest one (82% vs 22,6% by the 2nd best – restaurants lovers – and vs a total average of 11.4%). Even though when shrieked the period in analysis to January of 2015 to October of 2015, Suhi Lovers’ historical LTV is not yet the highest, the complementary metrics forecast a bright revenue stream to occur in the future (for example the average revenue in each of the last 3 months is still 73% of the average monthly revenue for the whole period – meaning that the revenue stream is not cooling down yet). In addition, CAC of sushi lovers is extremely low (only surpassed once in each period due to either statistically insignificance of another group or due to the fact that MyGon acquired an abnormal quantity of users in January of 2014 by appearing in the news prime time – groups of customers who have most of their users acquired in this month have that big advantage because those users were acquired at a cost of 0 €). Finally, Sushi Lovers also perform better than average in all other non-monetary parameters measured (Users Recommended; % Negative Reviews; % Cancellations and “No-shows”; and Points used). To reinforce the value of this suggestion, the lean analytics book offers the example of the case of Circle of Moms that pivoted its business from the originally Circle of Friends. The pivot meant a decrease in users from 10 to 4.5 million, however these 4.5 were actively engaged as opposed to the initial 10. Once the company found its target it focused. It led to a big, scary, gusty bet that was a gamble – but one that was based on data (Croll & Yoskovitz, 2013). It is true that startup's goal is growth, but it has to be one that is sustainable and organically repeatable and profitable.

An alternative, and less dramatic suggestion, in line with the above would be for MyGon to focus on Restaurants and Health and Beauty categories. These two categories include Dentist Lover; Wax + Hairdresser Lover; Spa Lover; Health Lover; Sushi Lovers and Restaurants Lover. This would focus MyGon in two main categories (the ones which are yielding better results for the company), improving the consistency of MyGon's message and communication, as well as its points of difference. In addition, it is a decision that is more suitable of reversion than the one of focusing just in Sushi Lovers.

Another important recommendation has to do with the paid channel "Facebook CPC". As Kevin O'Leary would say in "Shark Tank" TV show: "Stop the madness!". The users who are acquired via this channel have on average a negative estimated LTV of € -7,12 (meaning that the costs of acquiring and retaining these users exceeding 62% the revenue generated by them during their life as MyGon's customers. Besides, these costs do not include human labor, software that assists in the creation of the advertisement campaigns, etc.). Historical LTV (based on data from October 2014 to October 2015) not only confirms estimated LTV results as it even shows a darker picture (a negative net LTV of € - 11,23 or, in other words, the cost or acquiring and retaining these users surpasses the revenue they generate to the company in 2,5 times). The ratio revenue in last 3 months vs revenue in first month of 4% confirms that these customers are dying within a year as MyGon's customers (or in other words, the revenue generated by these users in the sum of the last 3 months represents only 3% of the total revenue they have generated from October 2014 to October 2015). In addition to the exaggerated cost to acquire users via this channel, another reason that helps to explain the negative LTV is the fact that users coming to MyGon via Facebook CPC are not being retained as desirable. In fact, that is a global problem of the firm (28082 out of 48939 customers of

MyGon never did a second transaction), but it is even worse for this specific channel (only 24% of the customers acquired via this channel from January 2015 to October 2015 did more than 1 valid transaction). It is true that growth is fundamental and Facebook CPC represents, nowadays, for MyGon the paid channel that brings more new customers for the company, though unsustainable growth is not the best option. In this sense, it is crucial that Mygon either finds other acquisition channels that can be more lucrative to the company or that implement measures to optimize this channel. To optimize the channel, the company may use retargeting and remarketing ads (as they already do but in a small scale. Appendix 6 shows the that these ads generate conversions at a much lower cost) to increase the retention of these users; or can also focus on categories and devices in which they are able to convert users at a lower cost (for example PC ads have proven to be cheaper than mobile ones but the company is not slowing down the proportion of the Facebook budget that goes for mobile. (See Appendix 15). Finally, it is also important to note that some of this reasoning is also true for Google CPC channel. However, this channel is more close to breakeven and users acquired via this channel remain longer with the company. In this sense, Google CPC users are more suitable of turning lucrative to the company with less adjustments needed in comparison with Facebook CPC users.

In the *Definitive Guide too Growth Hacking*, Patel and Taylor (n.d.) explain the concept of viral coefficient as the number of people each customer brings himself to the company. They also add that, to achieve exponential growth, the viral coefficient must be superior to 1, which means that each new customer brings with himself more than one other customer on average. Looking to the number of users, each MyGon customer has recommended on an general basis, it is possible to conclude they are far away from benefiting from this exponential growth (their recommendation rate is of 5,8%). The underlying problems behind this can be that the rewards they offer for users recommending others are not sufficient attractive; that their recommendation paths are not as effective as desired or that in general people are not passionate enough for the product. Nevertheless, what matters is that MyGon must find out why their viral coefficient is so low and attempt to improve it.

Other recommendations include:

- Increase the overall retention effectiveness of the company. Start thinking in retention as a priority instead of focusing mainly on acquisition. In addition, “retention can also have an effect in acquisition cost” (Marketing Tactics, n.d.);
- Improve the data tracking of the company. Google analytics could not keep trace of around 20% of the sources of the company’s transactions and hence had to be grouped into a group of customers named “Without Source”. For example, all transactions coming from an android device were not captured in analytics. As a consequence Facebook CPC or Google CPC CAC and cost of retention may be slightly overestimated;
- Work on cancellation rates from all groups of customers linked with the category “Health and Beauty”. These customers have cancellation rates (transactions cancelled divided by valid transactions) in between 34% and 40% which does not only mean that a lot of potential revenue is being loss but also that merchants may get unhappy and stop the partnership with MyGon. Pay even more attention to this issue in what relates to the group of customers “Always Cancelling” who have a cancellation rate of 251% and a No-Show rate of 27%. Furthermore this group represents 11% of the total customers of MyGon, who have more than 2 valid transactions. Doing it so can be of crucial importance for revenue increasing.

5. Final conclusions

This work project helped to demonstrate that data analysis is a key success factor for startups to redefine and tune their product-market fit and achieve their ultimate goal, which is finding a lucrative, repeatable and scalable business model. Especially in Portugal, most startups still ignore or disregard data based decisions and use intuition as main decision factor (as understood from interviews with Fernando Peres Ferreira from Portugal Ventures, Pedro Rebordão from Lispolis and Francisco Ferreira Pinto from Busy Angels) but they should start to complement it with data analysis and constant tracking of metrics. In order to corroborate this approach, startups (in particular technological ones) should have in mind since day one that they must have in place the right mechanisms to collect reliable data in order to create a good historical database that may be suitable of analysis. Furthermore, as McClure (2007) proposes, startups must acknowledge the importance of using a funnel for the relevant metrics and to breakdown the analysis as further as possible (up until the point where is no longer relevant to break it down anymore).

Another lesson to bear in mind is that even though startups may be tempted to try to reach multiple markets and diverse customers with a large product offering in order to achieve a bigger customer base and rhythm of growth, it may not always be the smartest strategy. Focusing and understanding which customers really value which products and product features as well as are available to pay a sustainable price (in comparison with the cost of having them as customer) is the key. This knowledge and focus allow the startup to constantly improve product-market fit and achieve a growth that is sustainable and not exclusively backed by investors' capital.

Finally, data analysis is not a one-time thing. It should be embedded in the startup's strategy and must be a means to constantly optimize all dimensions of the business.

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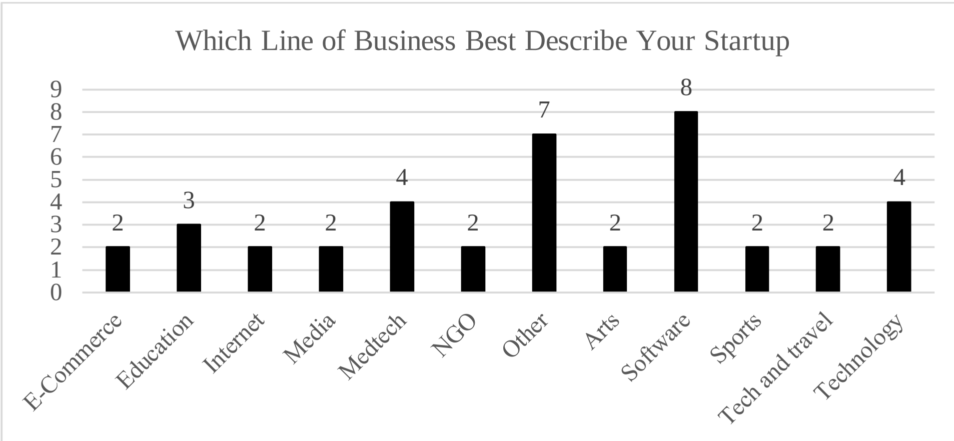
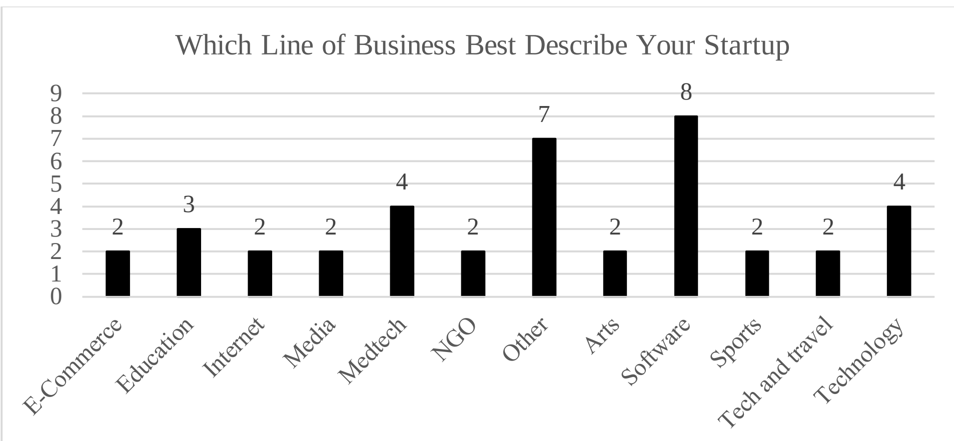
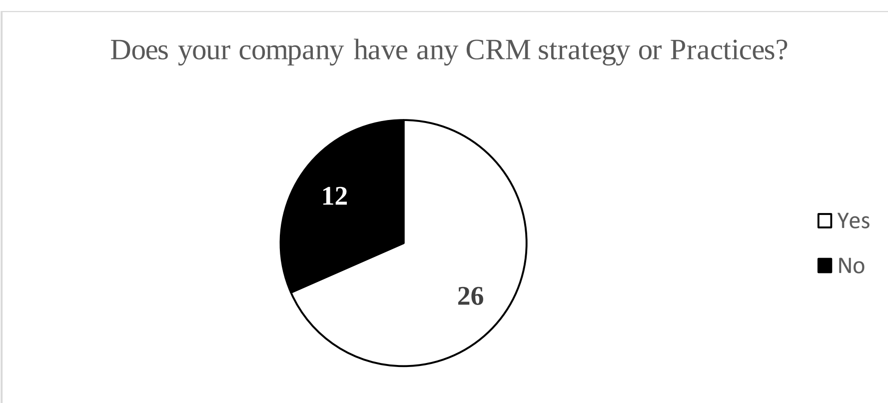
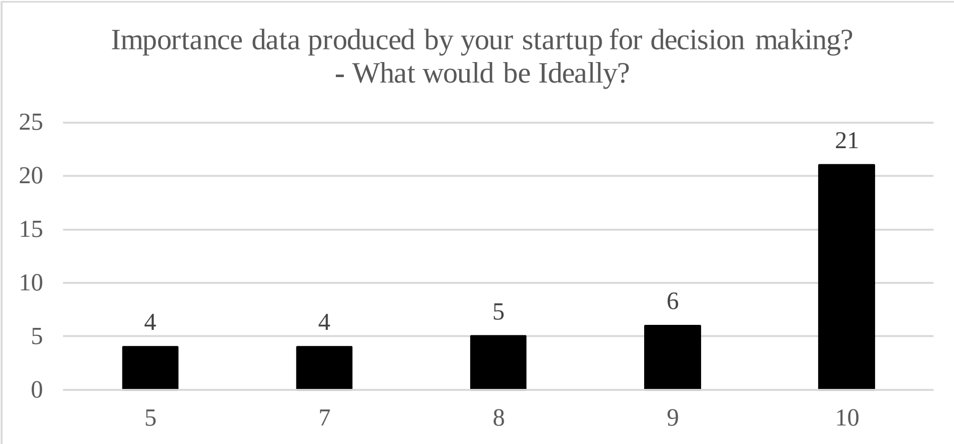
7. Appendices

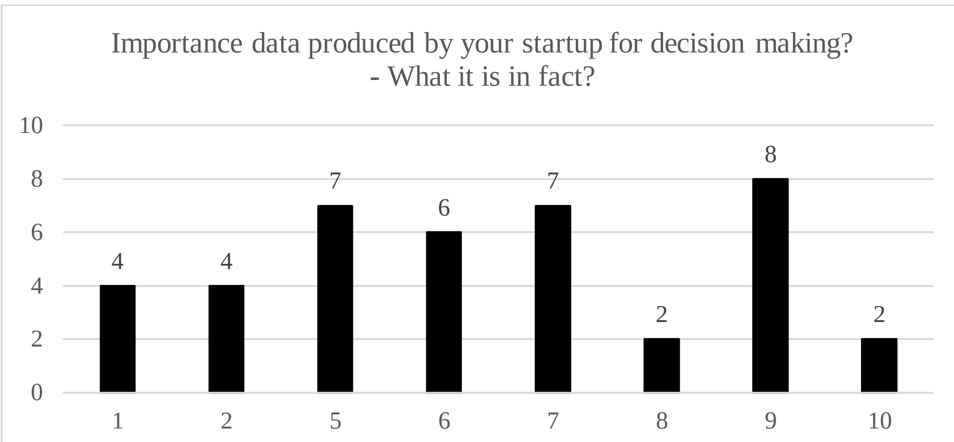
Appendix 1.
Startups' Questionnaire Results: The Importance of Data Driven Decisions

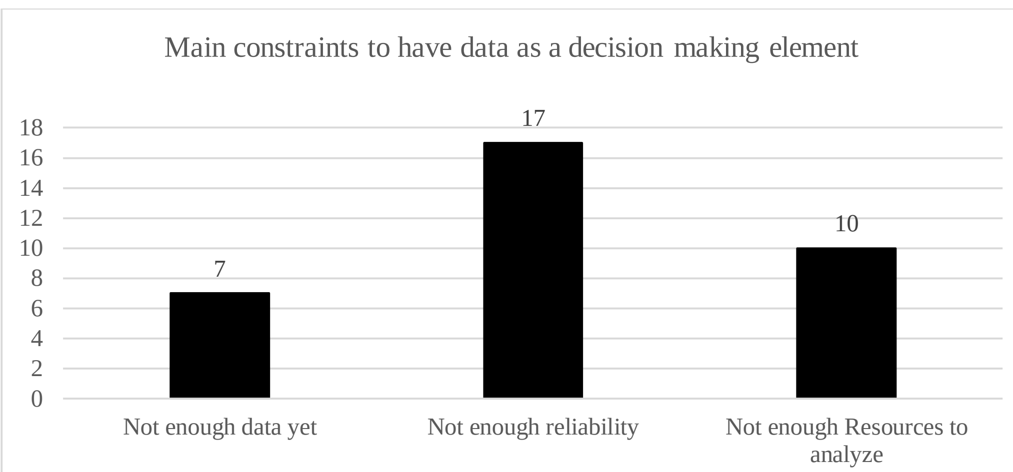


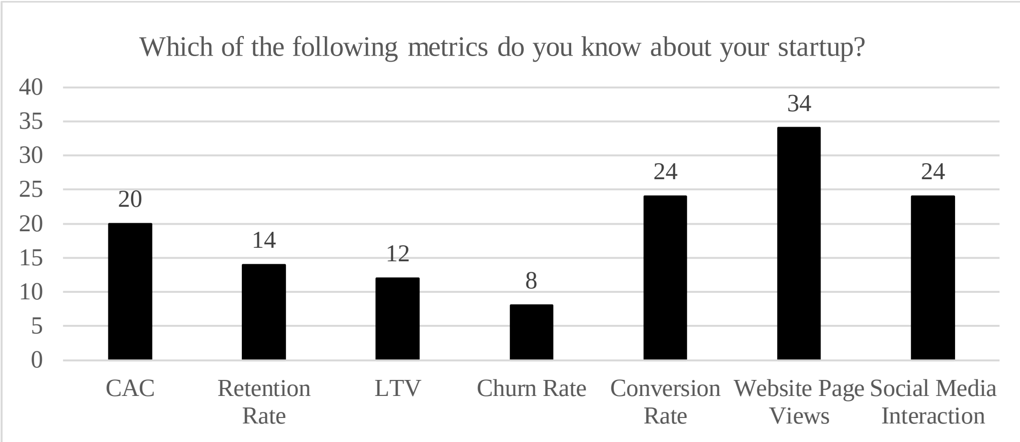


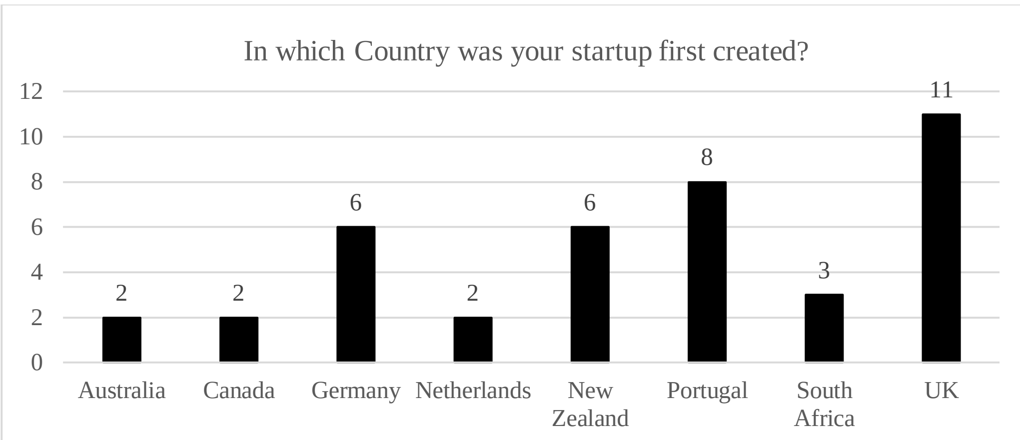



Importance data produced by your startup for decision making?
- What would be Ideally?
25
20
15
10
5
0
4
4
5
6
21
5
7
8
9
10


Importance data produced by your startup for decision making?
- What it is in fact?
10
8
6
4
2
0
4
4
7
6
7
2
8
2
1
2
5
6
7
8
9
10


Main constraints to have data as a decision making element
18
16
14
12
10
8
6
4
2
0
7
17
10
Not enough data yet
Not enough reliability
Not enough Resources to analyze

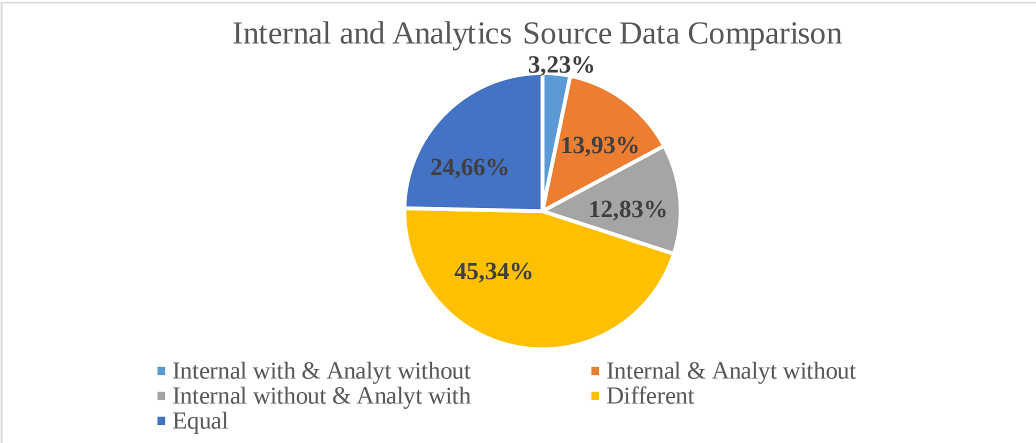




Appendix 2.
Metrics calculated in main analyses of Work Project

1. Cost of Acquisition (CAC);
2. Cost of Retention;
3. Lifetime Value Estimated
4. Historical Lifetime Value
5. Net Lifetime value (net of CAC and cost of retention)
6. Recommendation of users
7. Reviews per transaction;
8. % Cancelled/Invalid Transactions;
9. Points used per user.

Appendix 3.
Internal Data vs. Google Analytics - Source Tracking Comparison



Appendix 4.
Allocation of Marketing Spending to Acquisition and Retention (Example for channels in which Acquisition and Retention Demand Equal Efforts)

If 900€ were spent on channel x in month y, and in that month there were 30 transactions from current clients and 60 from new clients, then € 600 (900 *60 / (30 + 60)) are allocated to acquisition and the remaining to retention.

Appendix 5.
Allocation of Marketing Spending to Acquisition and Retention (Example for Facebook in which Acquisition and Retention Demand Different Efforts)

If the marketing spending with Facebook were of 1000€ in month z and it yield 10 conversions from new customers and 10 from existing ones them it is allocated 800€ to acquisition ((1000 * (10 * 4)) / (10 * 4 +10 * 1) and 200€ to retention.

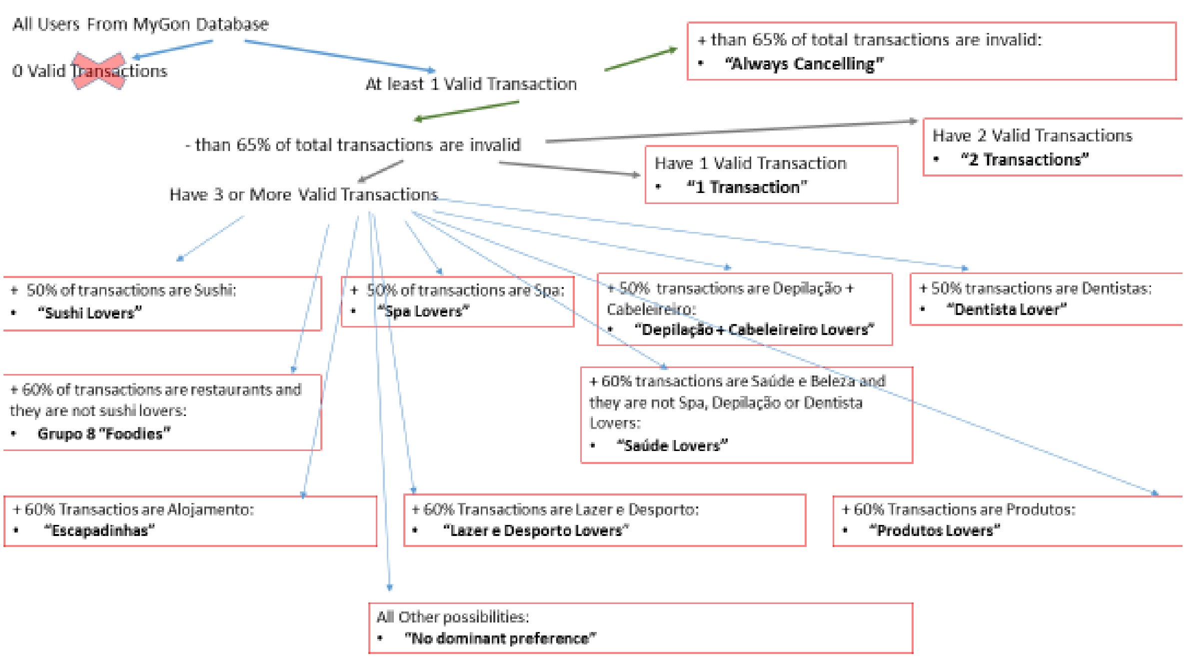
Appendix 6
Ratio of Cost per Converting one prospect client compared with converting one prospect plus an existing client. Values for Facebook Advertising on the two main categories of MyGon.

	Ratio Cost per Conversion Prospect Clients vs Cost per Conversion Prospect + Existing Clients
Mobile	-
Restaurantes	0,82
Saude e Beleza	0,74
PC	-
Restaurantes	0,87
Saude e Beleza	0,78
Average	0,80

Appendix 7
Segmentation Groups and respective number of customers in each Group

- "1 Transaction" – 28082 customers
- "2 Transactions" - 7627
- "Alojamento Lover" - 166
- "Dentista Lover"
- "Depilação + Cabeleireiro Lover" - 93
- "Lazer Lover" - 488
- "Produtos Lover" - 278
- "Restaurantes Lover" - 2005
- "Saúde Lover" - 1375
- "No Dominant Preference" - 2402
- "Always Cancelling" - 1490
- "Spa Lover" - 377
- "Sushi Lover" - 4421

Appendix 8
Segmentation Criteria



Appendix 9
Example Importance Cohort Analysis for monthly average revenue per customer (Croll & Yoskovitz, 2013).

Consider a company that has 1000 users in month 1, acquires 1000 more in month 2 to a total of 2000 and acquires another 1000 in month 3 to a total of 3000. First they look at average revenue per customer on a cumulative way and results are the following ones: Month 1 (1000 customers, average revenue = $ 5.00); Month 2 (2000 customers, average revenue = $ 4.50); Month 3 (3000 customers, average revenue = $ 4.33). However when broken down into cohorts by the month customers arrived to the company, results are considerably different: Users that arrived in month 1 (average revenue in their 1st month = $ 5.00, average in 2nd month = $ 3.00, average in 3rd month $ 2.00); Users that arrived in month 2 (average revenue in their 1st month = $ 6.00, average in 2nd month = $ 4.00); Users that arrived in month 3 (average revenue in their 1st month = $ 7.00). The conclusion that follows is that the aggregate average revenue was decreasing because users tend to purchase less month after month and on average the "maturity" of the users is increasing, but in fact the metrics are improving (each cohort is performing better than their antecessors).

Appendix 10.1
Total Transactions MyExp Example

Transactions (Total)				
	Month 1	Month 2	Month 3	Month 4
Channel 1	**15**	**30**	**45**	**65**
Channel 2	**35**	**55**	**65**	**80**

Transactions from New Users				
	Month 1	Month 2	Month 3	Month 4
Channel 1	**10**	**20**	**30**	**40**
Channel 2	**20**	**30**	**30**	**40**

Transactions from Existing Users				
	Month 1	Month 2	Month 3	Month 4
Channel 1	**5**	**10**	**15**	**25**
Channel 2	**15**	**25**	**35**	**40**

Customers acquired "A Lovers"				
	Month 1	Month 2	Month 3	Month 4
Month 1	20	-	-	-
via channel 1	**7**	-	-	-
via channel 2	**13**	-	-	-
Month 2		30	-	-
via channel 1		**16**	-	-
via channel 2		**14**	-	-
Month 3			35	-
via channel 1			**20**	-
via channel 2			**15**	-
Month 4				50
via channel 1				**30**
via channel 2				**20**

Customers acquired "B Addicted"				
	Month 1	Month 2	Month 3	Month 4
Month 1	10	-	-	-
via channel 1	**3**	-	-	-
via channel 2	**7**	-	-	-
Month 2		20	-	-
via channel 1		**4**	-	-
via channel 2		**16**	-	-
Month 3			25	-
via channel 1			**10**	-
via channel 2			**15**	-
Month 4				30
via channel 1				**10**
via channel 2				**20**

Transactions "A Lovers" (excluding 1st transaction)				
	Month 1	Month 2	Month 3	Month 4
Month 1	12	8	7	3
via channel 1	**3**	**2**	**2**	**1**
via channel 2	**9**	**6**	**5**	**2**
Month 2		11	9	7
via channel 1		**3**	**3**	**3**
via channel 2		**8**	**6**	**4**
Month 3			11	9
via channel 1			**4**	**4**
via channel 2			**7**	**5**
Month 4				12
via channel 1				**7**
via channel 2				**5**

Transactions "B Addicted" (excluding 1st transaction)				
	Month 1	Month 2	Month 3	Month 4
Month 1	8	7	5	3
via channel 1	**2**	**2**	**1**	**1**
via channel 2	**6**	**5**	**4**	**2**
Month 2		9	7	7
via channel 1		**3**	**2**	**2**
via channel 2		**6**	**5**	**5**
Month 3			11	9
via channel 1			**3**	**3**
via channel 2			**8**	**6**
Month 4				15
via channel 1				**4**
via channel 2				**11**

Appendix 10.2

Monthly Spending and monthly cost per acquisition transaction and per retention transaction in MyExp Example

Monthly Spending Channel 1				
	Month 1	Month 2	Month 3	Month 4
Acquisition	**80 €**	**200 €**	**280 €**	**343 €**
per acquisition	**8,0 €**	**10,0 €**	**9,3 €**	**8,6 €**
Retention	**20 €**	**50 €**	**70 €**	**107 €**
per retention	**4,0 €**	**5,0 €**	**4,7 €**	**4,3 €**

Monthly Spending Channel 2				
	Month 1	Month 2	Month 3	Month 4
Acquisition	**- €**	**- €**	**- €**	**- €**
per acquisition	**- €**	**- €**	**- €**	**- €**
Retention	**- €**	**- €**	**- €**	**- €**
per retention	**- €**	**- €**	**- €**	**- €**

Appendix 10.3
CAC (Cost of Acquisition) calculations in MyExp Example

$$\frac{\text{Nº Acq Transact Channel 1 (month x) * Cost per Acq Transact Channel 1 (month x)}}{\text{Nº Acq Transact Channel 1 (month x) + Nº Acq Transact Channel 2 (month x)}}$$, x equals 1; 2; 3; or 4. For whole period would be ∑ of this formula

Appendix 10.4
CAC (Cost of Acquisition) results in MyExp Example

Average CAC "A Lovers"				
Month 1	Month 2	Month 3	Month 4	Whole Period
2,80 €	**5,33 €**	**5,33 €**	**5,14 €**	**4,89 €**

Average CAC "B Addicted"				
Month 1	Month 2	Month 3	Month 4	Whole Period
2,40 €	**2,00 €**	**3,73 €**	**2,86 €**	**2,86 €**

Appendix 10.5
"Wrong" Calculation of Monthly Cost of Retention vs Cohort analysis of monthly cost of retention in MyExp

Average Monthly Retention Cost "A Lovers"(Wrong!)				
Month 1	Month 2	Month 3	Month 4	Total
0,60 €	**0,50 €**	**0,49 €**	**0,48 €**	**2,07 €**

Average Monthly Retention Cost "B Lovers" (Wrong!)				
Month 1	Month 2	Month 3	Month 4	Total
0,80 €	**0,83 €**	**0,51 €**	**0,50 €**	**2,65 €**

Average Monthly Retention Cost "A Lovers"				
	Month 1	Month 2	Month 3	Month 4
Month 1	**0,60 €**	**0,50 €**	**0,47 €**	**0,21 €**
Month 2		**0,50 €**	**0,47 €**	**0,43 €**
Month 3			**0,53 €**	**0,49 €**
Month 4				**0,60 €**

Average Monthly Retention Cost "B Lovers"				
	Month 1	Month 2	Month 3	Month 4
Month 1	**0,80 €**	**1,00 €**	**0,47 €**	**0,43 €**
Month 2		**0,75 €**	**0,47 €**	**0,43 €**
Month 3			**0,56 €**	**0,51 €**
Month 4				**0,57 €**

Appendix 10.6
Whole Period Average Cost of Retention Formula in MyExp

$$\frac{\sum \text{Cohortx RC in month 1}}{\text{Users Acquired month (1+2+3+4)}} + \frac{\sum \text{Cohortx RC in month 2}}{\text{Users Acquired month (1+2+3)}} + \frac{\sum \text{Cohortx RC in month 3}}{\text{Users Acquired month (1+2)}} + \frac{\sum \text{Cohortx RC in month 4}}{\text{Users Acquired month (1)}}$$, RC = Retention Costs

Appendix 10.7
Whole Period Average Cost of Retention Results in MyExp

Average Monthly Retention Cost "A Lovers"				
Month 1	Month 2	Month 3	Month 4	Total
0,56 €	**0,48 €**	**0,44 €**	**0,21 €**	**1,70 €**

Average Monthly Retention Cost "B Lovers"				
Month 1	Month 2	Month 3	Month 4	Total
0,64 €	**0,59 €**	**0,44 €**	**0,43 €**	**2,09 €**

(Please note month 1 here means "the 1st month after the users have been acquired, and so on)

Appendix 11
Historical LTV formula Calculation

$$\frac{\sum \text{Cohort}x\text{ Rev in month 1}}{\text{Users Acquired month }(1+2+\ldots+n)} + \frac{\sum \text{Cohort}x\text{ Rev in month 2}}{\text{Users Acquired month }(1+2+\ldots+[n-1])} + \ldots + \frac{\sum \text{Cohort}x\text{ Rev in month n}}{\text{Users Acquired month }(1)}$$

, Rev = Revenue Generated

Appendix 12
Historical LTV formula Calculation

$$\text{Estimated LTV} = \text{Average nº of transactions per month per active customer} * \text{Average Value Charged per transaction} * \text{Lifetime of Group of Customers in months}$$

$$\text{Lifetime} = \frac{1}{\text{Churn Rate}} \qquad \text{Churn Rate} = 1 - \text{Customer Retention Rate}$$

$$\text{Customer Retention Rate} = \frac{\text{Active Users Today} - \text{Active Users Today but inactive one year ago}}{\text{Active Users one year ago}}$$

Appendix 13

Full Results of 1st Analysis

	CAC (based on jan 14 - out 15 data)	CAC (based on jan 15 - out 15 data)
1 Transaction	2,20 €	3,53 €
2 Transactions	1,32 €	2,40 €
Alojamento Lover	0,40 €	9,10 €
Dentista Lover	2,29 €	3,45 €
Depilação + Cabeleireiro Lover	1,51 €	2,56 €
Lazer Lover	0,58 €	4,14 €
Produtos Lover	0,37 €	0,19 €
Restaurantes Lover	0,54 €	0,86 €
Saude Lover	2,18 €	4,01 €
No Dominant Preference	0,51 €	2,66 €
Always Cancelling	1,46 €	2,11 €
Spa Lover	1,93 €	3,77 €
Sushi Lover	0,48 €	0,62 €
TOTAL	1,74 €	3,07 €

	Cost of Retention (based on jan 14 - out 15 data)	Cost of Retention (based on jan 15 - out 15 data)	Cost of Retention (per lifetime)
1 Transaction	- €	- €	- €
2 Transactions	0,68 €	0,98 €	1,58 €
Alojamento Lover	0,28 €	2,28 €	3,31 €
Dentista Lover	3,26 €	3,47 €	7,22 €
Depilação + Cabeleireiro Lover	2,24 €	2,50 €	9,59 €
Lazer Lover	0,42 €	3,30 €	4,55 €
Produtos Lover	0,73 €	1,81 €	2,81 €
Restaurantes Lover	1,37 €	1,45 €	6,78 €
Saude Lover	3,15 €	3,94 €	12,58 €
No Dominant Preference	0,92 €	2,70 €	6,89 €
Always Cancelling	0,18 €	0,20 €	0,27 €
Spa Lover	2,49 €	2,71 €	9,01 €
Sushi Lover	2,12 €	1,50 €	15,54 €
TOTAL	0,59 €	0,48 €	0,79 €

	Customer Retention Rate	Churn Rate	Lifetime of Customer (In Years)
1 Transaction	0%	100%	1,00
2 Transactions	25%	75%	1,34
Alojamento Lover	17%	83%	1,21
Dentista Lover	42%	58%	1,73
Depilação + Cabeleireiro Lover	69%	31%	3,20
Lazer Lover	13%	87%	1,15
Produtos Lover	23%	77%	1,29
Restaurantes Lover	74%	26%	3,89
Saude Lover	62%	38%	2,66
No Dominant Preference	53%	47%	2,13
Always Cancelling	11%	89%	1,13
Spa Lover	64%	36%	2,77
Sushi Lover	88%	12%	8,63
TOTAL	27%	73%	1,36

	Average value Charged per transaction	Average nº of transactions per month
1 Transaction	4,15	0,10
2 Transactions	3,42	0,15
Alojamento Lover	5,63	0,10
Dentista Lover	7,94	0,15
Depilação + Cabeleireiro Lover	3,95	0,26
Lazer Lover	5,43	0,23
Produtos Lover	2,29	0,25
Restaurantes Lover	2,43	0,31
Saude Lover	4,11	0,32
No Dominant Preference	3,25	0,22
Always Cancelling	4,11	0,14
Spa Lover	3,58	0,25
Sushi Lover	2,08	0,53
TOTAL	3,02	0,21

	LTV (gross) (Estimated)	LTV (net)
1 Transaction	4,83 €	1,30 €
2 Transactions	8,24 €	4,26 €
Alojamento Lover	11,38 €	- 1,04 €
Dentista Lover	26,02 €	15,35 €
Depilação + Cabeleireiro Lover	39,90 €	27,75 €
Lazer Lover	21,24 €	12,55 €
Produtos Lover	8,92 €	5,93 €
Restaurantes Lover	35,94 €	28,30 €
Saude Lover	42,22 €	25,63 €
No Dominant Preference	18,86 €	9,31 €
Always Cancelling	8,07 €	5,69 €
Spa Lover	30,28 €	17,51 €
Sushi Lover	128,16 €	112,00 €
TOTAL	10,27 €	6,41 €

	LTV Historical (Jan 14 - Out 15)	LTV Historical (Net)
1 Transaction	3,30 €	1,10 €
2 Transactions	6,59 €	4,59 €
Alojamento Lover	6,47 €	5,79 €
Dentista Lover	21,43 €	15,88 €
Depilação + Cabeleireiro Lover	22,43 €	18,68 €
Lazer Lover	13,88 €	12,88 €
Produtos Lover	10,48 €	9,38 €
Restaurantes Lover	17,46 €	15,55 €
Saude Lover	23,52 €	18,19 €
No Dominant Preference	18,81 €	17,38 €
Always Cancelling	6,03 €	4,39 €
Spa Lover	18,36 €	13,94 €
Sushi Lover	24,23 €	21,63 €
TOTAL	8,19 €	5,86 €

	% Revenue not in 1st Month	Revenue in last 3 Months	Revenue Last 3 months / Revenue in 1st month
1 Transaction	0%	- €	0%
2 Transactions	40%	0,09 €	2%
Alojamento Lover	80%	0,07 €	6%
Dentista Lover	46%	2,16 €	19%
Depilação + Cabeleireiro Lover	71%	1,47 €	22%
Lazer Lover	47%	0,07 €	1%
Produtos Lover	52%	- €	0%
Restaurantes Lover	79%	0,83 €	23%
Saude Lover	69%	1,45 €	20%
No Dominant Preference	73%	0,64 €	13%
Always Cancelling	37%	0,33 €	9%
Spa Lover	64%	0,60 €	9%
Sushi Lover	87%	2,50 €	82%
TOTAL	56%	0,41 €	11%

	LTV Historical (Out 14 - Out 15)	LTV Historical (Net)
1 Transaction	3,98 €	0,45 €
2 Transactions	7,74 €	4,16 €
Alojamento Lover	n/a	n/a
Dentista Lover	n/a	n/a
Depilação + Cabeleireiro Lover	23,00 €	17,44 €
Lazer Lover	n/a	n/a
Produtos Lover	n/a	n/a
Restaurantes Lover	13,99 €	11,39 €
Saude Lover	23,19 €	14,45 €
No Dominant Preference	22,60 €	16,70 €
Always Cancelling	6,32 €	3,97 €
Spa Lover	18,26 €	11,24 €
Sushi Lover	18,78 €	16,36 €
TOTAL	7,46 €	3,81 €

	% Revenue not in 1st Month	Revenue in last 3 Months	Revenue Last 3 months / Revenue in 1st month
1 Transaction	0%	- €	0%
2 Transactions	38%	0,46 €	10%
Alojamento Lover	n/a	n/a	n/a
Dentista Lover	n/a	n/a	n/a
Depilação + Cabeleireiro Lover	65%	3,74 €	47%
Lazer Lover	n/a	n/a	n/a
Produtos Lover	n/a	n/a	n/a
Restaurantes Lover	69%	1,44 €	33%
Saude Lover	59%	1,84 €	19%
No Dominant Preference	69%	2,09 €	30%
Always Cancelling	27%	0,43 €	9%
Spa Lover	56%	0,94 €	12%
Sushi Lover	82%	3,18 €	95%
TOTAL	42%	0,68 €	16%

	Nº of users recommended per user
1 Transaction	2,41%
2 Transactions	7,12%
Alojamento Lover	5,42%
Dentista Lover	0,00%
Depilação + Cabeleireiro Lover	8,61%
Lazer Lover	13,31%
Produtos Lover	11,85%
Restaurantes Lover	25,49%
Saude Lover	10,04%
No Dominant Preference	15,40%
Always Cancelling	4,23%
Spa Lover	7,43%
Sushi Lover	17,94%
TOTAL	5,81%

	Reviews per Transaction	Average Review Score	% of Negative Reviews
1 Transaction	0,21	4,22	6,7%
2 Transactions	0,24	4,27	5,9%
Alojamento Lover	0,05	4,11	5,6%
Dentista Lover	0,14	4,58	3,0%
Depilação + Cabeleireiro Lover	0,25	4,26	7,4%
Lazer Lover	0,04	4,21	5,3%
Produtos Lover	0,11	4,26	7,1%
Restaurantes Lover	0,32	4,25	6,6%
Saude Lover	0,23	4,25	7,9%
No Dominant Preference	0,17	4,24	6,9%
Always Cancelling	0,26	4,24	8,3%
Spa Lover	0,23	4,34	7,7%
Sushi Lover	0,23	4,28	4,7%
TOTAL	0,23	4,26	6,0%

	% Cancellations vs Valid	% no-show vs Valid
1 Transaction	9,4%	1,4%
2 Transactions	17,9%	2,6%
Alojamento Lover	10,4%	0,8%
Dentista Lover	35,7%	3,5%
Depilação + Cabeleireiro Lover	37,7%	2,7%
Lazer Lover	8,6%	1,2%
Produtos Lover	17,6%	0,8%
Restaurantes Lover	18,7%	3,3%
Saude Lover	39,8%	4,8%
No Dominant Preference	11,7%	1,6%
Always Cancelling	250,9%	26,6%
Spa Lover	34,1%	2,7%
Sushi Lover	12,5%	2,4%
TOTAL	18,9%	2,7%

	Points used per user up to date
1 Transaction	0,1
2 Transactions	0,4
Alojamento Lover	0,0
Dentista Lover	0,0
Depilação + Cabeleireiro Lover	23,0
Lazer Lover	18,3
Produtos Lover	0,0
Restaurantes Lover	21,0
Saude Lover	28,5
No Dominant Preference	14,9
Always Cancelling	14,6
Spa Lover	9,3
Sushi Lover	38,5
TOTAL	6,8

1 Point used represents roughly € 0,1 in costs for MyGon

Appendix 14
Full Results of 2nd Analysis

	CAC (based on jan 15 - out 15 data)	CAC (based on apr 15 - out 15 data)
Directo MyGon	- €	- €
E-Mail	2,26 €	2,46 €
Facebook CPC	18,06 €	19,19 €
Facebook Organic	- €	- €
Forretas	3,80 €	3,89 €
Google CPC	10,51 €	8,21 €
Motor Busca	- €	- €
Referal MyGon	- €	- €
Sem Source	- €	- €
Wone	4,21 €	4,00 €
TOTAL	3,05 €	3,52 €

	Cost of Retention (based on jan 15 - out 15 data)	Cost of Retention (based on apr 15 - out 15 data)	Cost of Retention (per lifetime)
Directo MyGon	0,30 €	0,21 €	0,24 €
E-Mail	0,80 €	0,64 €	0,65 €
Facebook CPC	0,86 €	0,88 €	0,60 €
Facebook Organic	0,67 €	0,34 €	0,57 €
Forretas	0,93 €	0,97 €	0,73 €
Google CPC	0,71 €	0,62 €	0,57 €
Motor Busca	0,37 €	0,29 €	0,32 €
Referal MyGon	0,71 €	0,69 €	0,68 €
Sem Source	0,10 €	0,11 €	0,10 €
Wone	0,78 €	1,15 €	0,59 €
TOTAL	0,48 €	0,45 €	0,42 €

	Customer Retention Rate	Churn Rate	Lifetime of Customer (In Years)
Directo MyGon	27%	73%	0,68
E-Mail	26%	74%	0,68
Facebook CPC	14%	86%	0,58
Facebook Organic	30%	70%	0,71
Forretas	24%	76%	0,66
Google CPC	25%	75%	0,67
Motor Busca	30%	70%	0,71
Referal MyGon	37%	63%	0,79
Sem Source	40%	60%	0,83
Wone	20%	80%	0,63
TOTAL	32%	68%	0,73

	Average value Charged per transaction	Average nº of transactions per month
Directo MyGon	3,21	0,36
E-Mail	3,50	0,32
Facebook CPC	5,37	0,29
Facebook Organic	3,80	0,36
Forretas	3,27	0,25
Google CPC	3,09	0,34
Motor Busca	3,00	0,31
Referal MyGon	2,96	0,35
Sem Source	2,54	0,40
Wone	3,38	0,25
TOTAL	3,11	0,34

	LTV (gross) (Estimated)	LTV (net)
Directo MyGon	9,58 €	9,33 €
E-Mail	8,91 €	6,00 €
Facebook CPC	11,52 €	- 7,14 €
Facebook Organic	11,96 €	11,39 €
Forretas	6,60 €	2,07 €
Google CPC	8,35 €	- 2,73 €
Motor Busca	8,11 €	7,79 €
Referal MyGon	10,36 €	9,68 €
Sem Source	10,15 €	10,04 €
Wone	6,29 €	1,50 €
TOTAL	9,24 €	5,76 €

	LTV Historical (Out 14 - Out 15)	LTV Historical (Net)
Directo MyGon	6,67 €	6,38 €
E-Mail	7,19 €	4,13 €
Facebook CPC	7,69 €	- 11,23 €
Facebook Organic	8,05 €	7,38 €
Forretas	7,00 €	2,27 €
Google CPC	5,60 €	- 5,62 €
Motor Busca	6,46 €	6,08 €
Referal MyGon	6,86 €	6,15 €
Sem Source	7,61 €	7,50 €
Wone	5,54 €	0,55 €
TOTAL	7,03 €	3,49 €

	% Revenue not in 1st Month	Revenue in last 3 Months	Revenue Last 3 months / Revenue in 1st month
Directo MyGon	38%	0,43 €	10%
E-Mail	40%	0,60 €	14%
Facebook CPC	22%	0,24 €	4%
Facebook Organic	43%	0,85 €	18%
Forretas	30%	0,60 €	13%
Google CPC	41%	0,52 €	16%
Motor Busca	40%	0,56 €	14%
Referal MyGon	41%	0,51 €	13%
Sem Source	58%	0,84 €	26%
Wone	21%	0,07 €	2%
TOTAL	40%	0,60 €	14%

	LTV Historical (Apr 15 - Out 15)	LTV Historical (Net)
Directo MyGon	6,10 €	5,89 €
E-Mail	6,35 €	3,24 €
Facebook CPC	7,86 €	- 12,22 €
Facebook Organic	6,83 €	6,49 €
Forretas	5,86 €	1,00 €
Google CPC	4,56 €	- 4,27 €
Motor Busca	5,77 €	5,48 €
Referal MyGon	5,31 €	4,62 €
Sem Source	5,63 €	5,52 €
Wone	5,45 €	0,30 €
TOTAL	6,11 €	2,14 €

	% Revenue not in 1st Month	Revenue in last 3 Months	Revenue Last 3 months / Revenue in 1st month
Directo MyGon	28%	0,89 €	20%
E-Mail	24%	1,01 €	21%
Facebook CPC	11%	0,43 €	6%
Facebook Organic	19%	0,68 €	12%
Forretas	13%	0,45 €	9%
Google CPC	22%	0,52 €	15%
Motor Busca	24%	0,82 €	19%
Referal MyGon	23%	0,56 €	14%
Sem Source	41%	1,08 €	32%
Wone	17%	0,41 €	9%
TOTAL	23%	0,75 €	16%

	Nº of users recommended per user
Directo MyGon	4,91%
E-Mail	5,10%
Facebook CPC	0,46%
Facebook Organic	5,47%
Forretas	1,41%
Google CPC	1,92%
Motor Busca	4,09%
Referal MyGon	4,36%
Sem Source	11,10%
Wone	3,41%
TOTAL	5,81%

	Reviews per Transaction	Average Review Score	% of Negative Reviews
Directo MyGon	0,25	4,28	5,7%
E-Mail	0,31	4,25	5,4%
Facebook CPC	0,23	4,38	4,8%
Facebook Organic	0,25	4,24	6,2%
Forretas	0,25	4,29	5,8%
Google CPC	0,31	4,23	3,6%
Motor Busca	0,26	4,26	6,2%
Referal MyGon	0,24	4,32	4,1%
Sem Source	0,16	4,23	6,3%
Wone	0,25	4,28	7,3%
TOTAL	0,21	4,26	6,0%

	% Cancellations vs Valid	% no-show vs Valid
Directo MyGon	23,4%	2,6%
E-Mail	32,9%	3,2%
Facebook CPC	18,8%	2,0%
Facebook Organic	19,9%	3,1%
Forretas	22,1%	2,2%
Google CPC	18,8%	2,6%
Motor Busca	18,5%	2,8%
Referal MyGon	21,3%	2,7%
Sem Source	16,6%	2,6%
Wone	28,0%	3,1%
TOTAL	18,8%	2,6%

	Points used per user up to date
Directo MyGon	4,5
E-Mail	6,4
Facebook CPC	1,8
Facebook Organic	7,5
Forretas	3,5
Google CPC	0,9
Motor Busca	6,1
Referal MyGon	9,5
Sem Source	9,0
Wone	9,1
TOTAL	6,9

Appendix 15
Pc vs Mobile Facebook Ads performance from August 2015 to October 2015 in category “Saúde e Beleza” as per Facebook Reports and Conversion Tracking done in accordance with Facebook Software.

				August	September	October
Saúde e Beleza	Prospect Clients	PC	Cost per Conversion	3,91 €	6,39 €	5,54 €
			Conversion Rate	6,28%	4,39%	4,30%
			CPC	0,25 €	0,28 €	0,24 €
			CTR	0,61%	0,56%	0,58%
			CPM	1,50 €	1,57 €	1,37 €
			€ Spent	1 845,44 €	3 664,19 €	2 211,15 €
		Mobile	Cost per Conversion	4,99 €	10,53 €	10,74 €
			Conversion Rate	2,63%	0,86%	1,26%
			CPC	0,13 €	0,09 €	0,14 €
			CTR	0,84%	1,48%	1,18%
			CPM	1,11 €	1,34 €	1,60 €
			€ Spent	9,97 €	294,91 €	4 017,44 €