Growth Hacking:
A data-driven approach to achieve business growth

Diogo Almeida Castro

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Advisor at FEUP: Prof. Vera Miguéis

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

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In the spirit of science, there really is no such thing as a 'failed experiment'.
Any test that yields valid data is a valid test.
Adam Savage

Abstract

Business growth has always been a great indicator for company overall success and wellbeing with different companies approaching growth in different ways. For startups, growth is essential, either to cement their position in the market or to seize investment from venture capitalists. For more mature companies, growth can be slower, but they still need to ensure that their metrics are going in the right direction.

The focus of this project was to present Growth Hacking as a possible solution to capitalize on all growth opportunities that are appearing in the current digital era of products and services.

The Growth Hacking methodology combines the best of the world of engineering, marketing and creativity. The methodology represents a data-driven way to use the new growth opportunities that emerged to quickly, and with low resource usage, grow the businesses of companies of all sizes. This is possible with the usage of the famous Growth Hacking Cycle, to hack all the growth funnel, improving on all its levels. As well as with the usage of data analysis tools and machine learning techniques.

This approach rejects the traditional and time-consuming marketing campaigns, the pricey launches, and the big ad spending typically used by big corporations, focusing on building marketing into the products themselves.

To attest the potential of the Growth Hacking methodology in general, this dissertation depicts 3 case studies of the application of the methodology in companies with different sizes and online presences. Having a large company with a reduced online presence, a medium company that mixes the selling of products online and offline, and a startup with all its business on the web. Only this way it was possible to understand the challenges and to draw conclusions about the power of this methodology in the real world. Throughout this project, Growth Hacking cycles were developed for each of the companies in study, having their objectives and problems as a base.

The methodology had positive results in terms of growth on all 3 of the case studies, with the bonus of promoting the continuous improvement that prevents the stagnation of products and services provided by companies.

Growth Hacking: Uma abordagem movida por dados para atingir crescimento nos negócios

Resumo

O crescimento sempre foi um grande indicador do sucesso e do bem-estar geral das empresas, com diferentes empresas a abordar o crescimento de diferentes formas. Para as *startups*, o crescimento é essencial, seja para consolidar a sua posição no mercado ou para obter investimentos de *venture capitalists*. Para empresas mais maduras, o crescimento pode ser mais lento, mas estas ainda assim precisam de garantir que suas métricas estão a caminhar na direção correta.

O foco deste projeto foi apresentar *Growth Hacking* como uma possível solução para capitalizar todas as oportunidades de crescimento que estão a surgir na atual era digital de produtos e serviços.

A metodologia *Growth Hacking* combina o melhor do mundo da engenharia, marketing e criatividade. Esta metodologia representa uma maneira movida por dados de usar as novas oportunidades de crescimento que surgiram para fazer crescer rapidamente, e com poucos recursos, os negócios de empresas de todas as dimensões. Isso é possível com o uso do famoso *Growth Hacking Cycle*, para *hackear* todo o funil de crescimento, melhorando todos os seus níveis. É também possível com o uso de ferramentas de análise de dados e técnicas de *machine learning*.

Esta abordagem rejeita as campanhas de marketing tradicionais, os lançamentos caros e os grandes gastos com publicidade normalmente usados por grandes corporações, com foco na integração de marketing nos próprios produtos.

Para atestar o potencial da metodologia de *Growth Hacking* em geral, esta dissertação apresenta 3 casos de estudo da aplicação da metodologia em empresas com diferentes dimensões e presenças *online*. Conta com uma grande empresa com presença *online* reduzida, uma empresa de média dimensão que mescla a venda de produtos *online* e *offline* e uma *startup* com todos os seus negócios na *web*. Só assim foi possível compreender os desafios e tirar conclusões sobre a força desta metodologia no mundo real. Ao longo deste projeto, foram desenvolvidos ciclos de *Growth Hacking* para cada uma das empresas em estudo, tendo como base os seus objetivos e problemas.

A metodologia teve resultados positivos em termos de crescimento nos 3 casos de estudo, com o bónus de promover a melhoria contínua que evita a estagnação dos produtos e serviços prestados pelas empresas.

Acknowledgments

Part of the journey is the end, and this the end of a big chapter of my life. But, as much as I wanted to, I would not be able to do this all by myself. That is why I am thanking some people that had a big impact in this work and in my journey as a whole.

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Finally, I want to thank the Seekers, my friends who are always trying to better themselves. If this dissertation is about business growth, our movement is about our personal and professional growth. It changed my life in unimaginable ways. Let us keep up with it.

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1 Introduction

Business growth has always been a great indicator for company overall success and wellbeing but has become even more relevant in the last few years. While there is not a single metric to measure business growth, some aspects can show that a business is growing, such as revenue, sales, company value, profits, number of customers or even number of employees. A growing company can be increasing some of these metrics but not others. For example, revenue can increase without growing the customer base if the current customers are buying more.

Different companies approach growth in different ways. For startups, growth is essential, either to cement their position in the market or to seize investment from venture capitalists. In some cases, this means doing everything possible to increase the number of customers, even if that results in a decrease in revenue in the early phases of growth. More mature companies do not need to grow quite as fast, but they still need to ensure that their metrics are going in the right direction.

While all companies are trying to grow their businesses, Olson et al (2008) showed that 87% of the companies in a large study ran into one or more growth stalls (periods where growth slowed dramatically) and emphasized that the problem would be getting worse in the future. This is mostly because of "the failure to fully exploit growth opportunities in the existing core business" and difficulties in "updating existing products and services and creating new ones".

These problems are mostly related with product (or service) development and marketing, and as Sean Ellis and Morgan Brown (2017) state, "growth hacking is a powerful solution to both of these problems", since it mixes a quick development mindset, very focused on testing, with disruptive marketing techniques.

1.1 Motivation and aim

As presented before, the Growth Hacking methodology could be a great solution to achieve business growth. This project's main focus is to attest its viability in the real world. A methodology like this is especially important today, because of the increase in online growth opportunities for all types of businesses. Most of those appeared because of the digital transformation of the last few years, associated with the digitalization push of the pandemic. Pirc et al (2020) confirmed this trend, showing that digital sales in the first quarter of 2020 grew 18% when compared to the same period of 2019.

This digital era of products and services brings new opportunities but also new challenges to companies, particularly when it comes to marketing. The integration of analytics and big data on marketing initiatives are essential for companies to be competitive and to survive in the market (Erevelles et al, 2015). Otherwise, the prediction of the former Cisco CEO, John Chambers, which said that at least 40% of all business will die in this decade if unable to adapt to new technologies (Ross, 2015), will become true.

Having the new opportunities and challenges in mind, Growth Hacking appears as a way to make companies grow quickly and efficiently while promoting the use of new technologies, especially technologies related to data science.

To attest the viability of the Growth Hacking methodology in general, this dissertation depicts 3 case studies of the application of the methodology in companies with different sizes and online presences. Having a large company with a reduced online presence, a medium company that mixes the selling of products online and offline, and a startup with all its business on the web. Only this way it is possible to understand the challenges and to draw conclusions about the power of this methodology in the real world. Throughout this project, Growth Hacking cycles are developed for each of the companies in study, having their objectives and problems as a base.

1.2 Structure

This chapter introduces the concept of growth and its importance, followed by the motivation and aim of the project.

In the next chapter, the background knowledge needed and the theoretical foundations that support the theme of this work will be presented.

In chapter 3, there is a brief presentation of all 3 case studies of this dissertation as well as a contextualization of the agency where the work was developed.

Chapters 4, 5 and 6 will show the ideas and results of the Growth Hacking Cycles that were developed for each of the companies in the case studies.

The last chapter will present the conclusions and perspectives for future work, namely, some suggestions for improvement and future opportunities for each of the case studies and for the methodology in general.

2 Background Knowledge and Literature Review

This chapter will explore the background knowledge needed to carry out the work presented in the following chapters, as well as the state of the art of the Growth Hacking methodology. As this methodology is very focused on data analysis, a section on Analytics will also be included. It explores the use of tools such as Google Analytics, as well as the state of the art of machine learning techniques such as recommender systems.

2.1 Growth Hacking

2.1.1 Definition

According to Sean Ellis (2010), "a growth hacker is a person whose true north is growth". In a simplistic way, Growth Hacking is a mix between marketing, engineering, and creativity as illustrated in Figure 1. Bringing a data-driven and a "not afraid to fail" approach to marketing and product development initiatives.

Figure 1 - Growth Hacking diagram; Source: Gasteren (2021a)

Sean Ellis coined the term in 2010, and it started being really popular among startups in Silicon Valley, because of their limited budgets and resources, and also because the main KPI of success in startups is growth (Gasteren, 2021a). Sean defined a growth hacker as someone "laser focused on growth", who is always analyzing data, looking for growth opportunities and designing creative strategies to take advantage of them, even if that includes changing the product or service itself (Ellis and Brown, 2017).

Growth Hacking is normally associated with marketing, in some cases is referred as Growth Marketing, more prominently in Europe, which could not be further from the truth. Marketers are usually too busy with day-to-day marketing and branding, working on the Awareness and Acquisition areas of the customer funnel. A growth hacker uses the entire funnel to generate growth, as seen in Figure 2, using data to formulate hypotheses and to run small experiments to prove the viability of those hypotheses, which normally does not happen in common marketing departments (Gasteren, 2021a). Not only that, but a growth hacker has a bigger range of technical skills, especially in programing, tooling and automation. This makes it easier for them to be more involved in product development, serving as the interface between a marketer and a coder (Chen, 2018).

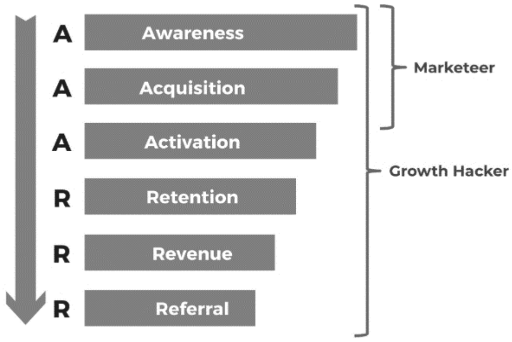

Figure 2 - Growth Hacking Funnel; Source: Gasteren (2021a)

The growth hacker mindset rejects the traditional and time-consuming marketing campaigns, the pricey launches, and the big ad spending typically used by big corporations, focusing on building marketing into the products themselves. This low-cost approach and companies' growing ability to collect, store, and analyze vast amounts of user data, has enabled all companies to experiment with new features, new messaging or branding, pricing, or other new marketing efforts, at an increasingly low cost, much higher speed, and greater level of precision, which enables them to grow at a much faster rate than ever before (Ellis and Brown, 2017).

It is also important to notice that traditional marketing tools, such as online advertising, are becoming more expensive and less viewed by potential customers. Kutcher (2014) showed that there is zero correlation between marketing investment and growth rates. Watts (2011) also highlights the lack of business credibility of marketers in the eyes of CEOs, with more than 70% of the CEOs believing that marketers are not capable of generating business growth with their initiatives. These two studies highlight the need of a new methodology to drive business growth.

2.1.2 Growth Pyramid

Figure 3 - Growth Pyramid

The implementation of a culture of growth was key to the success of breakout growth companies like Facebook, Twitter, AirBnB, Dropbox and many others. According to Sean Ellis (2018), to implement such a culture, some milestones must be achieved. These milestones are represented in Figure 3.

For Sean, the company should start by finding the product/market fit, then with that information, it should choose a North Star metric, following that comes the creation of the growth team, and then the start of the growth experiments. As the company runs the experiments, it should start seeing some big wins. Those wins will make even the most doubtful employees confident in the process, contributing to the mindset change. Needless to say, this process will be different for every company. On one hand, bigger companies can transfer more resources to growth (creating bigger teams for example), on another hand, smaller companies have more room to change (are less limited by corporate rules).

Each one of the mentioned milestones (apart from mindset change since it was already approached in this Section) are detailed in the following Sections.

2.1.3 Product/Market fit

Before running any experiments whatsoever, one needs to check if there is a fit between the product and the market, in other words, one needs to see if the product is a “must-have” (Ellis and Brown, 2017). If the product (or service) already exists, its value should be accessed, either by user data or with a survey to see what percentage of the customer base would be “very disappointed” if the product suddenly disappeared. If it is bigger than 40%, the product achieved the “must-have” status. Another way to check the usefulness of a product is the retention rate, i.e. if the customer comes back. If the retention rate is high, it should be good. If the product is in an early stage of development, there should be created a minimum viable product (a version of a product with just enough features to be usable by early customers), to enter the “Build-Measure-Learn” loop as soon as possible (Ries, 2018).

To better handle the product/market fit phase, and to have all the data needed, there should be put in place ways to track user behavior. If the focus is a website, maybe Google Analytics’ goals combined with tools like Hotjar could take care of the job. Without a way to track what the users are doing, the future tests would easily become inconclusive.

If the data indicates that the product is not a “must have” to most of the customers, there should be implemented changes to better suit what they expect. The developers should not try to solve the problem with some simple brainstorms. Instead, they should try to connect with the customers on a deeper level, either with more surveys and interviews or with a deep dive in the user data. With those insights, the changes should be implemented, and new surveys should be run (Ellis and Brown, 2017).

After achieving a “must-have” status, one needs to find the product’s “aha” or “wow” moment, i.e. the moment when the product exceeds the customers’ expectations, becoming essential. This will be particularly important to define the North Star metric.

2.1.4 North Star metric

The North Star metric is nothing less than the overall success metric that will be used to find out if the growth strategies are going in the right way. Normally, this metric is defined having the “aha” moment as a base, for example, for WhatsApp the “aha” moment is when the user finds out that he/she can send unlimited messages for free for everywhere in the world. So, the North Star for the app should be the number of messages sent, given that more messages indicate more users that find the app essential. This metric is a much more sustainable growth indicator than something generic as revenue or number of customers, and it will for sure increase the team’s productivity, because they will be more focused on what really matters. Some examples of North Star metrics can be seen in Figure 4.

	Monthly Active Users (MAU)
Spotify	Time spent listering
amazon	Number of purchases per month
airbnb	Booked nights
LinkedIn	Monthly Active Users (MAU)
	Messages Send
Quora	Number of answers to questions
Uber	Rides per week

Figure 4 - North Star Metrics; Source: Gasteren (2021b)

2.1.5 Growth Team

The establishment of the growth team is an indispensable part of the growth strategy success. The growth team should aggregate staff from different backgrounds, such as, strategy and business, data analysis, engineering and marketing to fill different roles. Some of the roles are growth lead (the one in charge of the operation), product manager, software engineer, marketing specialist, data analyst and product designer (Ellis and Brown, 2017).

The size of the growth team would be directly dependent on its scope and of the size of the company. Big companies can have diversified growth teams, with multiple people for each of the roles. Smaller companies can have just a few people on the team who play multiple roles. Of course, the number of experiments run will also be dependent on the size of the team.

2.1.6 Growth Hacking Cycle

With a “must-have” product, a defined North Star metric and a growth team ready to work, one is ready to start the growth cycle. The cycle should be completed in a consistent interval of one or two weeks, and consists of 4 phases: Analyze, Ideate, Prioritize and Test.

It is crucial to have in mind that the more experiments run, the more is learned about the business and customers, and with more information, better experiments with bigger results can be run in the future. Growth Hacking success is not measured by the success of one experiment, but by the accumulation of multiple small wins overtime.

Analyze

The first phase of the Growth Hacking Cycle is to analyze the data. According to Sean and Morgan (2017), Growth Hacking is not about throwing random ideas against the wall as fast as one can to see what sticks, it is heavily based on data to understand what tests to run.

As previously stated, to assemble the necessary data, it is essential to track user behavior across the website, the app or the platform in study. For example, if dealing with an e-commerce business it is smart to implement goals in Google Analytics or to create some heatmaps with Hotjar to track user’s behavior.

The main focus of this phase is to find and understand patterns, focusing on getting answers to questions like:

- What features are used by the best customers?
- What pages do they visit?
- What items do they buy?
- What sources were they acquired from?
- What is their demographic background?
- Where do they live?

- What pages have the highest exit rates?
- Are there bugs that are preventing users from taking certain actions?

Answers to these questions could be obtained either by crunching the numbers or with the use of surveys directly sent to the customers (Ellis and Brown, 2017).

It is important to note that the information studied in this phase is dependent on the level of the funnel that is trying to be “hacked”.

Ideate

Since ideas are the rocket fuel of growth, unbridled ideation is key to the Growth Hacking process (Ellis and Brown, 2017).

Ideas could be generated not only from the data that was previously analyzed, but from studying the competition’s approach to the level of the funnel in question, from case studies and from market research (Gasteren, 2021a).

Idea generation could be a little chaotic at this phase, but since prioritization is going to happen, there really is not a reason to worry about what is suggested. Even if it seems odd at first, self-censorship is discouraged, nothing should be considered too crazy to put out there.

To keep track of all the ideas, it is good to create an idea backlog for the growth team. Besides that, it is also advised to create a template for idea submission called “Experiment Doc” (Sean Ellis, 2016). It should contain a brief name that captures the essence of the idea, its main objective, a brief description that addresses what, where, why, how, and finally the most important metrics to track the success of the test.

Prioritize

The prioritization of the ideas helps the team select what experiments to run, since it is not possible to run everyone.

For this it is better to use an idea scoring system, such as (Time, Impact, Resources) TIR, (Potential, Importance, Ease) PIE, or the one used by Sean Ellis (2016) and his team at GrowthHackers.com, (Impact, Confidence, Ease) ICE. The specifics of each of these systems can be different but their objective is the same.

Using ICE, every idea is going to be evaluated on a scale from zero to ten in three criteria. Impact measures the expected improvement from the metric in study. Confidence is related to the level of certainty the idea generator has on it. Ease evaluates the time and resources needed for the execution of said idea (Ellis, 2016). After that evaluation, the ICE score is calculated with the arithmetic average of those three criteria. That score should always be revised by the growth lead to guarantee that it makes sense.

Test

As previously said, Growth Hacking is heavily dependent on testing, without it, the methodology does not really make sense, and as Gary Vaynerchuk usually says, “ideas are nothing, execution is the game”.

To guarantee great results, the growth team should choose at least two ideas every one or two weeks. Sometimes it is advised to choose ideas with high impact, but it is also advisable to choose ideas with low impact but easy to run, just to build up morale (Ellis, 2016).

Not only that but it is also advised to have a meeting just to choose the ideas, with every member of the team picking 2 ideas each and preparing a thirty second pitch about each of them. The focus is to better study the viability of the idea and each member of the team could not choose ideas generated by him/her.

There are two types of tests, tests to discover and tests to optimize. Tests to discover are deployed when there is not any data previously collected about that topic, for example, if a company is trying to enter a new uncharted market. Tests to optimize are used when there is previous data (from previous tests) that can help improve the results. In case of an inconclusive test, or if there is a tie between an older and test version, the company should stick with the original version (Ellis and Brown, 2017).

After the tests, it is very important to document everything, so that the data could be used in the future to better improve the tests.

2.1.7 Tactics used by growth hackers

Growth hackers use a very large set of tactics, or hacks, to achieve growth. These so-called hacks are no more than digitally enabled tactics resulting from product experimentation, marketing, and data analysis that can lead to extraordinary growth (Bohnsack and Liesner, 2019).

Many of these tactics use already established branches of Digital Marketing, such as Email Marketing, Search Engine Marketing and Optimization or even Social Media Marketing, but here they are approached in a different fashion, a brief presentation of each one follows:

- Email Marketing is, in its simplest form, the sending of emails to a customer list that usually contains a sales pitch, a "call to action" or even a newsletter to keep the customer engaged with the brand (Ryan, 2014).
- Search Engine Marketing (SEM) is based on the usage of ads in search engine pages to divulge the products or services of the companies next to organic (non-paid) results (Luo et al, 2011).
- Search Engine Optimization (SEO) is the process of making online pages easy to find, to explore and to categorize (Gupta, 2012).
- Social Media Marketing aims to create a more intimate relationship with the customers and to keep them engaged using social media (Tichindelean et al, 2012).

To better know what hacks to implement in each level of the marketing funnel, René Bohnsack and Meike Liesner (2019) developed a Growth Hack Taxonomy that can be found in the Figure 1 of Appendix A. A classification of each of the most common hacks according to resource intensity and time lag is introduced in Figure 2 of the same Appendix.

Besides these more established branches of Digital Marketing, the most commonly used tactics among growth hackers are presented in the following Sections.

Viral Marketing

According to Mares and Weinberg (2014), viral marketing is the process of getting the existing customers to refer others to the product. And, in the context of startups, literally "going viral" means that every user acquired brings in at least one other user.

To achieve viral status, some features should be put in place to facilitate the sharing of the product or service provided by the company. A great example is LinkedIn. Since the purpose of this platform is networking, it makes the process simple and quick to add friends who are already on LinkedIn or to invite those the user thinks should have an account on the platform, just by connecting an email account (Hoffman, 2009).

One way to achieve this virality is through referral programs. These programs focus on motivating the customers through a reward system, thus gifting current clients for bringing others to try the service. Subsequently, these new customers are rewarded for having accepted the respective invitation (Berman, 2016), which makes this strategy a "win-win" for both parties (Trusov et al, 2009). A company that benefited greatly from this was Dropbox, which offered 250MB of extra storage to users who got other users on the platform, reaching a 60% increase in sign-ups in the first few weeks of the program (Ellis and Brown, 2017).

Viral marketing is normally associated with word-of-mouth marketing, but they have some differences, since the last one fades after the first recommendation while the first one keeps on going (Lake, 2019). Regardless, the principle is the same, to get people talking about the product or service (Sernovitz, 2009), since no amount spent on advertising can compete with a direct recommendation from a trusted source (Bughin et al, 2010). This is confirmed by Nielsen (2012), who showed that 92% of the respondents of a large study trusted more on the recommendations from family and friends than on any other form of advertising.

A/B Testing

According to Peters (2014), A/B Testing refers to the comparison of two variables or versions to identify the best performer to use in support of a growth or optimization goal. This might include, but is not limited to versions of emails, variations in “calls to action” like buttons or links, and the arrangement of elements on a landing page. For context, according to Peters (2014), a landing page is the first page (also called the home page) that is visible when someone reaches a website either by clicking an inbound link (a link present in another website) or by typing the website’s address into a browser.

Ideally, A/B tests will optimize the communication to be used or the product to be presented, with only the features most appreciated by consumers, those with better results. This tactic will be more explored in the Section Hacking Acquisition.

Another way to test the impact of variables is to use multivariate testing, which uses the same core mechanism as A/B testing, but compares a higher number of variables, and reveals more information about how these variables interact with one another. For example, if a page is composed of a headline, an image and an accompanying text, then it could be created 8 different versions to test the impact of each one of those variables (Chopra, 2011).

No-code tools

No-code tools are software development platforms that allow even non-technical employees to build and deploy their own applications without writing a single line of code. These tools often feature a simple user interface with drag-and-drop features, enabling to easily visualize the development process and define the underlying business logic (Tobin, 2021).

These kinds of tools allow companies to produce apps, platforms, or even landing pages a lot faster. Enterprise software projects can take months or years to complete and often run late and over budget, in those cases these tools can reduce development costs by up to 80% (WEM, 2019). No-code platforms considerably shorten the development process, allowing iterations and quick changes in an instant, which are essential to the Growth Hacking Cycle, making testing a lot easier.

2.1.8 Growth Hacking Funnel

As previously said, unlike marketers, growth hackers work with all the funnel, mostly Acquisition, Activation, Retention and Revenue levels, developing methods to take advantage of each of those levels in the best way.

Hacking Acquisition

Acquisition focuses on attracting new users or customers to the business. Usually here companies invest a lot in advertisement in hopes of getting more customers through the door, as shown by eMarketer (2021) that highlights an increase of 12,7% in worldwide digital ad spending in 2020 and projects an increase of 20,4% in 2021.

Companies are investing a lot more money in ads, not only because of the competitiveness of the market (with more companies selling equal or similar products and services) but also because of the maturity of the audience. Confirming this, eMarketer (2016) shows that the growth of the online audience is slowing, especially in North America and Western Europe, which means companies are spending more money to chase fewer customers.

Big enterprises have the ability and resources to pay a lot for ads and other means of promotion, startups and small businesses, not so much. That is where Growth Hacking proliferates, finding low-cost ways to bring new customers and to grow sales.

For this, and after achieving Product/Market Fit (as previously mentioned), companies should study if there is a language/market fit, i.e. if the product and its features are being well communicated, and channel/market fit, i.e. if the right channels are being used.

To achieve language/market fit, there should be tests with different versions of the website, landing pages, creatives on social media or even email marketing. As previously presented, A/B Testing must be used for these tests, to compare two different versions, and in the end to choose the one with better results. The focus should be in making small changes, because those are the ones that usually drive bigger success. Testing should be seen as a continuous process (Ellis and Brown, 2017).

Talking about channel/market fit, many companies think that the best way to use different channels is to use all the available ones, spreading the resources thin in each one. As Larry Page, founder of Google, said in 2011, sometimes it is better to put “more wood behind fewer arrows”. For this, companies could start by testing the new channels with fewer resources to check their viability.

A great hack for acquisition is the development of viral loops like referral programs, such as previously mentioned. This way the customers would bring new ones with a small cost to the company. Another way to make customers bring other customers is with the creation of brand ambassadors, they could be influencers or micro-influencers that propagate the message of the company. Leads generated by ambassadors tend to convert 7% more than normal ones (Lopez, 2020).

Hacking Activation

With acquisition, companies bring more customers to the door figuratively, but the average conversion rate across all landing pages on the internet is about 2,35%, in other words, out of 100 people who visit a website, 98 do not engage (Austin, 2021).

This is where activation comes in, to activate the users, to make them get to the “aha” moment as soon as possible. So, the focus should be to study the customer journey through the website or app to remove all the frictions that could exist and to optimize it, using the conversion funnel reports to tackle the pages with more drop-offs. Some gamification systems could be put in place, gifting users who perform determined actions that bring them closer to the “aha” moment. Companies may also use customer triggers (actions that incite a reaction on the user), which could include emails or even app notifications.

To get better results from the triggers, one could try to personalize them as much as possible. For this, information about what features are more used by the user or what items are more interesting may be exploited. It would also be interesting to create a recommender system that is able to suggest interesting items to new and previous users based on overall user behavior (see Section 2.2.2).

Anyhow, companies need to be cautious with these tactics. If done in excess they could have inverse results. Not only that, but email marketing is generally considered an intrusive tool, and many customers (mostly the ones that value privacy) could be spooked by too many accurate personalized emails (Torres, 2009).

Hacking Retention

According to Reichheld (2006) a 5% increase in retention can lead to an increase in profits between 25 and 95%. Moreover, acquiring a new customer is anywhere from 5 to 25 times more expensive than retaining an existing one (Gallo, 2014).

Thus, it is very important to retain the users or customers as long as possible, and if they leave, there should also be placed a strategy to bring them back. For this purpose, some tactics similar to activation could be deployed. But first, there should be performed a deep cohort analysis. Google defines a cohort as a group of users who share a common characteristic (could be for example the date of the first purchase) and the analysis provides insights into the user's behavior overtime, especially about the drops in engagement.

With this analysis and with a better understanding of the customer behavior, then one can start implementing some hacks. Email marketing proves to be the better option here, either with personalized or more generic emails. Uber is an example of a company that provides offers and discount codes personalized to the users, keeping them engaged and making them come back for more (Nahdi, 2021). Again, recommender systems and machine learning in general are essential for these efforts.

Other ways to keep the customers coming back include the formerly mentioned ambassador programs and gamification systems.

Hacking Revenue

The main objective of activating and retaining clients is always to generate revenue from them, making the lifetime value (LVT) the biggest possible. Thus, actions on this level of the funnel are crucial for the wellbeing of the business.

When hacking revenue, all the pages that the customer visits are going to be key. So, it is very important to review all the customer journey and to remove all possible frictions as referred in Section Hacking Activation. But here, instead of focusing on the pages that lead to the "aha" moment, one should focus on the ones that are connected to payments, like the one that presents the products, the payment screen in the case of e-commerce businesses and the page that explains the different plans and features in the case of platforms. To optimize these pages, tactics like A/B testing could be used, as previously mentioned.

Not only the customer journey should be analyzed on this level, but also everything about the customer itself. The attention should be put on demographic and geographic data, always trying to understand what type of client is buying what type of product, looking for cross-selling opportunities.

Another way to increase revenue is to test new prices. This could be done by either starting with a price and changing it to some customers to see their response, or by directly asking them how much they were willing to pay, with a survey (Ellis and Brown, 2017).

A common mistake with price testing is to go directly to A/B testing, this could lead to the customer finding out that the company changes the price, creating the perception of discrimination, making the customers go away (Brandl, 2019).

The last hack involves the principle of reciprocity. A company that gives more to its customers, ends up having customers giving more (Spears, 2007). In other terms, if the company is willing to gift the customers with some free products, like free content, e-books, webinars or even free access to a software, the customers become more willing to pay back in the future with orders or sales (Ellis and Brown, 2017).

2.2 Analytics

Since Growth Hacking relies on data analysis and analytics to support the ideas before the testing phase, a Section on the topic of Analytics is crucial. Additionally, the work of the following chapters relies heavily on the use of machine learning techniques, such as the development of recommender systems, and multiple data analysis tools, such as Google Analytics, Hotjar, Power BI and many others to analyze data from websites and from customer orders.

Google Analytics and its reports and metrics are an important tool to draw many of the conclusions of this work, for that, a contextualization of the platform follows.

2.2.1 Google Analytics

Google Analytics is one of the most used website analysis platforms, and it aims to provide critical information to organizations about their webpages through extensive reports filled with metrics, so that more informed decisions can be made regarding web marketing strategies (Ascensão, 2010).

Some of the most important metrics that are going to be heavily explored in the next chapters are:

- Sessions: The volume of visits to the website.
- Users: Number of unique visitors to the website.
- Average time on page: The average amount of time users spend on a page.
- Average session duration: The average amount of time that a user spends on the website in a single session.
- Average pages per session: The average number of pages a user views in a single session.
- Bounce rate: The percentage of sessions that leave the website without any action.
- Exit rate: Rate at which visitors leave the website from specific pages.

The platform also allows the creation of goals, basically custom metrics that track how well the site fulfills some target objectives. It also allows the generation of multiple reports, such as audience reports (with demographics and geographic location), channel reports (to track the traffic coming from the multiple marketing channels) and many others that are going to be explored in future chapters.

2.2.2 Recommender systems

As previously mentioned, one way to hack activation and retention is to have personalized recommendations to users, for that goal, recommender systems are incredibly efficient.

Recommender systems are among the most visible and successful applications of artificial intelligence and machine learning technology in practice, being used in e-commerce stores, social media and streaming platforms (Jannach and Jugovac, 2019). These more complex systems came to be mostly because of the increase in diversity of customer needs and buying behavior, which made past segmentation approaches less effective (Miguéis et al, 2011).

Not only are these systems incredibly precise but they are also appreciated by the customers. Accenture (2018) indicates that 91% of consumers are more likely to shop with brands who recognize, remember and provide relevant offers and recommendations. But this is not limited to e-commerce, for example, 75% of what people watch on Netflix came from a recommendation and 60% of the clicks on the home screen of YouTube are also from recommendations (Jannach and Jugovac, 2019).

The most commonly used recommender systems are collaborative filtering, content-based filtering and hybrid models. These types of recommender systems are introduced in the following paragraphs (McGuire, 2015, Sardana, 2016).

Collaborative filtering systems

This kind of system has the basic assumption that people who had similar tastes in the past will also have similar tastes in the future (Çano and Morisio, 2019).

It builds a model from a user's past behaviors (items previously purchased or selected and/or numerical ratings given to those items) as well as similar decisions made by other users. This model is then used to predict items (or ratings for items) that the user may have an interest in (Liao, 2018).

It can be user-based, generating recommendations having similar users as a base, or item-based, using the same approach but for items. In a system where there are more users than items, item-based filtering is faster and more stable than user-based (Ajitsaria, 2019).

A key advantage of the collaborative filtering approach is that it does not rely on the content of the item and therefore it is capable of accurately recommending complex items without requiring an "understanding" of the item itself (Kashyap et al, 2020). For example, it can suggest a piece of clothing without knowing any characteristics, like the color or size.

These kinds of systems use ratings as a base for the recommendations, and there are mainly 2 methods for collecting these ratings. The first method is to ask for explicit ratings from a user, typically on a concrete rating scale (such as rating a movie from one to five stars). The second is to gather data implicitly as the user is in the domain of the system, i.e. to log the actions of a user on the site (such as adding an item to the basket or clicking on more item photos). The second approach is used by Amazon with great results (Lew et al, 2007).

The biggest limitation of these types of systems is that they cannot recommend new items or items with a very limited past user engagement.

Content-based filtering systems

This kind of system assumes that people who liked items with certain attributes in the past, will like the same kind of items in the future as well (Çano and Morisio, 2019). It is best suited to situations where there is known data on an item but not on the user. Content-based recommenders treat recommendation as a user-specific classification problem and create user's profiles based on likes and dislikes (Kashyap et al, 2020).

One of its limitations is the fact that this type of system only generates recommendations based on types of items previously engaged by the user, neglecting possible unpredicted tendencies and patterns.

Hybrid recommenders

The grand majority of recommenders today are hybrid systems that take the best from both of the previous approaches and remove some of their flaws. Hybrid approaches can be implemented in several ways, by making content-based and collaborative-based predictions separately and then combining them, by adding content-based capabilities to a collaborative-based approach (and vice versa), or by unifying the approaches into one model. Several studies that empirically compare the performance of the hybrid with the pure collaborative and content-based methods demonstrated that the hybrid methods can provide more accurate recommendations than pure approaches (Kashyap et al, 2020).

3 Case Study Presentation

To validate the application of the Growth Hacking methodology presented in Chapter 2, 3 different companies with different sizes and online presences were used as case study. The work was conducted in a marketing agency called Happyfact and in 3 of its clients. The clients are WINES, FASHION and FINTECH, the names were altered for confidentiality reasons. WINES is a big company, FASHION a medium one and FINTECH a startup. Moreover, WINES has a limited online presence, being a more traditional company focused on physical retail, FASHION has a medium presence, selling its products online and in physical stores and FINTECH only works digitally.

These 3 companies allow one to have a notion of how the Growth Hacking methodology can be applied in different contexts and what are the main difficulties and expected results in each one.

The next paragraphs contain a presentation and contextualization of Happyfact and the 3 clients in question.

3.1 Happyfact

Happyfact, aka Happiness Factory, is a Digital Marketing and Growth Hacking Agency that focuses on delivering happiness and growth to its clients. It was founded in April 2018 having the Growth Hacking methodology as a base, always trying to find growth solutions with the lowest cost possible to clients.

The agency works remotely with professionals from all around the globe. It has a heavy LEAN mindset and focuses only on what is necessary, reducing all the waste and noise. Happyfact places self-improvement above all, so much so that only this year did the agency launch its own website and developed a more elaborated image.

The main services of the agency are the development of growth hacking sprints, micro-targeted campaigns and digital strategies in general. These services involve a lot of data analysis, metrics tracking and user behavior study on websites, online stores and social media.

The goal is to promote clients’ growth in the most efficient way possible, always testing new solutions with fast iterations for faster results. Depending on the client, all levels of the Growth Hacking funnel could be worked, and the time of each growth cycle varies according to the needs of each one. A common timeline for a customer project is illustrated in Figure 5.

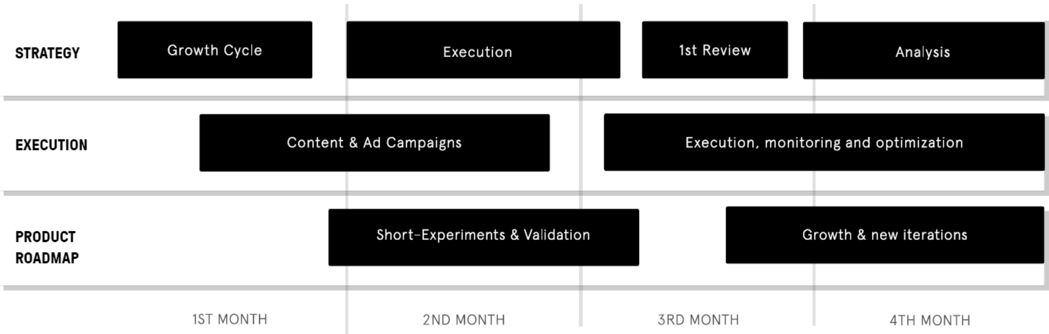

Figure 5 - Happyfact work timeline

Happyfact works with every type of client, from companies that want to start their online presence, celebrities who seek to connect more with their fans, or even startups who look to grow their user base. The agency's business model is based either in a monthly payment for the growth initiatives, a full payment for one or more growth cycles or, in the case of e-commerce businesses, a fee for every product sold.

The best clients are the ones that are willing to fully commit to the methodology, and, as the methodology indicates, these ones tend to have the best results. For that, the agency tries to include the clients as much as possible in every step of the way, either in the definition of the strategy and objectives, or even in some cases presenting the ideas and letting the client score them using ICE, as previously mentioned, adjusting the expectations of the client since the beginning.

The agency's biggest difficulty comes from the fact that many of the clients are afraid of risk, and for that reason many growth strategies are sacrificed. Furthermore, sometimes the day-to-day of the client is not totally aligned with the fast growth initiatives. The consequence of this is that in some of the projects, some cycles become too long and the testing becomes scarce.

In the next chapters, the results of Growth Hacking Cycles will be presented for each of the 3 clients introduced in this chapter.

3.2 WINES

WINES is a Portuguese company that works in the wine industry, is one of the most famous brands in Portugal, with more than 80 years of history and is the owner of one of the world's best-selling Portuguese white wines. The company has a wide catalog of products, from white wines, to sparkling wines and sangrias, and sells its products in more than 70 countries.

In the last few months, WINES sought Happyfact for a massive rebranding (which includes the launch of an online store in the not-so-distant future) and to increase its online presence, which was behind its main competitors. This because WINES is a more traditional company, focused on producing wines and delivering them to distributors who then take the job of selling them everywhere.

3.2.1 Company market

The company wants to increase its presence in Portugal, but also wants to increase sales in markets such as the USA, Canada, France and Brazil, where they have good distribution contracts. Figure 6 reveals that France and the USA are excellent markets as there is a large consumption of wines.

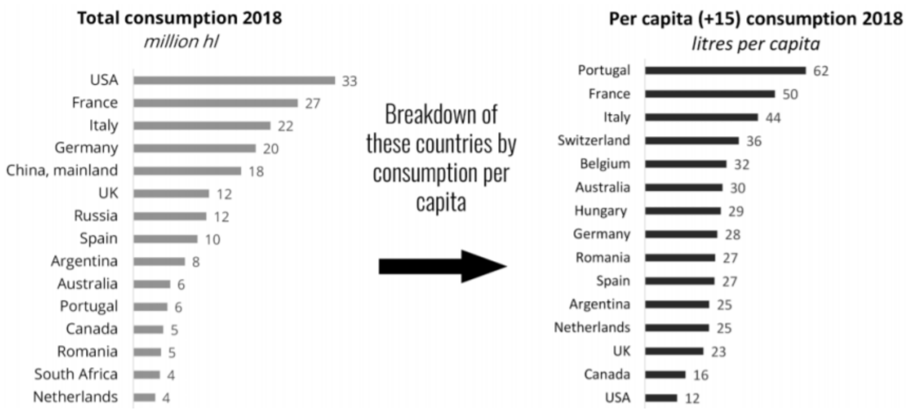

Figure 6 - World's wine consumption in 2018; Source: Wang (2019)

Currently, Portugal continues to be a market that consumes high volumes of wine. It was the country that consumed more per capita in 2018 as shown in Figure 6, continuing to be the market of excellence for the brand to sell and to have even more initiatives to increase sales in the future.

The pandemic has resulted in the acceleration of alcoholic beverage sales via e-commerce and the growing online engagement of consumers with the category. In the USA, 44% of alcoholic beverage consumers used the e-commerce channel for the first time in 2020, compared to 19% in 2019 (Wine Intelligence, 2021).

These markets and online sales represent excellent growth opportunities for the company and the following chapter will present ideas that aim to explore these opportunities.

3.2.2 Objectives and problems

As described before, the main objective of the company is to have a greater online presence, to solidify its market share in Portugal, as well as to reach new markets in other countries. The main objectives are as follows:

- Increase brand awareness in different markets.
- Increase interaction with consumers.
- Increase traffic across channels (especially the conversion ones).
- Discover and explore new acquisition channels.
- Remove friction (show where to get wines either online or in person).

When it comes to problems, these are related to both the company itself and to the difficulties that Happyfact will have to help them grow:

- WINES does not directly sell the products and consequently having to work with distributors makes marketing efforts difficult, mainly because one cannot have an accurate and up-to-date number of bottles being sold to link to the marketing efforts in place. Moreover, the company does not have a direct presence in the different markets. In fact, the distributor will often communicate for the brand and establish partnerships with the various stores locally and in some cases the partnerships may not be the most profitable or the most beneficial to move sales.
- There is virtually no digital data, which makes the work more difficult, having to start from scratch results in less growth in the first tests.

3.2.3 Previous tests

Since the company only initiated its journey with Happyfact in the past few months, it is not possible to go in depth with previous tests.

3.3 FASHION

Portuguese company in the luxury clothing business with over 20 years of history, mainly focused on footwear, which includes shoes, boots, sandals, stilettos, among other products. The company has physical stores in Porto and Lisbon, as well as an online store. It has already been present on the best catwalks in the world and its shoes have already been used by dozens of celebrities from all over the world, such as Michele Obama, Naomi Watts and Letizia Ortiz.

Happyfact is in charge of all the company's digital marketing, from social media to the online store. The agency has been working with this company since 2019, having over time made several growth cycles that included changes to the company's communication on social media and the relaunch of the online store (which greatly boosted sales, going from about 20 to more than 100 products sold per month in a few months), making the online store sell more on average than individual physical stores.

3.3.1 Company market

The Portuguese footwear industry exports over 95% of its production to 152 countries throughout the five continents and over the last ten years sales have increased over 45%, generating close to 2 billion euros in 2018, as shown in Figure 7.

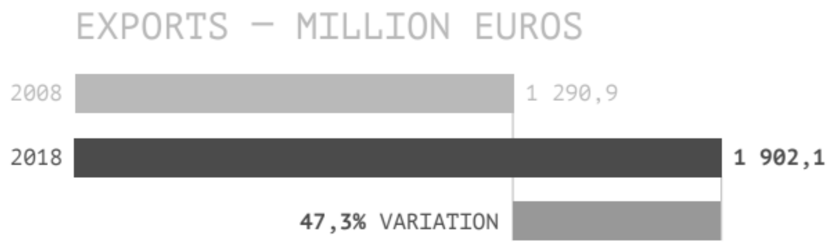

Figure 7 - Evolution of Portuguese footwear exports; Source: APICCAPS (2019)

With this, the enormous opportunity for the company to expand overseas is clear, since most of what is produced in the country goes abroad.

3.3.2 Objectives and problems

The company's main objective is to expand its sales both within Portugal and to other countries. The North Star metric for this business is Net Sales, which differs from many online businesses that consider (Gross Merchandise Value) GMV as their metric for success. In this case, Net Sales are a better indicator as they already include the cost of shipping the products.

Having in mind that the North Star metric is Net Sales, it is easy to see that the company wants to sell as many shoes and products as possible. So, its main objectives are:

- Increase sales in Portugal.
- Expand outside Portugal to other markets.
- More presence and more recognition online.
- Generate more sales by taking advantage of cross-sell and up-sell opportunities.

When it comes to problems, those are mostly related to the lack of information given to the agency and to the products themselves:

- Happyfact does not have access to the margins of the products, which prevents the agency from seeing which products effectively generate higher profits, the calculation is only made with the commercial sales price of the product plus the shipping prices.

- Product sales are seasonal (this will be further studied in Chapter 5), and this is something that causes a lot of suffering to the company, mostly because not all products can be sold throughout the whole year.

3.3.3 Previous tests

One of the biggest tests performed by Happyfact in this client was the implementation of an optimized Email Marketing strategy with promotions, announcements of new collection launches and opportunities in general. The strategy had multiple iterations to understand what content and copy would lead to more conversions (orders).

This strategy had very positive results, representing approximately 8% of the online store's revenue, as could be seen in Figure 8, and having assisted 12% of the sales from other channels from May 1 2020 to April 30 2021 (this choice of date will be explained in Chapter 5), with all emails sent in 2021 converting in at least one purchase.

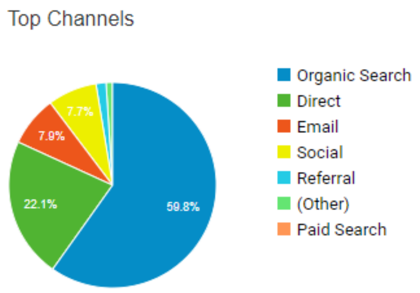

Figure 8 - FASHION online store revenue per channel

This email strategy mainly helped to increase the number of sales at festive times and at the launching of new collections, as shown by Figure 9, the number of Email Marketing transactions was quite large during and in anticipation of Christmas.

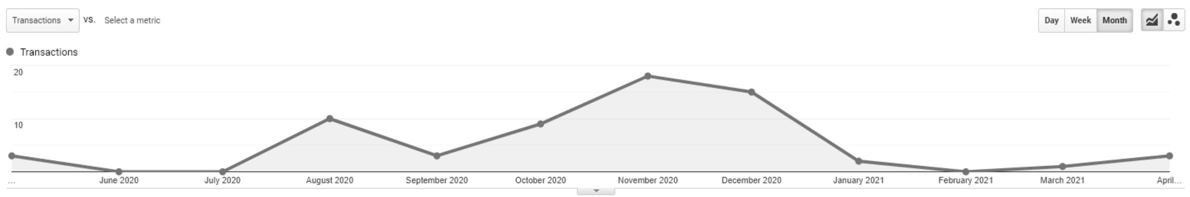

Figure 9 - FASHION Email Marketing conversions over time

3.4 FINTECH

FINTECH is a startup focused on revolutionizing the way people make their payments. Owner of a platform that allows users to make payments on websites with cryptocurrencies, allowing access to the blockchain by all types of businesses, bridging the gap between traditional businesses and the crypto community.

The platform allows merchants (sellers of online products or services that have accepted FINTECH as a payment method) to accept over 35 different types of cryptocurrencies as a payment method just as they would accept traditional currencies. In addition, it offers safe and fast transactions for both merchants and buyers (users who choose to use FINTECH to pay for their online purchases).

It works very easily, like other services such as PayPal or MBWay. FINTECH is simply added as a payment method by the merchant to its website, and as soon as a user wants to use FINTECH, a window opens to choose the cryptocurrency the user wants to pay with.

Happyfact has worked directly with FINTECH's marketing team since its launch in 2018, streamlining all levels of the Growth Hacking funnel, having pushed various initiatives and changes to the product itself, using data analysis and website and platform metrics to launch campaigns and ads, and to manage social media and produce content.

3.4.1 Company market

The company works with cryptocurrencies, and this market has been in constant evolution in recent years, with more and more people using this type of currency either for payments or as a means of investment. As can be seen in Figure 10, the increase in cryptocurrency users has been abysmal.

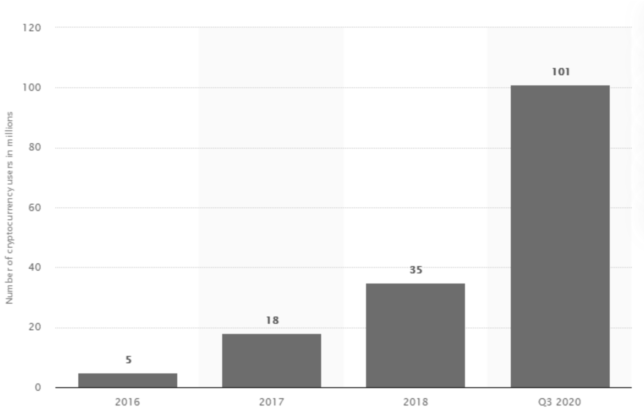

Figure 10 - Estimated number of cryptocurrency users worldwide; Source: Statista (2021)

Not only has the number of users of this type of currency increased, but the community has also expanded to multiple countries, with countries like Turkey, Brazil and Colombia leading in percentage, as seen in Figure 11.

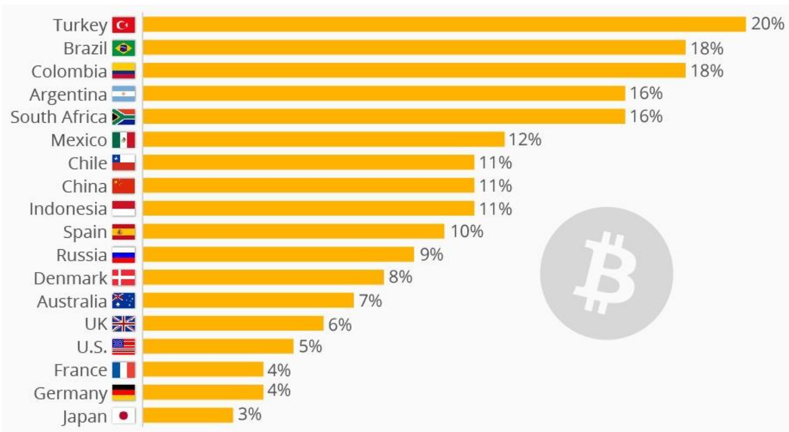

Figure 11 - Cryptocurrency around the world; Source: Statista (2019)

It is anticipated that this type of currency will not slow down in the near future, as it is becoming more and more mainstream. Thus, a platform like FINTECH has everything to be successful.

3.4.2 Objectives and problems

The North Star metric of the company is directly linked to how it makes money, in this case it is (Total Payment Volume) TVP, which is a very common metric in this type of business. PayPal defines this as “the value of payments, net of payment reversals, successfully completed through our Payments Platform, excluding transactions processed through our gateway products”.

Knowing the company's North Star metric, one can then talk about its objectives:

- More transactions made with the platform.
- More buyers using the platform more than once and on different merchants.
- New merchants with different offers.

Also, the company faces 2 big difficulties:

- People use cryptocurrencies for store of value, using them as savings and not spending them on simple things sold by merchants. This is very common in people who invest large amounts simply to collect gains when the value of the invested currency increases.
- The cryptocurrency market is extremely volatile, for example, today a cryptocurrency is worth 20 dollars and tomorrow it may be worth zero. The impact of changes in cryptocurrency values on transactions made with FINTECH will be studied in depth in Chapter 6.

3.4.3 Previous tests

One of the big tests that were done for FINTECH this year was the development of a Fees Calculator for merchants. Basically, a form that allowed online stores to enter some of their information in order to find out how much they would save on payments made with FINTECH compared with other services. The savings could reach up to 80% in some cases.

The idea for this calculator came to be after the release of a FINTECH article that highlighted how much traditional paying methods were charging per transaction. Multiple merchants were surprised by how much they were saving with FINTECH. For that reason, the company decided to create an easy way for merchants to see how much they were saving.

This calculator was released in April of this year, but it did not have the expected results, having converted zero new merchants to the platform.

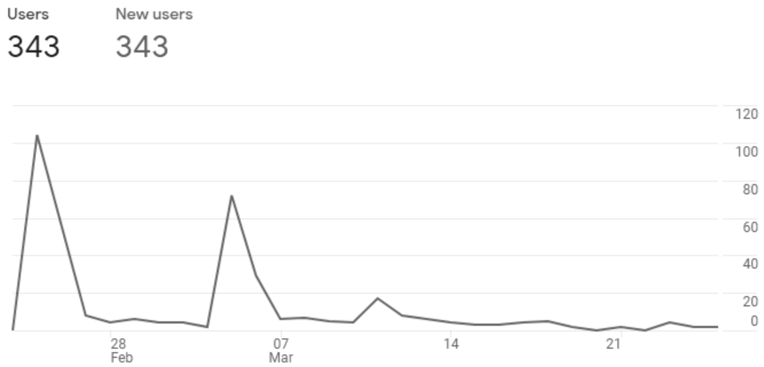

Figure 12 - Fees Calculator user evolution

In a period of 1 month and even with the help of some ads to increase the number of sessions, the calculator had a very small number of users, which did not justify future investment.

This result reinforced that some Growth Hacking tests may fail, and in this case, a lot of information was taken which allowed FINTECH to change their approach to attract new merchants.

4 WINES Case Study

In this project, the company WINES serves as a case study for a large, more traditional company that has a very limited online presence. That said, there is not much previous concrete data to be analyzed and to generate ideas for improvement like for the other two case studies, FASHION and FINTECH. Anyway, and as mentioned above, the Growth Hacking methodology is not limited to the analysis of the company's own data, having a very strong component of market analysis and competition “espionage”.

The ideas that will be presented below, result from an Happyfact's growth cycle. They are based on a strong market analysis and translate some of the solutions and hacks that were presented by Happyfact to the company WINES to boost its digital presence and to increase its sales in different markets. In this case study, the ideas will be less specific, because they are not focused on altering or improving something that already exists, but rather on creating and developing something new. Basically, WINES still has to discover its language/market fit and channel/market fit in the different markets.

4.1 Data analysis and ideation

4.1.1 Wine in a can

Growth Hacking is not limited to changing communication approaches, but also on changing the product itself to generate growth as mentioned above. A simple change like selling the wine in a can, can have a lot of impact as it is a huge market trend and the competition is already doing it.

This idea can be excellent to reach new demographics more interested in innovation and environmental protection, because the market, in addition to looking for different things, also looks for better solutions for the environment. If the cans are recyclable, they are a much better solution than the glass bottles. The success metric of this idea would be linked to the profit generated by this new product line.

4.1.2 Different approach to social media

The company's social media has very little engagement, that is, a very low percentage of followers interact with the published content. In addition, social media represents 17,7% of the users who visit the website (from June 10 2020 to June 10 2021), illustrated in Figure 13. This is a high percentage for this market, which demonstrates that, despite having little engagement, WINES generates enough curiosity for consumers to visit the website and later search for the company on Google.

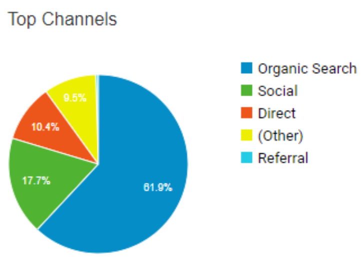

Figure 13 - WINES website users per channel

As such, and to take better advantage of the social media channel, some hacks have been suggested. In the case of Facebook and Instagram (which are the platforms the company already uses), all types of available content should be explored, notably Reels on Instagram, which have a greater chance of going viral, especially if they include challenges. Takeovers can and should be made (in essence allowing another person to take over the WINES account for a period to interact with the brand's followers). As well as partnerships with different types of influencers (which can be paid or unpaid partnerships) and giveaways of bottles of wine to users who complete a challenge or interact with the brand's posts the most.

In addition, it would be interesting to develop an ad strategy for these platforms, especially if these ads take advantage of content produced as a result of partnerships with influencers, who are already more established in the platforms in question.

The success metrics of this idea would be the increase in post engagement (likes, shares and saves) as well as the number of followers and likes of the pages.

4.1.3 Website changes

The company already has a website, but it is not built in the best way to foster growth, with most of the sessions taking less than 10 seconds, as shown in Figure 14, which is not entirely positive.

Session Duration Bucket	Sessions
0-10 seconds	44,215
11-30 seconds	16,918
31-60 seconds	10,479
61-180 seconds	12,418
181-600 seconds	5,532
601-1800 seconds	2,443
1801+ seconds	317

Figure 14 - WINES website sessions duration

To improve this, SEO changes must be made, as mentioned before in Chapter 2, to make the website more easily found in search engines, allowing an increase in the number of users who arrive organically. Different versions of the website should also be studied and tested for the different markets that the company wants to penetrate, in order to find the best language for each market. Basically, find the language/market fit for each of the markets using A/B testing or multivariate testing, part of these tests will already be done in one of the following ideas.

Another common hack that can be used, which has not been mentioned before in this project, is the creation of a chat bot, which makes the user experience much more interesting by being able to respond in a personalized way to some of the questions that the user has. This bot can help by suggesting the best places to consume the company's wines, making it easier for consumers to find them.

Still on the topic of facilitating the finding of the wines, the page should have an option to “buy now”. This either sends the user to the online store (still being developed for this brand), to a page that shows a map of nearby locations who sell the wine or a shortcut to a delivery app like Glovo to immediately order the wine for the user’s home.

Another way to increase the number of website users and sessions is to develop Google Ads campaigns using specific keywords, these can include “vinho branco”, “vinho branco Portugal” and other variations in order to attract people who search for these terms.

The essential success metrics for this website changes would be the number of sessions and users (which hopefully would be increasing) as well as the quality of the sessions (long duration with a low bounce rate).

4.1.4 Explore new channels

In the spirit of channel/market fit, the company must explore new channels to attest their viability. WINES has many fans of the brand referring to it on platforms such as Twitter, on average 15 references a day (a statistic obtained using Awario, a tool that allows the measuring of how many times certain keywords are referred to on Twitter). Starting a new social media account in a platform like this one could greatly increase consumers' trust, as well as the loyalty they have with the brand, thereby increasing the number of times they refer it to their friends, inevitably driving sales.

Other interesting channels to increase brand awareness and the consequent acquisition of new customers are the brand's participation in podcasts on various social media platforms to get more people talking and recommending the wines. Partnerships with companies such as Uber Eats and Glovo can also be used to create unique promotions, as these were proven to be very interesting channels for other brands in the consumer goods market.

4.1.5 Ad campaign for foreign countries

In order to test the viability of the different markets in which the company wants to communicate, an ad campaign must be created that tests different forms of communication with different creatives (images that are associated with the ads) to see what works best in each of the markets. This information will help not only to better define the approach of future campaigns, but also to define how the social media of the different markets and the website should be built for the future rebranding of the company.

The campaign can consist of a set of ads on Facebook and Instagram focused on the different markets, changing the properties of the ads for each country or even for different cities in the same country (mainly in the USA, as consumer tastes change a lot from city to city and from state to state).

This campaign should run mainly in the USA, Germany and France. Not only because they are the markets that the company wants to explore, but also because they are the destinations with the highest number of sessions and website users, as seen in Figure 15. Brazil should not be the focus of this campaign, as communication will always be very similar to the one used for Portugal.

Country	Acquisition			Behavior		
	Users	New Users	Sessions	Bounce Rate	Pages / Session	Avg. Session Duration
	80,675 % of Total: 100.00% (80,675)	79,896 % of Total: 100.12% (79,797)	92,322 % of Total: 100.00% (92,322)	25.64% Avg for View: 25.64% (0.00%)	2.62 Avg for View: 2.62 (0.00%)	00:01:20 Avg for View: 00:01:20 (0.00%)
1. Brazil	37,916 (47.29%)	37,888 (47.42%)	43,524 (47.14%)	19.58%	2.81	00:01:32
2. Portugal	29,998 (37.41%)	29,799 (37.30%)	34,384 (37.24%)	32.05%	2.31	00:00:59
3. United States	5,790 (7.22%)	5,792 (7.25%)	6,657 (7.21%)	35.15%	2.55	00:01:12
4. Germany	797 (0.99%)	792 (0.99%)	928 (1.01%)	20.47%	3.48	00:01:49
5. France	558 (0.70%)	554 (0.69%)	606 (0.66%)	22.44%	2.90	00:01:11

Figure 15 - WINES website users and sessions per country

The campaign should then include the following ad sets (grouping of ads with the same objective, audience and location) with the corresponding ads, described in Table 1.

Table 1 - Ad sets and ads for WINES international campaign

Ad Set	Ad	Ad Set	Ad
France	Ad 1 - Portuguese Heritage	USA (New Jersey)	Ad 1 - Fruity Wine
	Ad 2 - Social Proof (Brand Awards)		Ad 2 - Fruity Wine + Friends
	Ad 3 - Modern and Sophisticated Wine		Ad 3 - Porch Wine + Portuguese Wine
	Ad 4 - Fresh wine to drink with friends		Ad 4 - Social Proof (Brand Awards)
Germany	Ad 1 - Beer Audience		Ad 5 - Low Cal
	Ad 2 - Portuguese Wine	USA (Texas)	Ad 1 - Fruity Wine
	Ad 3 - Social Proof (Brand Awards)		Ad 2 - Fruity Wine + Friends
	Ad 4 - Next competitive price great wine		Ad 3 - Porch Wine
USA (Colorado)	Ad 1 - Fruity Wine		Ad 4 - Social Proof (Brand Awards)
	Ad 2 - Fruity Wine + Friends		Ad 5 - Low Cal
	Ad 3 - Porch Wine	USA (Washington)	Ad 1 - Fruity Wine
	Ad 4 - Social Proof (Brand Awards)		Ad 2 - Fruity Wine + Friends
	Ad 5 - Low Cal		Ad 3 - Porch Wine
USA (Massachusetts)	Ad 1 - Fruity Wine		Ad 4 - Social Proof (Brand Awards)
	Ad 2 - Fruity Wine + Friends		Ad 5 - Low Cal
	Ad 3 - Porch Wine		
	Ad 4 - Social Proof (Brand Awards)		
	Ad 5 - Low Cal		

The US states were chosen based on the top states with the highest consumption of wine, data from Statista (2020), and based on the information WINES provided about their distributors. The types of ads aim to test which is the best communication for each of the states, based on 5 types of ads, one that highlights the fact that the wine has a fruity taste, one that highlights moments spent with friends while drinking the wine, one that highlights the growing trend of porch wines in the US, another that presents the international awards received by the brand and, finally, the fact that the wine is low in calories.

In the case of France, and given that there are many Portuguese in different cities, it would be advisable to run the ad set with 2 different audiences, one defined based on interests and location and the other "lookalike", which basically looks for users similar to the brand's followers in France. Also because of the presence of many Portuguese in France, one of the ads aims to test the impact of the Portuguese heritage, given that many of the users who are going to see the ad are Portuguese, this type of ad that highlights the users origins can have a lot of impact on that market. In addition, it is also intended to test the impact of the communication of the brand's international awards, the fact that the wine is widely used for times spent with friends and a last ad that aims to present the wine as a modern and sophisticated choice.

For Germany, the ads will try to present the wine as an alternative to beer that is widely consumed in the country, highlight that the wine is Portuguese, present the international awards received and present the wine brand as an alternative at an excellent price, in order to discover which of these will have the most impact on the German audience.

4.2 Prioritization and testing

Based on WINES objectives presented previously in the last Chapter, a correspondence was then established between the objectives and the ideas presented in this Chapter in Table 2.

Table 2 - Correspondence between WINES objectives and ideas presented

Objective	Idea number
Increase brand awareness in different markets	1 / 2 / 4 / 5
Increase interaction with consumers	2 / 4
Increase traffic across channels	2 / 3 / 4 / 5
Discover and explore new acquisition channels	1 / 4
Remove friction	3 / 5

In addition, idea number 5 also helps to solve the problem of the lack of online data, giving many insights into the communication preferences of different audiences.

Based on the correspondence presented in Table 2, the ICE scoring of the ideas was then carried out and is shown in Table 3.

Table 3 - WINES ICE Score

Idea number	Idea	Impact	Confidence	Ease	ICE Score
1	Wine in a can	6	6	2	4,7
2	Different approach to social media	7	8	6	7,0
3	Website changes	8	7	4	6,3
4	Explore new channels	8	8	7	7,7
5	Ad campaign for foreign countries	9	9	8	8,7

This ICE Score then allows one to see that the main ideas to be applied are the “Ad campaign for foreign countries” and the “Explore new channels”. As for tests, not all ideas could be implemented at the time of the project. Nonetheless, the “Ad campaign for foreign countries” was executed because of its importance in the gathering of data for future efforts.

The previously presented ad sets were then run from May 20th to June 11th (when the results were exported) on Instagram and Facebook, both in the feed and in the stories, as well as in Instagram's explore page. The results of the ad sets are then presented in Table 4.

Table 4 - WINES results for each ad set

Ad Set	Reach	Frequency	Impressions	Link clicks	CTR (link)	Clicks (all)	CTR (all)
France	826412	1,436	1186390	443	0,037	860	0,072
France (Lookalike)	306057	1,610	492748	342	0,069	688	0,140
Germany	491572	1,838	894577	425	0,048	715	0,081
USA (Colorado)	99751	1,677	167291	76	0,045	123	0,074
USA (Massachusetts)	106881	1,591	170008	62	0,036	120	0,071
USA (New Jersey)	112377	1,646	184977	71	0,038	140	0,076
USA (Texas)	148116	1,512	224006	73	0,033	145	0,065
USA (Washington)	115351	1,607	185331	91	0,049	144	0,078

To give some context on the metrics in Table 4: reach corresponds to the number of people who saw the ads at least once; frequency is the average number of times that each person saw the ad; impressions corresponds to the number of times that the adverts were on-screen; link clicks are the number of clicks on links within the ad that led to advertiser-specified destinations, in this case each ad took the user to a website that sold the wine in their country; CTR (link) is the click-through-rate of the link , the percentage of times people saw the ad and performed a link click; clicks is the number of clicks on the adverts in general and CTR (all) is the percentage of times that people saw the ad and performed a click not only in the link for the page that sells the wine.

It is possible to see that the ad sets with the best performance were France (Lookalike) and Germany. Even though having a high reach, it managed to get the highest CTRs, demonstrating that they had the greatest impact on those audiences.

Table 5 presents the outcomes for each ad.

Table 5 - WINES results for each ad

Ad set name	Ad name	Reach	Frequency	Impressions	Link clicks	CTR (link)	Clicks (all)	CTR (all)
France	Ad 1 - Portuguese Heritage	166885	1,198	199901	120	0,060	313	0,157
	Ad 2 - Social Proof (Brand Awards)	64947	1,024	66513	29	0,044	96	0,144
	Ad 3 - Modern and Sophisticated Wine	487866	1,348	657887	209	0,032	281	0,043
	Ad 4 - Fresh wine to drink with friends	226912	1,162	263780	85	0,032	170	0,064
France (Lookalike)	Ad 1 - Portuguese Heritage	134814	1,318	177693	152	0,086	353	0,199
	Ad 2 - Social Proof (Brand Awards)	18815	1,000	18815	7	0,037	17	0,090
	Ad 3 - Modern and Sophisticated Wine	124165	1,265	157101	82	0,052	125	0,080
	Ad 4 - Fresh wine to drink with friends	115600	1,205	139270	101	0,073	193	0,139
Germany	Ad 1 - Beer Audience	28604	1,000	28604	8	0,028	24	0,084
	Ad 2 - Portuguese Wine	117572	1,264	148901	87	0,059	130	0,088
	Ad 3 - Social Proof (Brand Awards)	154555	1,241	192332	76	0,039	158	0,082
	Ad 4 - Next competitive price great wine	343456	1,535	524955	254	0,050	403	0,079
USA (Colorado)	Ad 1 - Fruity Wine	7332	1,012	7421	2	0,027	3	0,040
	Ad 2 - Fruity Wine + Friends	33071	1,238	40949	9	0,022	27	0,066
	Ad 3 - Porch Wine	6418	1,028	6596	2	0,030	5	0,076
	Ad 4 - Social Proof (Brand Awards)	75067	1,467	110132	63	0,057	87	0,079
	Ad 5 - Low Cal	2257	1,003	2263			1	0,044
USA (Massachusetts)	Ad 1 - Fruity Wine	5210	1,016	5295	4	0,076	4	0,076
	Ad 2 - Fruity Wine + Friends	683	1,006	687	1	0,146	1	0,146
	Ad 3 - Porch Wine	54161	1,305	70695	20	0,028	52	0,074
	Ad 4 - Social Proof (Brand Awards)	34889	1,172	40903	13	0,032	27	0,066
	Ad 5 - Low Cal	40447	1,296	52428	24	0,046	36	0,069
USA (New Jersey)	Ad 1 - Fruity Wine	47374	1,218	57713	28	0,049	45	0,078
	Ad 2 - Fruity Wine + Friends	6536	1,015	6636	2	0,030	3	0,045
	Ad 3 - Porch Wine + Portuguese Wine	53269	1,221	65048	17	0,026	40	0,061
	Ad 4 - Social Proof (Brand Awards)	17291	1,040	17988	6	0,033	17	0,095
	Ad 5 - Low Cal	31583	1,193	37669	18	0,048	35	0,093
USA (Texas)	Ad 1 - Fruity Wine	87150	1,349	117592	34	0,029	79	0,067
	Ad 2 - Fruity Wine + Friends	3133	1,000	3134	1	0,032	1	0,032
	Ad 3 - Porch Wine	3083	1,005	3098	1	0,032	3	0,097
	Ad 4 - Social Proof (Brand Awards)	48160	1,181	56876	27	0,047	40	0,070
	Ad 5 - Low Cal	36772	1,181	43415	10	0,023	22	0,051
USA (Washington)	Ad 1 - Fruity Wine	55318	1,235	68344	26	0,038	47	0,069
	Ad 2 - Fruity Wine + Friends	2028	1,003	2034			0	0,000
	Ad 3 - Porch Wine	38216	1,211	46273	15	0,032	37	0,080
	Ad 4 - Social Proof (Brand Awards)	51993	1,242	64575	45	0,070	53	0,082
	Ad 5 - Low Cal	4084	1,024	4183	5	0,120	7	0,167

With this data, it is possible to have an idea about which ads worked best within each ad set. Given that different ads had different reach values, one cannot limit the analysis to the CTR of each one of the ads, but it is necessary to consider both the CTR and reach to choose the one that had the best performance.

In the case of the ad sets France and France (Lookalike), largely because of the huge number of Portuguese in that country, the ads with the best performance were “Ad 1 - Portuguese Heritage”, which highlights the Portuguese origins of the wine. In the case of Germany, the highlight of the competitive price was what had the best results. For the states of Colorado, Texas and Washington, the awards received by WINES generated the most curiosity and, consequently, the greatest number of clicks per impression. For Massachusetts it was the low calorie content of the wine and for New Jersey it was the highlight of its fruity taste. This information is extremely useful not only for future campaigns, but also for the rebranding that WINES is considering doing in the coming months, as mentioned before.

5 FASHION Case Study

As mentioned above, FASHION represents the case study of a medium-sized company with some online presence, which mixes both the online sale of products with the sale in the company's own physical stores.

The ideas that are going to the presented in this chapter emerged from a Growth Hacking Cycle, based on analyses of data from various sources, namely the company's social media, Google Analytics, Hotjar, WooCommerce (the e-commerce platform used) and exports provided by the company with the sales of physical stores.

The company's sales export contained the sales history from March 2019 to April 2021. Thus, this was the period used for all sales analysis. Regarding the analysis of the website, given that the new version of the online store went live on February 13 2020, and that online sales only started to take shape since the beginning of May of the same year (they went from less than 20 sales per month to more than 100 in some months), the period from May 1 2020 to April 30 2021 will be considered. The number of orders and revenue over time are presented in Figure 16.

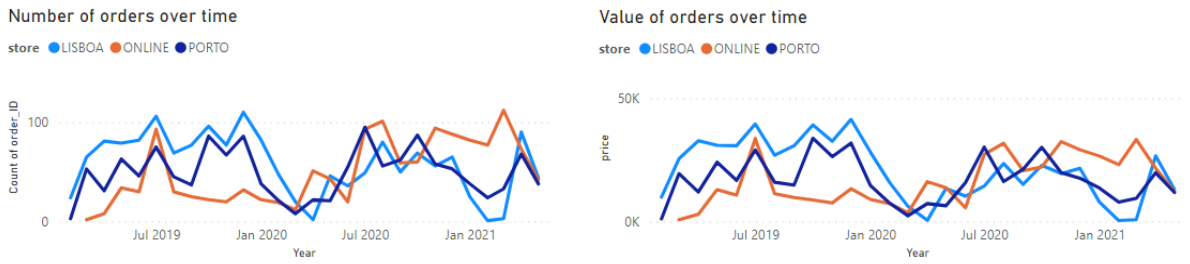

Figure 16 - FASHION orders and revenue over time

It is clear that the online store only began to be a true asset after the new version was launched and that physical stores had a huge shakeup with the beginning of the pandemic. In addition, it is also interesting to compare the percentage of the number of orders for each of the stores either for the entire data set, which includes a very low period for the online store, present in Figure 17, or for the same timeframe used for the website analysis, that is, since 1 year ago, present in Figure 18.

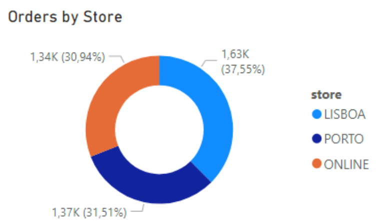

Figure 17 - FASHION orders by store considering all the data set

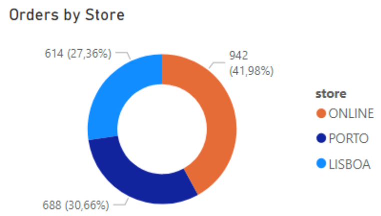

Figure 18 - FASHION orders by store after the launch of the new online store

Figure 18 reveals that the online store for 1 year now has become a huge asset for the company, selling more than the other two stores, largely because of the pandemic that forced the stores to close and to have zero sales in some months, or to sell a very low number of products, with orders placed over the phone or by text and picked up at store doors.

Now that a general context of the orders and revenue of the different stores has been introduced, the next paragraphs present the ideas, with the presentation of the data on which they were based and the expected results for each one.

5.1 Data analysis and ideation

5.1.1 Campaign for men

All of the company's marketing initiatives have been focused on the female audience, but, according to data from the website's Google Analytics, males represent around 24% of the users who visit the website and around 27% of the revenue coming from sales, with a conversion rate 1/4 larger than females as visible by Figure 19.

Gender	Acquisition			Behavior			Conversions eCommerce		
	Users	New Users	Sessions	Bounce Rate	Pages / Session	Avg. Session Duration	Transactions	Revenue	Ecommerce Conversion Rate
	30,554 % of Total: 29.91% (102,146)	28,629 % of Total: 28.31% (101,118)	57,490 % of Total: 31.74% (181,122)	22.48% Avg for View: 26.15% (-14.02%)	18.06 Avg for View: 18.46 (-2.20%)	00:03:52 Avg for View: 00:03:41 (5.27%)	272 % of Total: 30.80% (883)	€66,980.25 % of Total: 28.71% (€233,325.49)	0.47% Avg for View: 0.49% (-2.95%)
1. female	23,818 (76.01%)	21,852 (76.33%)	45,870 (79.79%)	23.29%	17.96	00:03:49	203 (74.63%)	€49,205.22 (73.46%)	0.44%
2. male	7,516 (23.99%)	6,777 (23.67%)	11,620 (20.21%)	19.31%	18.42	00:04:03	69 (25.37%)	€17,775.03 (26.54%)	0.59%

Figure 19 - FASHION website demographics by gender

On social media this demographic only represents 8,7% of the Facebook audience and 10% of the Instagram audience as seen in Figure 20. This is due to the fact that the strategy for these platforms was always set to focus the content on women's products.

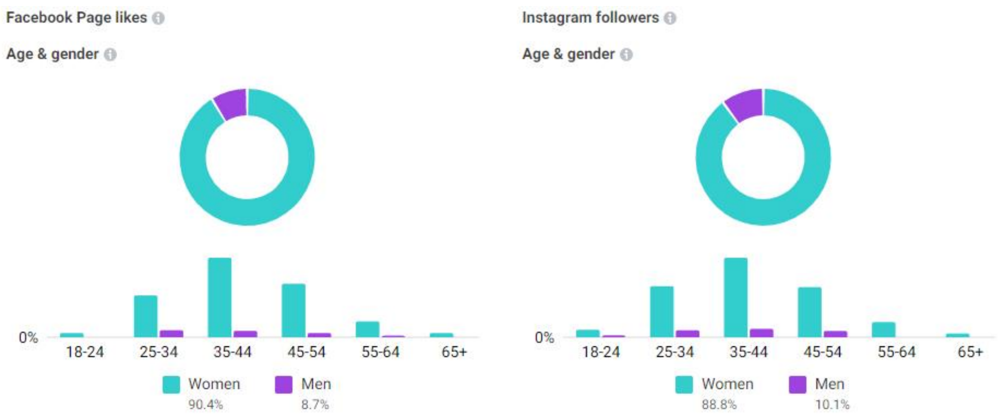

Figure 20 - FASHION social media audience by gender

A good way to lightly hack the acquisition, could include a campaign aimed at men's products, which could consist of a set of ads on social media. This could help to understand the potential of this demographic.

Even if the campaign is not aimed at men's products, it may be aimed at women's products, but focusing on the male audience. This may be particularly useful when FASHION products can serve as a gift, like Christmas or Valentine’s Day.

The metric that would indicate the success of the men's campaign would be the number of transactions coming from it. The more transactions, the more successful it was.

5.1.2 Spain Campaign

Knowing that one of the company's goals is to expand and increase its sales abroad, one of the most interesting countries to hack the acquisition would be Spain.

The website data indicates that there are many Spanish users, with many quality sessions (low bounce rate and high session duration) with a conversion rate of 0,2%, representing 2% of online sales revenue, as seen in Figure 21.

Country	Acquisition			Behavior			Conversions eCommerce		
	Users	New Users	Sessions	Bounce Rate	Pages / Session	Avg. Session Duration	Transactions	Revenue	Ecommerce Conversion Rate
	102,146 % of Total: 100.00% (102,146)	101,484 % of Total: 100.36% (101,118)	181,122 % of Total: 100.00% (181,122)	26.15% Avg for View: 26.15% (0.00%)	18.46 Avg for View: 18.46 (0.00%)	00:03:41 Avg for View: 00:03:41 (0.00%)	883 % of Total: 100.00% (883)	€233,325.49 % of Total: 100.00% (€233,325.49)	0.49% Avg for View: 0.49% (0.00%)
1. Portugal	**72,251** (69.77%)	70,677 (69.64%)	132,674 (73.25%)	23.51%	20.00	00:03:56	787 (89.13%)	€203,515.46 (87.22%)	0.59%
2. Spain	**6,446** (6.23%)	6,320 (6.23%)	9,037 (4.99%)	23.91%	17.49	00:03:44	18 (2.04%)	€5,551.63 (2.38%)	0.20%
3. United States	**5,980** (5.78%)	5,964 (5.88%)	7,289 (4.02%)	47.56%	8.82	00:01:46	6 (0.68%)	€1,833.62 (0.79%)	0.08%
4. United Kingdom	**2,384** (2.30%)	2,346 (2.31%)	3,095 (1.71%)	23.10%	14.43	00:02:49	4 (0.45%)	€760.60 (0.33%)	0.13%
5. France	**2,151** (2.08%)	2,107 (2.08%)	3,329 (1.84%)	25.17%	17.48	00:04:02	11 (1.25%)	€3,240.98 (1.39%)	0.33%
6. Switzerland	**1,409** (1.36%)	1,376 (1.36%)	2,325 (1.28%)	26.02%	17.97	00:03:48	9 (1.02%)	€2,660.39 (1.14%)	0.39%
7. Germany	**1,259** (1.22%)	1,223 (1.21%)	1,837 (1.01%)	26.29%	17.13	00:04:27	10 (1.13%)	€3,415.06 (1.46%)	0.54%
8. Canada	**936** (0.90%)	930 (0.92%)	1,250 (0.69%)	27.60%	16.63	00:03:00	3 (0.34%)	€769.34 (0.33%)	0.24%
9. Netherlands	**822** (0.79%)	810 (0.80%)	1,225 (0.68%)	26.86%	16.40	00:03:37	2 (0.23%)	€653.30 (0.28%)	0.16%
10. Brazil	**765** (0.74%)	765 (0.75%)	945 (0.52%)	34.18%	8.84	00:02:41	0 (0.00%)	€0.00 (0.00%)	0.00%

Figure 21 - FASHION website data by country

In addition, the Spanish public already follows the company's social media, representing about 6% of Facebook followers and 5% of Instagram followers, as shown in Figure 22.

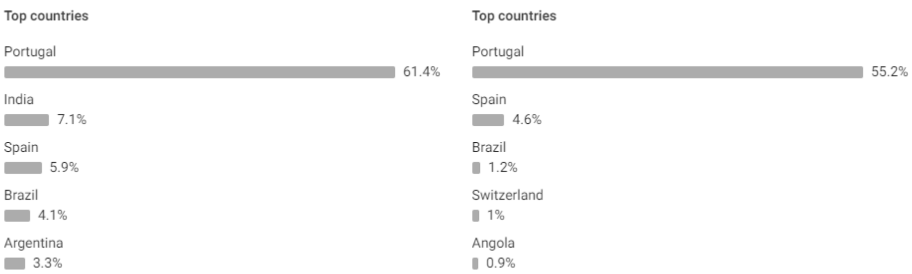

Figure 22 - FASHION social media audience by country

Initially, a more general campaign should be carried out to confirm the potential of this market, with and without a “lookalike” audience. With this information, a more elaborated campaign could then be carried out with the objective of making FASHION products reach the Spanish users' feed.

5.1.3 USA Campaign

Another very interesting market for the brand is the USA, representing around 6% of the users who visit the website, as seen in Figure 21. For this market, and as previously explored for WINES, digital campaigns should bear in mind that user tastes and interests differ a lot from state to state. But as for Spain, a test ad can be run simply to confirm the potential of this market.

Some things that can be tested, either with A/B testing or with multivariate testing presented in Chapter 2, in this ad or in the following ones can be:

- Refer Portugal or not?
- Which cities sell the most? High income ones?
- Is the price of the products too high or too low for Americans?

This campaign can have ads on social media, like the one created for WINES, but also Google Ads with some keywords that can help to get more Americans directly in the store page.

5.1.4 Size guide USA

Still focusing on the American market and going back to Figure 21, the sessions from the USA market have a very high bounce rate, close to 48%. One of the reasons for this could be the fact that the product pages do not present American sizes and only European ones.

This kind of friction towards American users could easily be removed by adding a size conversion table on each of the product pages. In addition, the price in dollars could also be displayed, since the conversion between dollar and euro is not always simple, especially for the American market.

The success of this idea could be measured with an event that counts how many times the guide has been opened and inevitably with the number of sales in the American market.

This small change would undoubtedly hack the activation of the website and would be an excellent complement to the US Campaign previously presented.

5.1.5 Reduce Friction

Since changes were made to the website in the previous idea, a few more can be introduced that would undoubtedly help to hack activation and revenue. The majority of website orders, over 40%, are made up of just one product. Thus, it would make sense to add a "pay now" button instead of forcing all users to add the product to their cart and have to pass through all the normal customer journey, mainly because there is a huge cart abandonment rate, about 60% of the carts are abandoned, as seen in Figure 23.

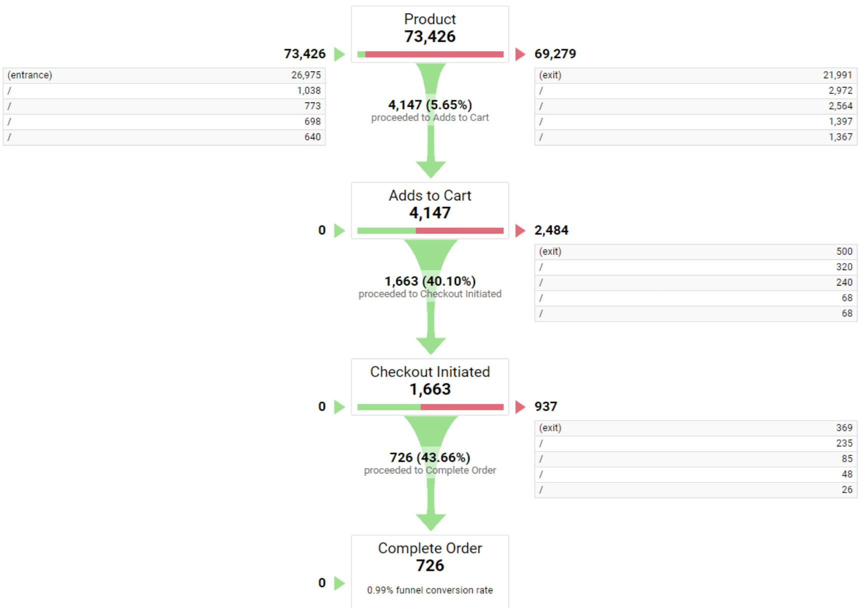

Figure 23 - FASHION funnel visualization

Another funnel zone that also has a lot of abandonment is the checkout zone, with around 60% of orders being abandoned. To prevent this abandonment, the final price of the product or the shipping value based on the user's location should be added to product pages, so that the user understands if he/she really wants the product before proceeding with the order.

One way to increase the number of products sold or added to the cart can be the addition of a special message to the top selling product pages, such as “This product is a best-seller and will be out of stock soon”, thus creating a sense of urgency on the customer who is left thinking that the product will sell out quickly and needs to grab it as fast as possible. This implementation can be crucial, as only 5% of the products viewed proceed to the cart.

5.1.6 Landing Page Implementation

Landing pages, as mentioned in Chapter 2, would be particularly useful for campaigns, ads or for posts on social media. This is because they could be directed to the products or collections presented, without having to deal with the rest of the information that the normal website has. These could be generated with previously mentioned no-code tools to facilitate their implementation.

One of the heatmaps generated by Hotjar indicated that in 1000 sessions studied, only 6% of users reached the end of the FASHION store's main page, that is, few people end up seeing all the available content. Landing page creation could help target this, reducing the bounce rate and ultimately driving more conversions.

5.1.7 Remarketing Campaign

As mentioned before, it is very important to reduce friction in order to make fewer users abandon products and carts. But, if with these changes the users continue to leave the website without converting, remarketing can be relevant.

Remarketing is a brilliant way to hack activation and retention and is nothing more than using ads to re-present products to users who have already visited the store, have already interacted in some way with it, or even made purchases in it in the past. In this case, remarketing has the goal of bringing potential customers back to the store in hope of converting again.

The returning users (those who returned to the store after one or multiple visits that may or may not have converted) represent only 20% of website users but at the same time 64% of the revenue generated comes from them, as visible in Figure 24.

User Type	Acquisition			Behavior			Conversions eCommerce	
	Users	New Users	Sessions	Bounce Rate	Pages / Session	Avg. Session Duration	Transactions	Revenue
	102,146 % of Total: 100.00% (102,146)	101,484 % of Total: 100.36% (101,118)	181,122 % of Total: 100.00% (181,122)	26.15% Avg for View: 26.15% (0.00%)	18.46 Avg for View: 18.46 (0.00%)	00:03:41 Avg for View: 00:03:41 (0.00%)	883 % of Total: 100.00% (883)	€233,325.49 % of Total: 100.00% (€233,325.49)
1. New Visitor	100,521 (79.84%)	101,484 (100.00%)	101,484 (56.03%)	24.25%	18.75	00:03:26	313 (35.45%)	€83,921.58 (35.97%)
2. Returning Visitor	25,381 (20.16%)	0 (0.00%)	79,638 (43.97%)	28.57%	18.10	00:03:59	570 (64.55%)	€149,403.91 (64.03%)

Figure 24 - FASHION store stats by user type

Furthermore, if one studies the sales, 38% of the customers only made one purchase, as seen in Figure 25. This means that customers did not return to physical or online stores, and consequently there is a huge margin here to make them return.

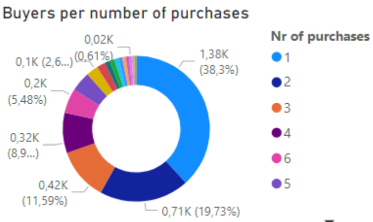

Figure 25 - FASHION buyers per number of purchases

If we focus this same analysis only on the online store, we find that the situation is even worse, with about 45% of customers making a single purchase (which may or may not include multiple items) and never buying anything on the website again.

For the remarketing campaign, Google Ads or ads on social media such as Facebook and Instagram can be used, as these platforms already have simple ways to apply these remarketing initiatives.

In the case of Google Ads, and after analyzing the website data, the best way to optimize the investment would be to bet on users who visit the website on the desktop. Despite being less than those visiting on mobile, they have a much higher conversion rate, as can be seen in Figure 26. This suggests that when users visit with a computer, they have much more intentions of buying.

Device Category	Acquisition			Behavior			Conversions eCommerce		
	Users	New Users	Sessions	Bounce Rate	Pages / Session	Avg. Session Duration	Transactions	Revenue	Ecommerce Conversion Rate
	102,146 % of Total: 100.00% (102,146)	101,484 % of Total: 100.36% (101,118)	181,122 % of Total: 100.00% (181,122)	26.15% Avg for View: 26.15% (0.00%)	18.46 Avg for View: 18.46 (0.00%)	00:03:41 Avg for View: 00:03:41 (0.00%)	883 % of Total: 100.00% (883)	€233,325.49 % of Total: 100.00% (€233,325.49)	0.49% Avg for View: 0.49% (0.00%)
1. mobile	**70,279** (68.63%)	70,046 (69.02%)	126,761 (69.99%)	29.20%	17.15	00:03:10	456 (51.64%)	€116,565.51 (49.96%)	0.36%
2. desktop	**28,536** (27.86%)	27,894 (27.49%)	48,693 (26.88%)	18.46%	22.00	00:04:57	400 (45.30%)	€109,450.35 (46.91%)	0.82%
3. tablet	**3,595** (3.51%)	3,544 (3.49%)	5,668 (3.13%)	23.91%	17.53	00:04:15	27 (3.06%)	€7,309.63 (3.13%)	0.48%

Figure 26 - FASHION stats by device used

In addition, these initiatives should focus on users who left the website in the previous 2 weeks, as conversions are practically non-existent in the weeks following that, according to the cohort analysis present in Figure 27.

	Week 0	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Week 8	Week 9	Week 10	Week 11	Week 12
All Users 30,486 users	124	26	5	0	6	2	3	3	0	0	0	1	0
Mar 21, 2021 - Mar 27, 2021 2,281 users	13	4	2	0	0	1	1	0	0	0	0	1	0
Mar 28, 2021 - Apr 3, 2021 2,274 users	7	3	1	0	0	1	0	2	0	0	0	0	
Apr 4, 2021 - Apr 10, 2021 2,292 users	14	3	0	0	3	0	0	1	0	0	0		
Apr 11, 2021 - Apr 17, 2021 1,960 users	5	1	0	0	1	0	0	0	0	0			
Apr 18, 2021 - Apr 24, 2021 2,310 users	11	2	0	0	0	0	1	0	0				
Apr 25, 2021 - May 1, 2021 2,797 users	13	3	1	0	1	0	1	0					
May 2, 2021 - May 8, 2021 2,108 users	9	1	0	0	0	0	0						
May 9, 2021 - May 15, 2021 2,020 users	9	2	0	0	1	0							
May 16, 2021 - May 22, 2021 2,036 users	15	3	0	0	0								
May 23, 2021 - May 29, 2021 2,022 users	8	2	0	0									
May 30, 2021 - Jun 5, 2021 3,274 users	8	2	1										
Jun 6, 2021 - Jun 12, 2021 5,112 users	12	0											

Figure 27 - FASHION cohort analysis

5.1.8 Explore cross-sell opportunities

To cross-sell is to sell related or complementary products to a customer. With the analysis of sales data, it is possible to see that of all sales made in all stores (online and physical), 30% of customers only bought one product, and that in the online store the situation worsens, with 41% of customers. That said, cross-sell opportunities should really be seized, to make these customers who only bought a specific product to buy others that might be interesting to them.

FASHION divides its products into 5 categories (Sandals, Boots, Shoes, Sneakers and Accessories) and into 23 subcategories (Accessories, Ankle, Ballerinas, Boots, Casual, Classic, Espadrilles, Handbags, Knee-High, Loafers, Men, Mules, Over-the-Knee, Pumps, Sandals, Shoes, Slides, Slingback, Slippers, Sneakers, Stilettos, Strappy and Women), the correspondence is shown in Table 6.

Table 6 - FASHION types and subtypes

Type	Subtype	Type	Subtype	Type	Subtype
Accessories	Accessories	Sandals	Ballerinas	Shoes	Casual
	Handbags		Mules		Classic
Boots	Ankle		Sandals		Espadrilles
	Boots		Slides		Loafers
	Knee-High		Slingback		Men
	Over-the-Knee		Slippers		Pumps
Sneakers	Sneakers		Stilettos		Shoes
			Strappy		Women

To understand the relationship that exists between the various types and subtypes of products, the Jaccard Index, also known as the Jaccard similarity coefficient, was calculated. The Jaccard Index is obtained with the equation (5.1). The measurement emphasizes similarity between finite sample sets, and it is formally defined as the size of the intersection divided by the size of the union of the sample sets.

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|} \tag{5.1}$$

It is not a perfect indicator of similarity, but it is enough to see the relationships that exist between types, in Table 7, and subtypes, in Table 8.

Table 7 - Top 3 more similar types for each type

	1	Index	2	Index	3	Index
Accessories	Sneakers	1,37%	Boots	0,78%	Shoes	0,66%
Boots	Sandals	38,11%	Shoes	27,51%	Sneakers	10,71%
Sandals	Boots	38,11%	Shoes	34,52%	Sneakers	7,63%
Shoes	Sandals	34,52%	Boots	27,51%	Sneakers	12,35%
Sneakers	Shoes	12,35%	Boots	10,71%	Sandals	7,63%

Table 8 - Top 5 more similar subtypes for each subtype

	1	2	3	4	5
Accessories	Stilettos	Boots	Classic	Ankle	Ballerinas
Ankle	Slingback	Knee-High	Women	Pumps	Sneakers
Ballerinas	Loafers	Sneakers	Over-the-Knee	Men	Shoes
Boots	Casual	Classic	Sneakers	Men	Loafers
Casual	Men	Boots	Classic	Sneakers	Shoes
Classic	Men	Loafers	Boots	Casual	Sandals
Espadrilles	Loafers	Women	Slingback	Ankle	Ballerinas
Handbags	Slipers	Strappy	Sandals	Mules	Sneakers
Knee-High	Ankle	Pumps	Sneakers	Slingback	Women
Loafers	Classic	Pumps	Espadrilles	Ballerinas	Mules
Men	Classic	Casual	Sneakers	Sandals	Boots
Mules	Slipers	Slingback	Pumps	Ankle	Sneakers
Over-the-Knee	Shoes	Knee-High	Sandals	Slingback	Ankle
Pumps	Ankle	Knee-High	Slingback	Sandals	Mules
Sandals	Pumps	Ankle	Knee-High	Sneakers	Classic
Shoes	Over-the-Knee	Ankle	Knee-High	Mules	Women
Slides	Strappy	Slingback	Ankle	Ballerinas	Boots
Slingback	Ankle	Women	Pumps	Knee-High	Mules
Slipers	Mules	Strappy	Women	Handbags	Sandals
Sneakers	Women	Knee-High	Ankle	Mules	Men
Stilettos	Boots	Loafers	Knee-High	Pumps	Shoes
Strappy	Pumps	Slipers	Mules	Sneakers	Ankle
Women	Slingback	Ankle	Sneakers	Pumps	Knee-High

Since the subtypes defined by the company for its orders are not at all a good indication, the values from the types table will then be considered, because in some cases multiple subtypes could be used for each product, in the case of the subtype “Women”, clearly a “Women” shoe could be a “Shoe” or a “Classic”. The division does not make much sense and just complicates the calculation.

With the calculations of these indexes, one can realize, for example, that in the case of “Accessories”, what would make more sense to be suggested for cross-sell would be “Sneakers”. This information can be useful to present more interesting suggestions on the website itself, on the page of each of the products, on the cart page or even on the payment page. This way, the customer is tempted to add one more product to their purchase. In physical stores, these products can even be suggested by employees or strategically positioned close to one another, for example, it is smart to always keep “Accessories” close to “Sneakers”.

Another usefulness of this information can be Email Marketing, but the following idea takes this topic further.

5.1.9 Personalized offers by email

As previously presented, Email Marketing was a very successful test on the FASHION company by Happyfact. As such, and to further optimize the results of this initiative, personalized suggestions can be created and sent by email for each of the customers based on past transactions.

In Chapter 2 the recommender systems were introduced, and here a recommender system based on collaborative filtering was developed, which, as said before, considers the past transactions of other users to create suggestions for them. Since there is a greater number of users than items, a Neighborhood Item-based approach was used to obtain better similarity values.

First the system will fetch the information from past transactions that is available in the complete dataset, which looks like Table 9. The product names were removed to protect the identity of the company, as they could be easily searched and found online.

Table 9 - Dataset used to generate recommendations

order_ID	store	store_location	product_name	product_ID	buyer_ID	buyer_name	product_type	product_subtype	price	date
1	LISBOA	PHYSICAL	XXXX		2	XXXX	Sandals	Slingback	448	19/02/2019
2	LISBOA	PHYSICAL	XXXX	XXXX	1	XXXX	Sneakers	Sneakers	323	19/02/2019
3	LISBOA	PHYSICAL	XXXX	XXXX	3	XXXX	Sandals	Sandals	470	20/02/2019
4	LISBOA	PHYSICAL	XXXX	XXXX	4	XXXX	Shoes	Shoes	370	20/02/2019
5	LISBOA	PHYSICAL	XXXX	XXXX	6	XXXX	Sandals	Slingback	495	21/02/2019
...	…	…	…	…	…	…	…	…	…	…
4218	LISBOA	PHYSICAL	XXXX	XXXX	1701	XXXX	Sandals	Slingback	279	30/04/2021
4219	LISBOA	PHYSICAL	XXXX	XXXX	370	XXXX	Sandals	Slingback	318	30/04/2021
4220	ONLINE	ONLINE	XXXX	XXXX	1692	XXXX	Sandals	Mules	279	30/04/2021

Then the system transforms the dataset information into a matrix of ones and zeros presented in Table 10. This is because it was not possible to obtain any implicit or explicit ratings. It is simply known if the item was purchased or not, without knowing what the user’s level of interest or satisfaction with the product was.

Table 10 - Buyer vs Product Matrix

buyer_ID/product_name	XXX	XXX	XXX	XXX	…	XXX	XXX
1	0	0	1	0	…	1	0
2	0	0	0	0	…	0	1
3	1	0	1	1	…	1	0
…	…	…	…	…	…	…	…
1739	0	0	0	1	…	1	0
1740	0	0	1	0	…	0	0

This matrix is then used to calculate the similarity between each of the items in space with the Nearest Neighbor method and with the Cosine metric instead of the Euclidean. Euclidean distance is unhelpful in high dimensions because all vectors are almost equidistant to the search query vector. Cosine similarity works better because it is not based on traditional distance but in an angle. It ranges from -1 to 1 and it is calculated as the dot product between two vectors divided by their magnitudes, as seen in equation (5.2).

$$sim(A,B) = \cos(\theta) = \frac{A \cdot B}{\|A\|\|B\|} \tag{5.2}$$

After calculating the similarity between each of the items, the system identifies the top 5 items for each of the users. These items are suggested having previous purchases as a base. The result is then saved in an excel file with a table like Table 11.

Table 11 - Representation of the table of recommendations generated by the system

buyer_ID	Recomendation	Similarity	product_type	product_subtype
1	XXXX	0,40824829	Sandals	Slingback
1	XXXX	0,40824829	Boots	Ankle
1	XXXX	0,377964473	Sandals	Slingback
1	XXXX	0,377964473	Sandals	Sandals
1	XXXX	0,377964473	Sandals	Mules
2	XXXX	0,353553391	Sandals	Slingback
2	XXXX	0,353553391	Shoes	Shoes
…	…	…	…	…
1740	XXXX	0,25	Sandals	Sandals
1740	XXXX	0,25	Sandals	Slingback
1740	XXXX	0,204124145	Sandals	Slingback

With this final table it is then possible to recommend the top 5 products to each of the customers, or, even better, if Happyfact wants to increase sales of a specific type, subtype or specific product, simply sort this table and send an email to the users who have greater similarity to those products.

To rate the recommender system its hit rate was calculated. Other metrics like mean absolute error or root mean square error were not used, because many of those depend on the existence of a rating other than 1 or 0 in order to determine how accurate the system is. Given that in this case the variables are binary, the hit rate was adopted.

To calculate the hit rate, the data set was divided into 2, a training set, which serves to train the model, and a test set, to calculate the hit rate. To determine this division, the k-fold cross-validation was used. The data set was split into k sets (called folds) of approximately the same size. Since the number of folds was the same as the number of buyers, it represents a special case called Leave-one-out cross validation. In this case, to create the folds, the system took a random transaction from each of the users and removed it from the training set and added it to the test set, to see if the training set could suggest it. Users with only 1 order in the system ended up being excluded from this test, as it would not be possible to ascertain whether the recommendation was correct or not.

After having the training set and test set ready, the system ran and generated a list of recommendations for each user. This list was then compared to the order in the test set. If any of the top 5 product recommendations matched the one product ordered in the test set, it counted as a hit. The number of hits was then divided by the number of users, reaching a hit rate of 1.95%. The value is not at all high and demonstrates that more data is needed for the recommendations to be more accurate.

5.1.10 Summer and Winter Campaign

A visual analysis of the number of orders over time at the different stores suggests that there is some seasonality, as can be seen in Figure 28.

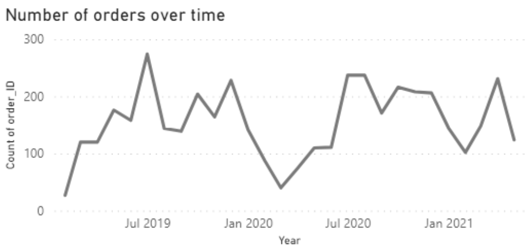

Figure 28 - FASHION orders over time

With this in mind, a sales forecast was made for the rest of the year 2021. This forecast may help define how to take advantage of the seasonality that sales appear to have, thus increasing the chance of hacking the revenue. The Classical Decomposition method was used, more specifically Additive Decomposition, as the graph presented seasonality but a very low trend. The result of the forecast is presented in Figure 29.

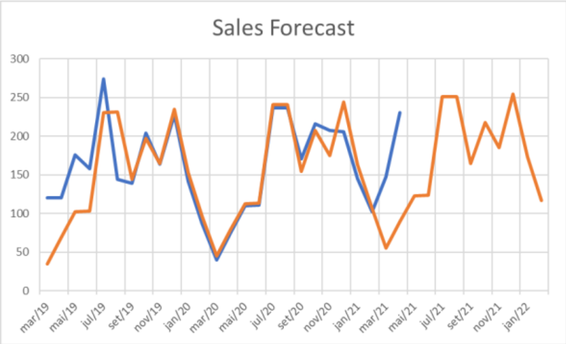

Figure 29 - FASHION sales forecast

This forecast had an uncertainty coefficient (U) of 0,72, which demonstrates that this model is much better than the Naïve one, and a mean absolute percentage error (MAPE) of 19,63 %, which is not particularly high and demonstrates a good forecast. Nevertheless, there are 2 outliers in the graph of Figure 29. One of them corresponds to the months of March and April of 2020, when the stores were closed with near to no sales. This caused an abrupt and abnormal drop in sales at that time. The other outlier is the month of April of 2021, with sales too high that do not match the forecast, because it was the month when the stores reopened to the public in 2021 with a big promotion, which generated a lot of sales.

That said, the forecast was once again made with the correction of these outliers, for the months of March and April 2020, the sales were exchanged for the 2019 sales of the same months, forecast present in Figure 30. This change had very positive effects on the forecast, having an uncertainty coefficient of 0,55 (the closer to zero, the better) and a MAPE of 11.7%. The month of April 2021 has not changed, but the irregularity of this one due to the reopening of physical stores is hereby noted.

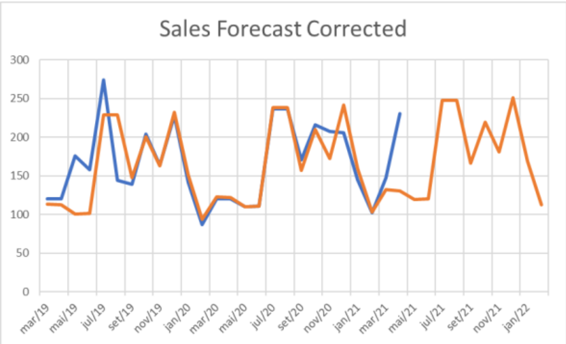

Figure 30 - FASHION sales forecast corrected

This forecast allows one to see when there will be more sales, thus allowing the development of 2 online campaigns (and perhaps these campaigns could even work physically) one in the summer and one in the winter, given that the 2 peaks occur in the months of July and August in the summer and December in the winter.

In order to understand which products to recommend for each of these campaigns, the best-selling types of products were then analyzed, with the graph in Figure 31, reaching the conclusion that the best-selling ones are sandals, boots and shoes, respectively.

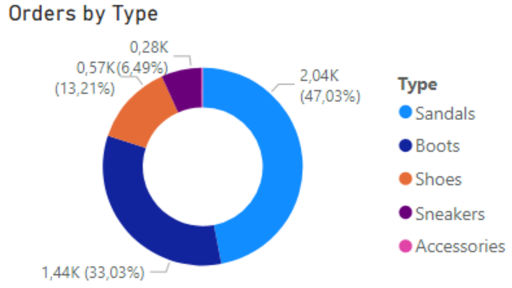

Figure 31 - FASHION orders by type of product

The variation in sales of these products throughout the year was then studied, showing that boots sell much better in winter and sandals in summer, as shown in Figure 32 and 33, respectively. As for shoes, they did not seem to have much seasonality, having the same sales throughout the whole year.

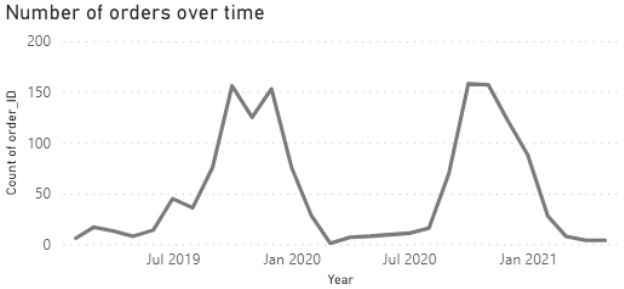

Figure 32 - FASHION orders of boots over time

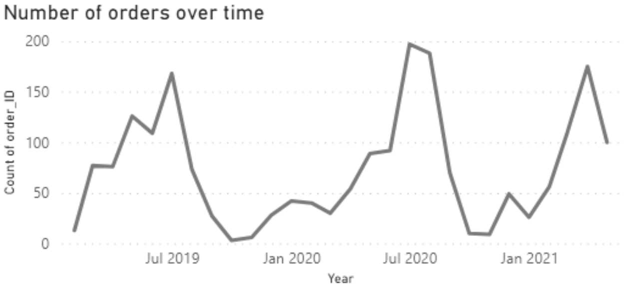

Figure 33 - FASHION orders of sandals over time

With this, it is more than appropriate to suggest a boost in boot's sales during the month of December and a boost in sandals' sales in July and August. These campaigns could further raise the values that will certainly be high in these months. Either way, to get a sense of what to expect in terms of sales, a sales forecast was then made for the boots and sandals, in Figure 34 and 35, respectively.

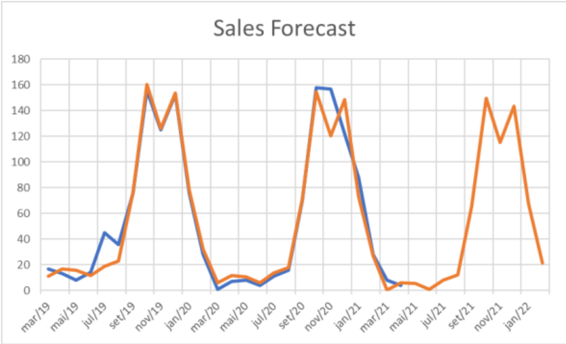

Figure 34 - FASHION sales forecast for boots

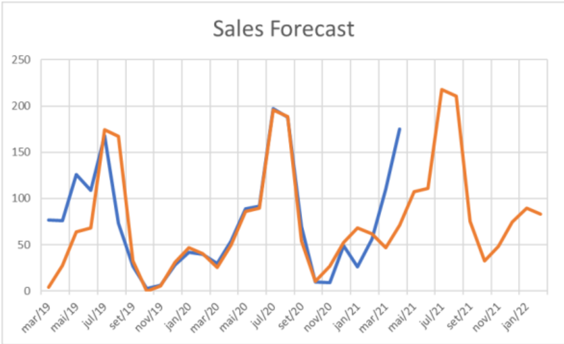

Figure 35 - FASHION sales forecast for sandals

Using this forecast information, it is expected to sell around 143 boots in December in all stores, with a U of 0,63 and a MAPE of 45,63%. It is also expected to sell around 217 and 210 sandals in the months of July and August respectively, this forecast having a U of 0,44 and a MAPE of 55%. These 2 forecasts had a very high error, so they are not highly reliable. In addition, the outlier for the month of April mentioned above, due to the opening of stores, is once again visible in the sales forecast of sandals.

5.1.11 New Channels

FASHION already uses Facebook and Instagram to communicate with its clients, but it is missing a great opportunity by not investing in new platforms, especially TikTok.

The website data show that the 18-24 year-old demographic is the one with the lowest presence on the website, at the same time having the lowest growth from 2019 to 2020, as can be seen in Figure 36.

Age	Acquisition			Behavior			Conversions eCommerce	
	Users	New Users	Sessions	Bounce Rate	Pages / Session	Avg. Session Duration	Transactions	Revenue
	394.99% 30,328 vs 6,127	416.84% 28,416 vs 5,498	566.69% 57,202 vs 8,580	18.90% 22.48% vs 18.90%	6.89% 18.07 vs 16.90	9.21% 00:03:52 vs 00:03:33	988.00% 272 vs 25	722.52% €66,980.25 vs €8,143.25
1. 18-24								
May 1, 2020 - Apr 30, 2021	**2,848** (8.65%)	2,488 (8.76%)	4,054 (7.09%)	18.75%	18.85	00:03:52	25 (9.19%)	€6,299.10 (9.40%)
May 2, 2019 - Apr 30, 2020	**773** (12.37%)	713 (12.97%)	1,026 (11.96%)	14.81%	18.49	00:03:57	2 (8.00%)	€801.00 (9.84%)
% Change	**268.43%**	**248.95%**	**295.13%**	**26.54%**	**1.96%**	**-2.15%**	**1,150.00%**	**686.40%**

Figure 36 - FASHION website stats for ages between 18 and 24

TikTok's 1,2 billion active user population is 70% Gen Z, neatly capturing a high-value market every luxury brand will need to capture to ensure survival in the future. This could then be a way to attract new customers from a younger age group, thus ensuring the future of the brand.

Moreover, as Instagram and Facebook are becoming more and more competitive, being one of the first Portuguese luxury footwear brands to reach TikTok fame would help to differentiate FASHION from the competition. Large luxury brands such as Moncler, Gucci and Dior are already present on the platform and have had excellent results this year (Fanbytes, 2021).

5.1.12 Influencers and Brand Ambassadors

As mentioned in Chapter 2, recommendations from friends or influencers have much more impact on the purchase decision than any type of ad that can. As such, and being an excellent way to hack the acquisition, FASHION could develop its own ambassador program which could be made up of influencers and bloggers who would receive the brand's products or discounts in order to produce content for social media about them. A great example that could be followed is the Farfetch ambassador program, which allows the company to have a much greater reach and exposure, as well as facilitate the production of visual content for posts, because the influencer photos can be used for ads, for website product promotion, or even for physical banners, reducing production costs as well (Afluencer, 2021).

5.1.13 Referral program

Another great way to hack acquisition that was also covered in Chapter 2 was the development of referral programs. So, it is mentioned again here as an excellent opportunity to bring in more customers. This program could consist of a simple discount given to users whenever they can get a friend to make a purchase using their user code (the friend also has a benefit for using this code). But it also could consist of a points scheme in the customer's account, and whenever a friend buys a product with the code, they get a set of points that can later be exchanged for FASHION products.

For this, it should be tested which incentive generates more conversions. Will it be a discount? Is it a set of points? Will it be free shipping on the next purchase? For this, A/B testing can be used, as mentioned many times throughout this project.

Again, Farfetch can and should be an example to follow in this regard, with a referral program at a very advanced stage, available in 7 different languages, with excellent results. "The results have been tremendous, and we look forward to seeing where it can still go from here", Andrew Robb, ex-COO of Farfetch about its referral program (Mention Me, 2021).

5.2 Prioritization and testing

After the presentation of this panoply of ideas, now follows their correspondence with the main objectives of the company presented in Chapter 3. In addition, it should be noted that idea 10 directly tackles the reported problem about the seasonality of the products, offering a practical solution to make the best use of this seasonality.

The correspondence between objectives and ideas is now available in Table 12.

Table 12 - Correspondence between FASHION objectives and ideas presented

Objective	Idea number
Increase sales in Portugal	1 / 5 / 6 / 7 / 9 / 10 / 12 / 13
Expand outside Portugal to other markets	2 / 3 / 4
More presence and more recognition online	11 / 12 / 13
Generate more sales by taking advantage of cross-sell and up-sell opportunities	8 / 9

The ICE Score for each idea is also present in Table 13, noting that the best ideas to test are the ones related to the “Spain Campaign” and the “USA Campaign”.

Table 13 - FASHION ICE Score

Idea number	Idea	Impact	Confidence	Ease	ICE Score
1	Campaign for men	6	6	8	6,7
2	Spain Campaign	8	7	8	7,7
3	USA Campaign	8	7	8	7,7
4	Size guide USA	6	8	5	6,3
5	Reduce Friction	7	7	2	5,3
6	Landing Page Implementation	5	6	6	5,7
7	Remarketing Campaign	8	7	6	7,0
8	Explore cross-sell opportunities	7	5	5	5,7
9	Personalized offers by email	8	8	6	7,3
10	Summer and Winter Campaign	7	5	6	6,0
11	New Channels	4	7	5	5,3
12	Influencer and Brand Ambassadors	7	7	1	5,0
13	Referral program	6	7	1	4,7

As for the tests carried out throughout the project, and due to its ease of implementation, it was possible to start with an experimental version of the US Campaign. An Instagram ad was then run whose creative was a GIF with 8 photo slides with specific copy to test the interest of the American public in the type of content. It was also tested if there was interest in the shoes and if the word “Portuguese” had an effect. To keep the brand's identity a secret, it will not be possible to attach a print of the GIF in question, but the message in each slide follows:

- Slide 1: "This famous Portuguese shoe designer is a name to know".
- Slide 2: "Bold handmade designs you won't see anywhere else".
- Slide 3: "These styles are unique pieces of art".
- Slide 4: "Completely handmade to last for years".
- Slide 5: "They're a fashionista's secret weapon".
- Slide 6: "Seen on celebrities everywhere".
- Slide 7: "Every collection is daring & statement-making".
- Slide 8: "Shop FASHION now".

The ad ran from April 20th to May 4th and had as audience people living in the cities of Los Angeles, Sacramento, San Francisco, Miami and New York, who were female with interests in Women's Shoes, Fashion & Style and Portugal. Although everything indicates that the ad would have had excellent results, it failed to convert in the 2 weeks it was on the air. Nevertheless, it was possible to get useful information for an ad correction that will be presented next, but before, the results of the ad in question are presented in Table 14.

Table 14 - Results from the GIF test in the USA

Metric	Value	Metric	Value
Reach	7785	Video percentage watched	16,23
Frequency	2,26	Video average play time	00:00:02
Impressions	17587	ThruPlays	471
Link clicks	179	Video plays at 25%	2209
CTR (link)	1,02	Video plays at 50%	990
Clicks (all)	280	Video plays at 75%	626
CTR (all)	1,59	Video plays at 95%	472
Website purchases	0	Video plays at 100%	452
3-second video plays	3288	Video plays	16380

It is possible to see that the ad had many impressions and an interesting CTR, but not interesting enough to convert later into sales. This may happen because the website did not have the size guide or the price in dollars as suggested in idea 4. Still, very few people watched the entire GIF, with the average viewing time being just 2 seconds, and of the 17587 impressions, only 452 watched the video in its entirety.

That said, and given that the first slide contained a reference to Portugal, there is a suggestion for a new ad with the same creative but with slight changes to the copy and the audience. The audience would no longer have Portugal in its interests and copy would give more emphasis to the reduced price of FASHION products in the American context:

- Slide 1: "Have you heard of this amazing shoe designer?".
- Slide 2: "Premium handmade designs FROM $X to $X".
- Slide 3: "These styles are unique pieces of art".
- Slide 4: "Completely handmade to last for years".
- Slide 5: "They're a fashionista's secret weapon".
- Slide 6: "Seen on celebrities everywhere".
- Slide 7: "Every collection is daring & statement-making".
- Slide 8: "Shop FASHION now".

When launching this enhanced version of ad, a test could be launched for the Spanish market using the same creative in Spanish, with a similar audience, but with the addition of speaking English, given that the website is all in English, the new copy for the GIF follows:

- Slide 1: "¿Has oído hablar de este increíble diseñador de zapatos?".
- Slide 2: "Diseños hechos a mano de primera calidad DESDE $ X a $ X".
- Slide 3: "Estos estilos son piezas de arte únicas ".
- Slide 4: "Hechas a mano para durar años".
- Slide 5: "Son el arma secreta de una fashionista".
- Slide 6: "Visto en celebridades en todas partes".
- Slide 7: "Cada colección es atrevida y llamativa".
- Slide 8: "Compra FASHION ahora".

With this, it would then be possible to test the American market again and without much effort already do a test in Spain to open doors to more complex campaigns in the future.

6 FINTECH Case Study

FINTECH represents the case study of a startup that has its entire business online, unlike the 2 companies previously presented. Since its inception, FINTECH has used the methodology to grow all aspects of its business with Happyfact. Still, some analyzes were neglected, especially those related to orders.

Most of the ideas that will be presented in the next paragraphs result from a Growth Hacking Cycle. The ideas will be based on the analysis of the export that was received by the company that has all placed orders from January 2020 to April 2021. For each order, the dataset has the date it was placed; the merchant on which the order was placed; the buyer who placed the order; the cryptocurrency used; the total in dollars; the buyer's country and the status of the order, that is, whether paid, cancelled, refunded or in process of refunding.

Later, a document with the merchants' industries was also received, which allowed for the gathering of merchants into groups, thus facilitating some of the analyzes.

6.1 Data analysis and ideation

6.1.1 Email strategy for abandonment

FINTECH has been receiving an increasing number of orders on the platform over time. It managed to evolve from 800 orders in March 2020 to close to 14 thousand in the same month of 2021. The almost exponential evolution of the number of orders can be found in Figure 37.

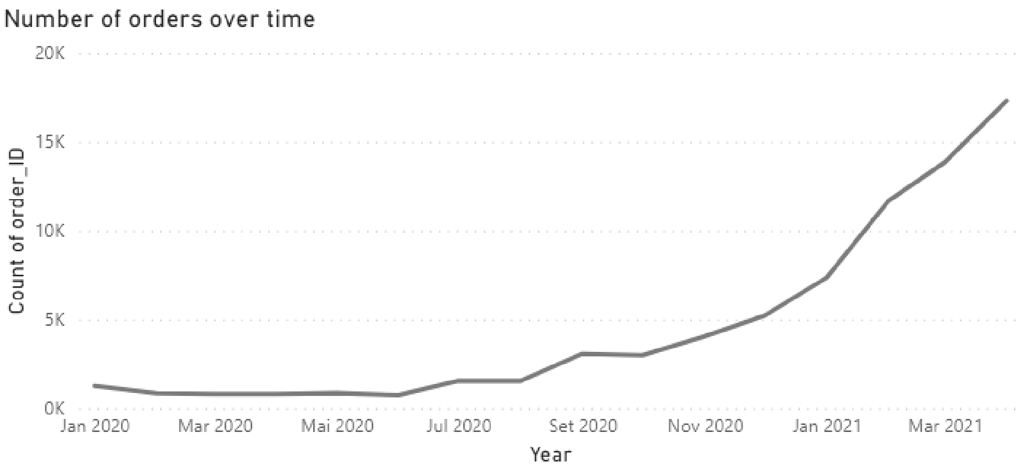

Figure 37 - FINTECH orders over time

Still, many of the orders that are registered in the system are canceled orders, about 87% of them, as shown in Figure 38. In other words, 87% of the orders were abandoned.

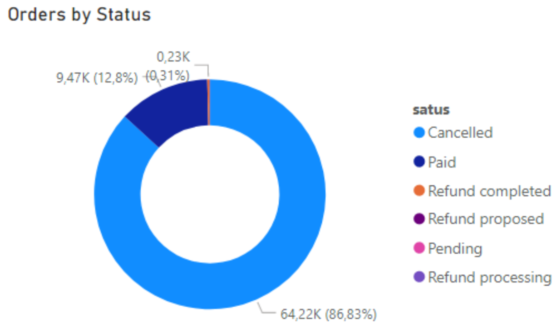

Figure 38 - FINTECH orders by status

To proceed with the payment, first the buyer needs to select FINTECH as the payment method on the website of one of the merchants. Then the buyer will have to choose the cryptocurrency wanted on a page similar to the one in Figure 39. Due to the variation in prices of cryptocurrencies, FINTECH can only guarantee a 15-minute window with those values presented on the page. As such, the buyer has 15 minutes to finish the payment process with the platform. If the time exceeds 15 minutes or if the buyer simply clicks on the “Cancel Order”, it is registered in the system as a canceled order.

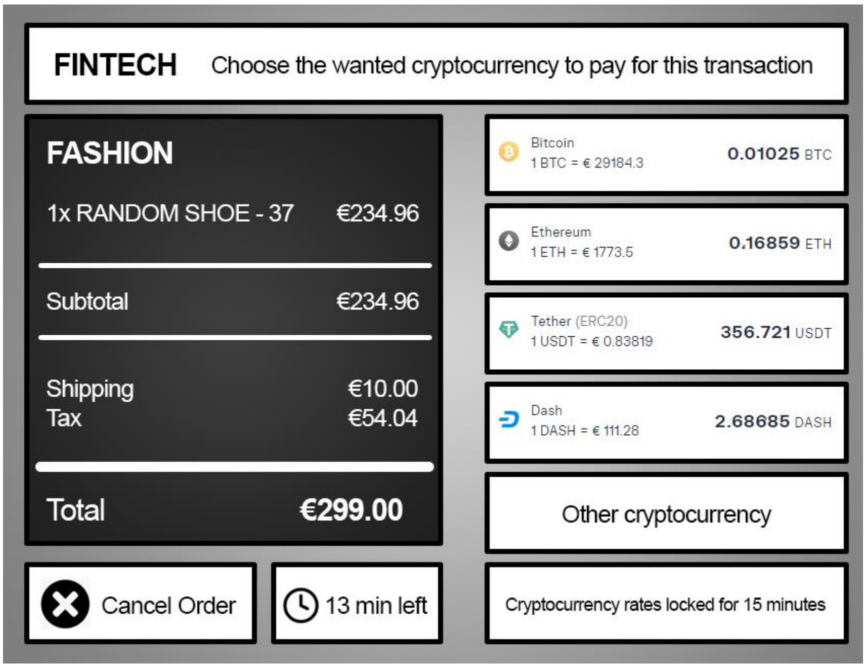

Figure 39 - Window that allows users to choose cryptocurrencies when using FINTECH

One of the company's theories for the huge number of cancellations and orders in general has to do with the variation in the value of cryptocurrencies. When the value of cryptocurrencies increases, buyers get more money in their wallets (much of this money is investment earnings). This leads users to carry out more transactions or at least to test on websites that accept payment with FINTECH.

In order to understand whether or not there is a relationship between the value of cryptocurrencies and orders, the correlation between the number of orders and the value of the most used cryptocurrency was studied. In this case, the most used cryptocurrency is Bitcoin, in more than 40% of the orders. The data from the evolution of the value of Bitcoin was obtained from CoinMarketCap.

To study the correlation, a linear regression analysis was then performed, which in essence is an analysis that assesses whether one or more predictor variables explain the dependent variable. With this analysis, it was possible to find a correlation coefficient of 0,926, with an

R Squared of 0,858. For context, R-squared measures the strength of the relationship between the model and the dependent variable on a convenient 0 to 1 scale, meaning that about 86% of orders are explained by Bitcoin value variation.

In addition, it was then possible to trace a trend line, which generally indicates that an increase of 1 unit in the value of the Bitcoin causes an increase of about 10 orders. The trendline and its equation can be seen in Figure 40. The hypothesis test of the coefficients also proved that there is statistical evidence that they are different from zero, with the p-value much lower than 5%. All the results of this regression can be found in the Appendix E.

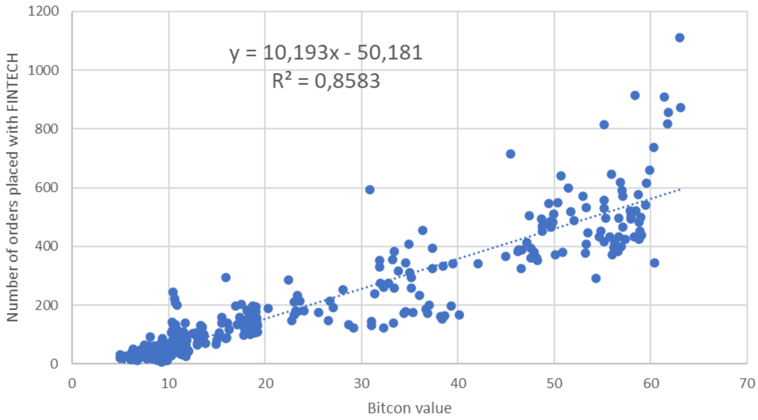

Figure 40 - Bitcoin value vs Number of orders with FINTECH

To study in more depth the relationship between canceled orders and Bitcoin value, the same analysis was performed, but now only for canceled orders. The values are even higher with a correlation coefficient of 0,948 and an R Squared of 0,899, which demonstrates an even stronger relationship between the two variables. The same analysis was performed to only the paid orders, with a correlation coefficient of 0,91 and an R Squared of 0,829, which indicates that they are also explained by Bitcoin value. And to all orders of 2021, with a correlation coefficient of 0,958 and an R Squared of 0,918, having an even higher relationship than the entire dataset.

With this analysis it is then possible to confirm one of the triggers of the high number of canceled orders, i.e. the increase in the value of cryptocurrencies. As such, one can then develop a strategy that keeps this in mind. Whenever the price of cryptocurrencies in general increases (especially Bitcoin), FINTECH can launch a set of emails to buyers presenting some recommendations and highlighting the fact that "there is no better time to buy with FINTECH". Moreover, the company can streamline a set of automatic emails for when an order is canceled to ask why it was abandoned, in order to make fewer users abandon orders forever.

6.1.2 Emails with recommendations

The main objective of this idea was to create a recommender system that was able to suggest new merchants to buyers based on past transactions. This form of retention hacking is incredibly cost effective, as the cost of retaining buyers is much lower than acquiring new ones, as previously reported in Chapter 2.

Of the paid orders, the number of buyers purchasing from more than one merchant is extremely low. Out of 5056 buyers, only 16 bought from more than 1 merchant. Of those, only 2 bought at 3 and 1 bought at 9, which is clearly an outlier (Figure 41 shows this). In total, these buyers only made 69 orders, which are not at all significant for running the recommender system. This is mostly due because the buyer vs merchant matrix was going to be very sparse, with merchants having very little similarity to each other.

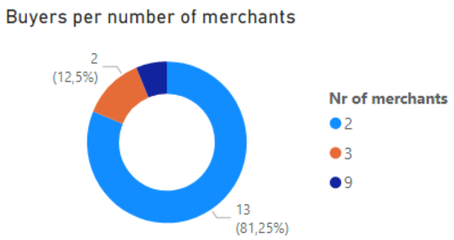

Figure 41 - FINTECH buyers who bought in more than 1 merchant

The Jaccard Index was calculated, with the same logic as the one calculated for FASHION. Given that the number of orders under study was very small, it was only possible to confirm the relationship between some of the industries. The relationships that can then be confirmed are between Fashion and Music, with an index of 3,7% and between Fashion and Watches with 4,6%.

Since it was not possible to establish a relationship between the remaining merchants, these relationships must be established with guesses and then tested. For example, it will be possible to foresee a relationship between Fashion and Health & Beauty. These relationships created based on guesses could then be tested with email recommendations, having as a metric of success the number of conversions.

Another thing that could help, is to develop a web page where the buyer could see all merchants that accept payment with FINTECH, so buyers could be more tempted to visit their stores.

6.1.3 Choose the best merchants

Since acquiring merchants is a process that also requires costs to FINTECH, it would be interesting to understand which merchants the company should focus on, in this case which industries are the best based on past transactions.

For this, the value generated by buyer, merchant and order for each of the industries was calculated, and the results are illustrated in Table 15.

Table 15 - FINTECH merchant study

Industry	N Orders	N Merchants	N Buyers	Sum Value	Value per Order	Value per Merchant	Value per Buyer
Advertising	17	2	11	$ 490,53	$ 28,85	$ 245,26	$ 44,59
CBD Products	47	8	39	$ 39 843,63	$ 847,74	$ 4 980,45	$ 1 021,63
Charity	3	2	3	$ 83,03	$ 27,68	$ 41,52	$ 27,68
Consulting	11	4	11	$ 1 972,21	$ 179,29	$ 493,05	$ 179,29
E-Commerce-Solution	291	2	149	$ 155 887,84	$ 535,70	$ 77 943,92	$ 1 046,23
Educational	1054	2	990	$1 073 603,56	$ 1 018,60	$ 536 801,78	$ 1 084,45
Fashion	19	7	14	$ 2 164,56	$ 113,92	$ 309,22	$ 154,61
Gambling	427	2	204	$ 135 692,89	$ 317,78	$ 67 846,45	$ 665,16
Health & Beauty	224	9	207	$ 25 876,32	$ 115,52	$ 2 875,15	$ 125,01
Home Appliances	4	3	4	$ 79,15	$ 19,79	$ 26,38	$ 19,79
Hosting	555	5	303	$ 76 789,36	$ 138,36	$ 15 357,87	$ 253,43
Marketplace	5336	25	2418	$1 921 295,75	$ 360,06	$ 76 851,83	$ 794,58
Music	18	2	17	$ 28 579,21	$ 1 587,73	$ 14 289,60	$ 1 681,13
Tech	935	10	336	$ 349 834,90	$ 374,15	$ 34 983,49	$ 1 041,18
Trading	33	4	33	$ 10 721,15	$ 324,88	$ 2 680,29	$ 324,88
Travel	478	3	320	$ 488 101,97	$ 1 021,13	$ 162 700,66	$ 1 525,32
Watches	12	3	11	$ 103 767,75	$ 8 647,31	$ 34 589,25	$ 9 433,43

It is easy to see that the best industry to bet on is Watches. Watches are very expensive goods, which make the value of each order and buyer very high. Since FINTECH makes money based on the volume of orders, it would be important to increase the number of merchants that sell watches as much as possible.

Given that the acquisition cost of merchants must be calculated, the industry that generates the most revenue per merchant is Educational. Each merchant from this industry generates on average more than 500 thousand dollars. For this reason, it would be a good industry to bet, allowing a lot of value with very little acquisition work. To acquire these merchants, the Fees Calculator mentioned in Chapter 3 could be a great solution, to show them how much they can save when using FINTECH.

6.1.4 Reward system

The “aha” moment of the FINTECH platform occurs when the buyer realizes how easily he/she can pay with the different cryptocurrencies. Unfortunately, what happens is that the buyer realizes this, but ends up canceling the order anyway.

To fight this problem, and as presented in Chapter 2, a reward system must be created that gives a reward as soon as the user makes the first purchase. In addition, the reward system must also give a reward to the buyer if the buyer makes a purchase on more than one merchant.

These rewards can be FINTECH tokens, a discount on one of the transactions (previously agreed with the merchants). In principle, merchants will not mind giving a discount to users, since they are already saving a lot by using FINTECH to accept payments.

6.1.5 Referral program

On the same basis as the previous idea, and in order to hack buyer’s activation, a referral program could be created. It could work similarly to the reward system, but the reward would arise if the buyer managed to bring another buyer onto the platform. Both could benefit from some credit to spend (which was the strategy that PayPal applied at its beginning) or a discount on an upcoming transaction.

These initiatives can have a very high cost for FINTECH, as giving credit or discounts involves giving up part of the profits. Nonetheless, at the end of the day, this could leverage both the number of users with paid orders and the number of users buying in more than one merchant.

6.1.6 New Channels

Another way to attract more buyers to the platform is to use new channels to communicate its features. FINTECH is already present in many of the social media platforms of the moment, but it has not taken the opportunity to run ads on new platforms and to have moments of sponsorship.

Studying the company's social media as well as the audience of its website, it is possible to see that the main audience is men aged 25 to 34 years, visible in Figure 42 and 43.

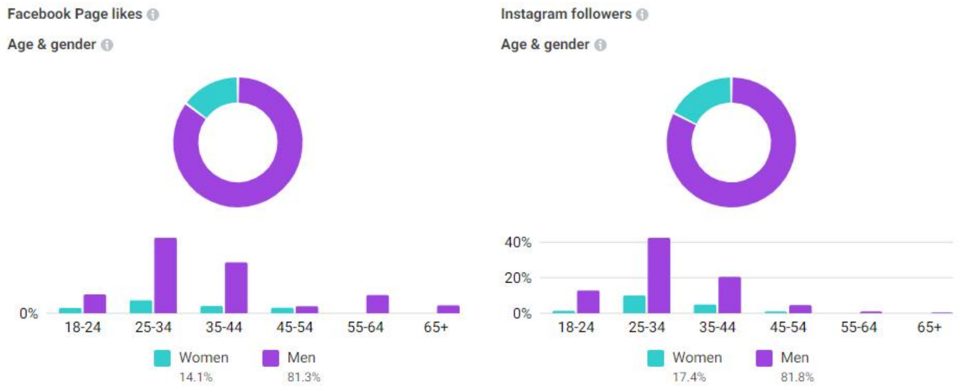

Figure 42 - FINTECH social media audience by gender and age

Age	Acquisition		
	Users	New Users	Sessions
	94,037 % of Total: 36.46% (257,940)	93,473 % of Total: 36.30% (257,512)	140,313 % of Total: 36.81% (381,175)
1. 25-34	**37,626** (39.17%)	36,517 (39.07%)	55,176 (39.32%)
2. 35-44	**18,867** (19.64%)	18,432 (19.72%)	27,900 (19.88%)
3. 18-24	**18,543** (19.30%)	18,066 (19.33%)	26,844 (19.13%)
4. 45-54	**11,239** (11.70%)	11,053 (11.82%)	16,242 (11.58%)
5. 55-64	**5,466** (5.69%)	5,251 (5.62%)	7,981 (5.69%)
6. 65+	**4,325** (4.50%)	4,154 (4.44%)	6,170 (4.40%)

Figure 43 - FINTECH website stats by ages

That said, 2 opportunities can be considered. The first one is reddit, mainly because the main age group of the network is 25 to 29, which is exactly right for FINTECH. Not only that, but reddit users, especially those from communities related to cryptocurrencies, tend to be interested in platforms like FINTECH. The company already has a presence on the platform, having its own community and communicating with its users. It would be interesting to try a targeted ads campaign for some communities focused on crypto to attest the potential of paid media on this platform.

The second opportunity are sponsored moments on YouTube. This is an excellent way to bring cryptocurrencies to the mainstream, which is one of the pillars of FINTECH's creation. The focus is to communicate with users who are already interested in technology, as they tend to be more aware of what cryptocurrencies are and how to use them. For this, paid moments on YouTube's technological or financial channels could help bring a better reputation to the platform and attract users who otherwise would not know about the company.

6.2 Prioritization and testing

Remembering the company's objectives shown in Chapter 3, which were mostly related to increasing the number of orders, now follows the correspondence between objectives and ideas, in Table 16.

Table 16 - Correspondence between FINTECH objectives and ideas presented

Objective	Idea number
More transactions made with the platform	1 / 2 / 4 / 5 / 6
More buyers using the platform more than once and on different merchants	2 / 4
New merchants with different offers	3

Table 17 - FINTECH ICE Score

Idea number	Idea	Impact	Confidence	Ease	ICE Score
1	Email strategy for abandonment	7	6	8	7,0
2	Emails with recommendations	7	7	8	7,3
3	Choose the best merchants	8	8	8	8,0
4	Reward System	8	8	4	6,7
5	Referral Program	7	7	3	5,7
6	New Channels	7	8	9	8,0

In this case study, it was not possible to test many of these ideas, but they were backlogged for future testing. Nonetheless, one of the tests that was done in these last months was the launch of paid media on reddit, to understand the potential of this platform. The test consisted in running ads in some subreddits with communities that might be interested in learning about

FINTECH. These ads had different messages to see what resonated better. The results are compiled in Table 18.

Table 18 - Results of reddit test

Subreddit	Impressions	eCPM	Clicks	CPC	CTR	Amount Spent
accounting	98,151	$2.33	193	$1.18	0.197%	$229.47
dropship	21,675	$3.33	57	$1.26	0.263%	$72.24
ecommerce	23,133	$3.33	56	$1.37	0.242%	$77.15
entrepreneur	161,319	$2.70	360	$1.21	0.223%	$436.13
smallbusiness	79,119	$3.10	195	$1.26	0.246%	$245.95
Total	321,991	$2.69	711	$1.21	0.221%	$866.65

The CPC (cost-per-click) was very high, much higher than what is achieved with Google Ads, so the viability of reddit as a platform for paid media was sacrificed despite having good results with a 0,2% CTR and lots of clicks.

Even though the test did not have positive results in terms of the return on investment, Growth Hacking works on a test basis, this allowed FINTECH to draw a lot of conclusions for the future of the company's ad campaigns and communication in general.

7 Conclusions and Future Work

Business growth has always been a great indicator for company overall success and wellbeing with different companies approaching growth in different ways. For startups, growth is essential, either to cement their position in the market or to seize investment from venture capitalists. For more mature companies, growth can be slower, but they still need to ensure that their metrics are going in the right direction.

The digital transformation of the last few years, associated with the digitalization push of the pandemic, contributed for an increase in online growth opportunities and challenges for all types of businesses. For that reason, the focus of this project was to present Growth Hacking as a possible solution to capitalize on all those opportunities.

The Growth Hacking methodology combines the best of the world of engineering, marketing and creativity. The methodology represents a data-driven way to use the new growth opportunities that emerged to quickly, and with low resource usage, grow the businesses of companies of all sizes. This is possible with the usage of the famous Growth Hacking Cycle, to hack all the growth funnel, improving on all its levels.

To attest the potential of the Growth Hacking methodology in general, this dissertation depicted 3 case studies of the application of the methodology in companies with different sizes and online presences. Only this way it was possible to understand the challenges and to draw conclusions about the power of this methodology in the real world. Growth Hacking cycles were developed for each of the companies in study, having their objectives and problems as a base.

The company WINES represented a large company in this project, with a more traditional approach and focused on the physical market, consequently having a reduced online presence. The methodology had positive results, allowing to test in weeks what would take months or years to test with other approaches. This greatly accelerated the rebranding process that the brand intends to carry out in the coming months. Moreover, it is possible to say that the main challenge of applying this methodology in a large company as an agency involves the company's fear of risk. Part of this fear was overcome after the positive results of the tests carried out throughout the dissertation.

For WINES and for large companies that want to apply or continue to apply this methodology, they should allocate more budget for testing. Moreover, if possible, they should create an internal task force that begins to apply this methodology not only in terms of communication and marketing, but also in product development as a whole. This way big companies can have a competitive advantage through innovation.

The case of the FASHION company represents the middle ground of the entire dissertation, both in terms of size and in terms of the business approach. In this company the methodology was able, with small tests, to accelerate the increase in the number of sales of the online store, making it the best store of the 3 that the company has. This online growth was mostly due to the application of the methodology, but it also benefited from the pandemic that moved sales from physical to online. In addition, it allowed the brand to now start testing new markets that without a methodology like this, would never be considered or tested.

The main challenge for companies like FASHION is not to give up applying the methodology even after considering that everything has already been improved and that the results are already "good enough". There is always more to improve and to develop. Standing still in time is the end of all business and, if there is one thing Growth Hacking stands for, it is the concept of continuous improvement.

Finally, FINTECH was the project's startup, and in the past it was undoubtedly the one that benefited the most from the methodology, like all startups do. It took advantage of the low cost aspect of Growth Hacking to raise the number of orders from 800 to 14 thousand in a year. Although other factors may have had some impact in this growth (like the growing value of cryptocurrencies or the increasing number of crypto users), these are abysmal figures that confirm the success of the methodology and the work carried out by the company.

Nonetheless, the biggest current and future challenge for startups like FINTECH is not to stop testing even though tests have generated poor results in recent months. Growth Hacking does not promise that all tests will be successful, but the constant generation of ideas and tests is what drives business growth and product improvement. Even if the test has poor results, it allows the company to draw conclusions for the future.

In conclusion, it is now possible to have a final verdict on the potential of the application of the methodology in the context of several companies in Portugal. And the result is frankly positive. In addition to the methodology having positive results in terms of growth, what sets it apart from the rest is the mindset of continuous improvement that prevents the stagnation of products and services provided by companies. Even if it does not always have the best results, or that some tests are not so successful, the fact that it allows a cyclical review of the entire business of the company, in itself, is enough to justify its application. Hopefully, this work will help advance the Growth Hacking literature, bringing some new perspectives from its application in real life scenarios.

In terms of future steps for the ideas presented, it is expected that the companies will use them to drive further growth to their businesses. In terms of the future of the methodology, and given that there is not much literature on the subject, it is expected that it will continue to be applied in more and more companies, generating increasingly more interesting case studies that at the end of the day will move all companies to where they want to go.

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APPENDIX A: Growth Hack Taxonomy

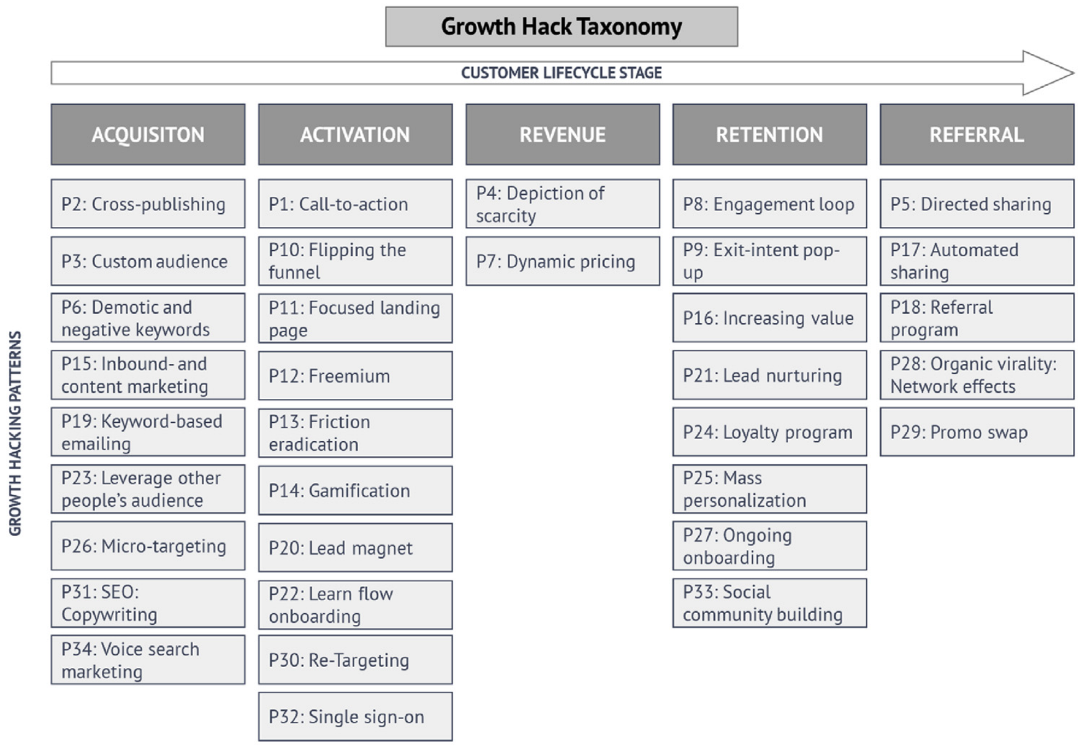

Figure 1 – Growth Hack Taxonomy; Source: Bohnsack and Liesner (2019)

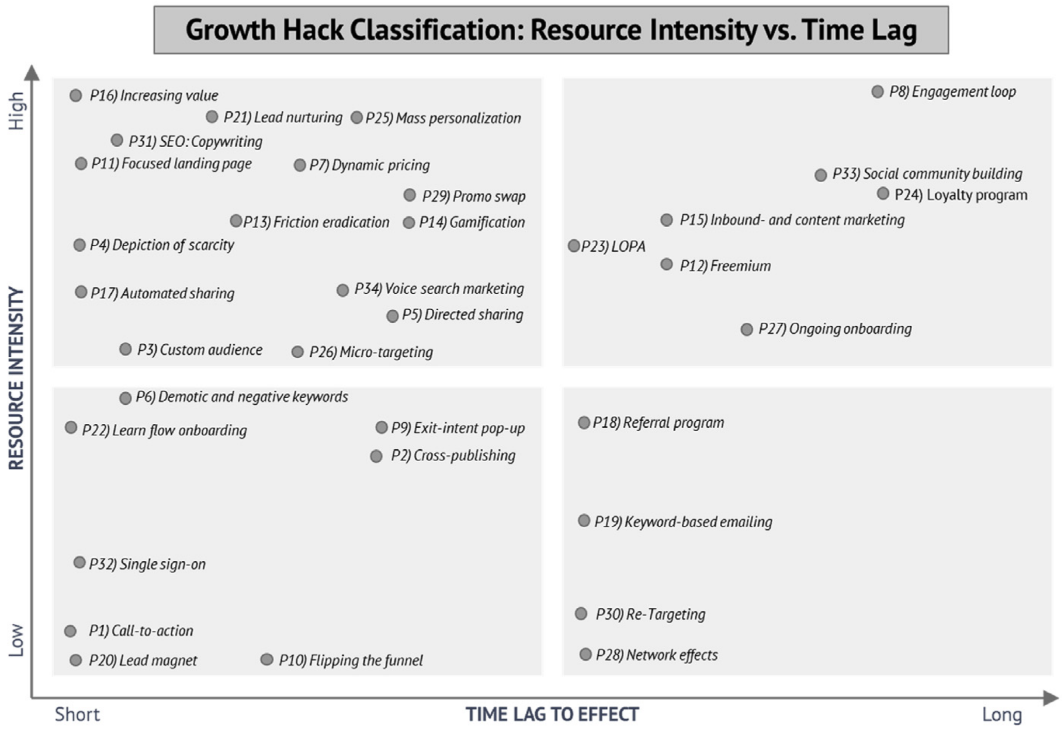

Figure 2 – Resource Intensity vs Time Lag; Source: Bohnsack and Liesner (2019)

APPENDIX B: FASHION sales dashboard on Power BI

Figure 1 - FASHION sales dashboard dedicated to orders

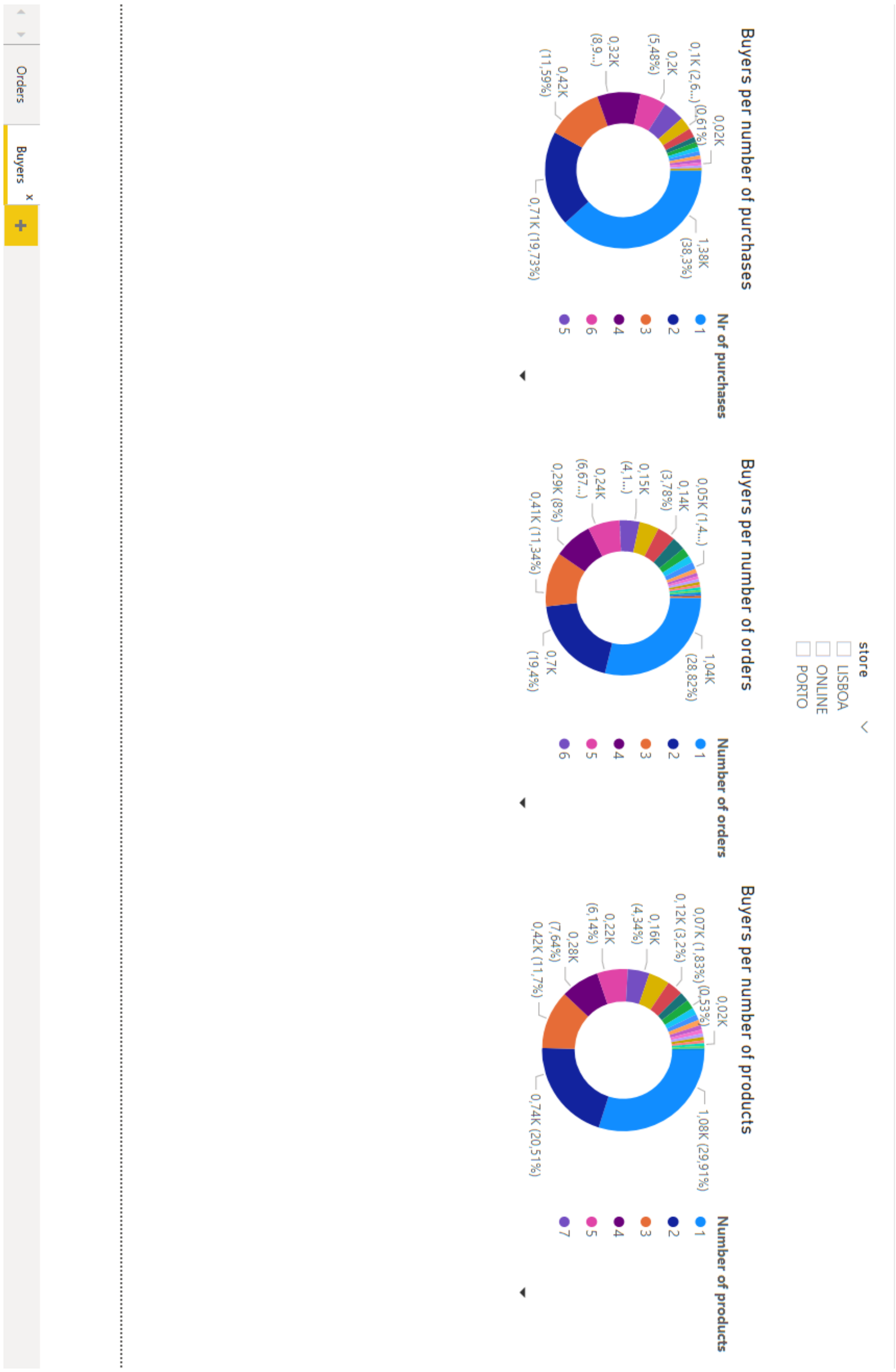

Figure 2 - FASHION sales dashboard dedicated to buyers

APPENDIX C: FASHION sales forecasts

Intercept	141,4731
Slope	0,841941

U
0,724343

Correlação entre Erros			
Lim Inf	r	Lim Sup.	> r está dentro dos limites,
-0,5658	-0,1798119	0,565803	não há correlação dos erros

date	t	Zt	Mt (N=12)	Tt	Ct	dt	S't	stdev	Lim inf	Lim sup	OK?	St	Et	Z^t	VRR	VRR^2	VRP	(VRR-VRP)^2	E^t	E^t2	APE
mar/19	1	120		142,315			-109,167					-107,345		34,96953					85,03047	7230,18	70,86%
abr/19	2	120		143,157			-76					-74,1788		68,97814	0	0	-0,42518	0,18077987	51,02186	2603,23	42,52%
mai/19	3	176		143,9989			-43,3333					-41,5122		102,4867	0,466667	0,217778	-0,14594	0,37529154	73,51325	5404,198	41,77%
jun/19	4	158		144,8408			-43,25					-41,4288		103,412	-0,10227	0,01046	-0,41243	0,09619858	54,58798	2979,847	34,55%
jul/19	5	274		145,6828			83,54167					85,36285		231,0456	0,734177	0,539016	0,462314	0,07390954	42,95437	1845,078	15,68%
ago/19	6	144		146,5247			82,79167					84,61285		231,1376	-0,47445	0,225105	-0,15643	0,10113694	-87,1376	7592,957	60,51%
set/19	7	139	159,6667	147,3667	12,3	-20,6667	-4,5	22,86312	-49,3117	40,31171	OK	-2,67882	-17,9878	144,6878	-0,03472	0,001206	0,004777	0,00156017	-5,68785	32,35161	4,09%
out/19	8	204	154,4583	148,2086	6,249725	49,54167	47,60417	2,740039	42,23369	52,97464	OK	49,42535	0,116319	197,634	0,467626	0,218674	0,421827	0,00209754	6,366045	40,52653	3,12%
nov/19	9	164	149,8333	149,0505	0,782784	14,16667	14,16667					15,98785	-1,82118	165,0384	-0,19608	0,038447	-0,19099	2,591E-05	-1,0384	1,078268	0,63%
dez/19	10	228	145,125	149,8925	-4,76749	82,875	82,875					84,69618	-1,82118	234,5887	0,390244	0,15229	0,430419	0,00161402	-6,58867	43,41059	2,89%
jan/20	11	142	141,625	150,7344	-9,10943	0,375	0,375					2,196181	-1,82118	152,9306	-0,37719	0,142275	-0,32925	0,00229837	-10,9306	119,4783	7,70%
fev/20	12	87	143,9583	151,5764	-7,61804	-56,9583	-56,9583					-55,1372	-1,82118	96,43922	-0,38732	0,15002	-0,32085	0,00441871	-9,43922	89,09889	10,85%
mar/20	13	40	149,1667	152,4183	-3,25165	-109,167	-109,167					-107,345	-1,82118	45,07283	-0,54023	0,291848	-0,48192	0,00339987	-5,07283	25,73359	12,68%
abr/20	14	75	151	153,2603	-2,26026	-76	-76					-74,1788	-1,82118	79,08144	0,875	0,765625	0,977036	0,01041133	-4,08144	16,65813	5,44%
mai/20	15	110	153,3333	154,1022	-0,76886	-43,3333	-43,3333					-41,5122	-1,82118	112,59	0,466667	0,217778	0,501201	0,00119259	-2,59005	6,708333	2,35%
jun/20	16	111	154,25	154,9441	-0,69414	-43,25	-43,25					-41,4288	-1,82118	113,5153	0,009091	8,26E-05	0,031957	0,00052288	-2,51532	6,326833	2,27%
jul/20	17	237	153,4583	155,7861	-2,32775	83,54167	83,54167					85,36285	-1,82118	241,1489	1,135135	1,288532	1,172513	0,00139709	-4,14893	17,2136	1,75%
ago/20	18	237	154,2083	156,628	-2,41969	82,79167	82,79167					84,61285	-1,82118	241,2409	0	0	0,017894	0,00032019	-4,24087	17,98497	1,79%
set/20	19	171	159,3333	157,47	1,86337	11,66667	11,66667					-2,67882	14,34549	154,7911	-0,27848	0,077552	-0,34687	0,00467744	16,20886	262,727	9,48%
out/20	20	216	170,3333	158,3119	12,02143	45,66667	45,66667					49,42535	-3,75868	207,7373	0,263158	0,069252	0,214838	0,00233484	8,262748	68,273	3,83%
nov/20	21	208		159,1538								15,98785		175,1417	-0,03704	0,001372	-0,18916	0,02314104	32,85831	1079,668	15,80%
dez/20	22	206		159,9958								84,69618		244,692	-0,00962	9,25E-05	0,176404	0,0346031	-38,692	1497,068	18,78%
jan/21	23	145		160,8377								2,196181		163,0339	-0,29612	0,087685	-0,20857	0,00766382	-18,0339	325,2219	12,44%
fev/21	24	102		161,6797								-55,1372		106,5425	-0,29655	0,087943	-0,26522	0,00098143	-4,54252	20,63447	4,45%
mar/21	25	148		162,5216								-107,345		55,17613	0,45098	0,203383	-0,45906	0,82816913	92,82387	8616,272	62,72%
abr/21	26	231		163,3636								-74,1788		89,18473	0,560811	0,314509	-0,3974	0,91816882	141,8153	20111,57	61,39%
mai/21	27			164,2055								-41,5122		122,6933							
jun/21	28			165,0474								-41,4288		123,6186							
jul/21	29			165,8894								85,36285		251,2522							
ago/21	30			166,7313								84,61285		251,3442							
set/21	31			167,5733								-2,67882		164,8944							
out/21	32			168,4152								49,42535		217,8405							
nov/21	33			169,2571								15,98785		185,245							
dez/21	34			170,0991								84,69618		254,7953							
jan/22	35			170,941								2,196181		173,1372							
fev/22	36			171,783								-55,1372		116,6458							

ME	MSE	MAPE
15,41165	2309,75	19,63%

Figure 1 - FASHION sales forecast values

Intercept	151,4401
Slope	0,765018

U
0,557107

Correlação entre Erros			
Lim Inf	r	Lim Sup.	> r está dentro dos limites,
-0,5658	0,14744873	0,565803	não há correlação dos erros

date	t	Zt	Mt (N=12)	Tt	Ct	dt	S't	stdev	Lim inf	Lim sup	OK?	St	Et	Z^t	VRR	VRR^2	VRP	(VRR-VRP)^2	E^t	E^t2	APE
mar/19	1	120		152,2051			-39,5833					-38,6302		113,5749					6,42508	41,28165	5,35%
abr/19	2	120		152,9701			-41,4167					-40,4635		112,5066	0	0	-0,06244	0,00389937	7,493395	56,15097	6,24%
mai/19	3	176		153,7352			-53,75					-52,7969		100,9383	0,466667	0,217778	-0,15885	0,39126808	75,06171	5634,26	42,65%
jun/19	4	158		154,5002			-53,6667					-52,7135		101,7866	-0,10227	0,01046	-0,42167	0,10201258	56,21336	3159,942	35,58%
jul/19	5	274		155,2652			73,125					74,07813		229,3433	0,734177	0,539016	0,45154	0,07988377	44,65667	1994,218	16,30%
ago/19	6	144		156,0302			72,375					73,32813		229,3583	-0,47445	0,225105	-0,16293	0,09704895	-85,3583	7286,047	59,28%
set/19	7	139	163	156,7952	6,204762	-24	-9,70833	20,21147	-49,3228	29,90615	OK	-8,75521	-15,2448	148,04	-0,03472	0,001206	0,028056	0,00394108	-9,04003	81,72214	6,50%
out/19	8	204	163	157,5603	5,439744	41	42,39583	1,974006	38,52678	46,26489	OK	43,34896	-2,34896	200,9092	0,467626	0,218674	0,44539	0,00049443	3,090785	9,552954	1,52%
nov/19	9	164	160,25	158,3253	1,924725	3,75	3,75					4,703125	-0,95312	163,0284	-0,19608	0,038447	-0,20084	2,2684E-05	0,9716	0,944007	0,59%
dez/19	10	228	155,5417	159,0903	-3,54863	72,45833	72,45833					73,41146	-0,95313	232,5018	0,390244	0,15229	0,417694	0,00075349	-4,50175	20,26577	1,97%
jan/20	11	142	152,0417	159,8553	-7,81364	-10,0417	-10,0417					-9,08854	-0,95312	150,7668	-0,37719	0,142275	-0,33874	0,00147846	-8,76677	76,85625	6,17%
fev/20	12	87	154,375	160,6203	-6,24533	-67,375	-67,375					-66,4219	-0,95313	94,19845	-0,38732	0,15002	-0,33663	0,00256981	-7,19845	51,81775	8,27%
mar/20	13	120	159,5833	161,3853	-1,80201	-39,5833	-39,5833					-38,6302	-0,95313	122,7551	0,37931	0,143876	0,410979	0,00100288	-2,75514	7,590795	2,30%
abr/20	14	120	161,4167	162,1504	-0,7337	-41,4167	-41,4167					-40,4635	-0,95313	121,6868	0	0	0,014057	0,0001976	-1,68682	2,845377	1,41%
mai/20	15	110	163,75	162,9154	0,834615	-53,75	-53,75					-52,7969	-0,95313	110,1185	-0,08333	0,006944	-0,08235	9,7531E-07	-0,11851	0,014045	0,11%
jun/20	16	111	164,6667	163,6804	0,986264	-53,6667	-53,6667					-52,7135	-0,95313	110,9669	0,009091	8,26E-05	0,00879	9,0758E-08	0,033139	0,001098	0,03%
jul/20	17	237	163,875	164,4454	-0,57042	73,125	73,125					74,07813	-0,95313	238,5235	1,135135	1,288532	1,148861	0,00018839	-1,52355	2,321193	0,64%
ago/20	18	237	164,625	165,2104	-0,58544	72,375	72,375					73,32813	-0,95313	238,5386	0	0	0,006492	4,2144E-05	-1,53856	2,367181	0,65%
set/20	19	171	166,4167	165,9755	0,441209	4,583333	4,583333					-8,75521	13,33854	157,2202	-0,27848	0,077552	-0,33662	0,00338054	13,77975	189,8815	8,06%
out/20	20	216	172,2083	166,7405	5,467857	43,79167	43,79167					43,34896	0,442708	210,0894	0,263158	0,069252	0,228593	0,00119472	5,910565	34,93478	2,74%
nov/20	21	208		167,5055								4,703125		172,2086	-0,03704	0,001372	-0,20274	0,02745677	35,79138	1281,023	17,21%
dez/20	22	206		168,2705								73,41146		241,682	-0,00962	9,25E-05	0,161933	0,0294287	-35,682	1273,203	17,32%
jan/21	23	145		169,0355								-9,08854		159,947	-0,29612	0,087685	-0,22356	0,00526469	-14,947	223,4125	10,31%
fev/21	24	102		169,8005								-66,4219		103,3787	-0,29655	0,087943	-0,28704	9,0404E-05	-1,37867	1,900743	1,35%
mar/21	25	148		170,5656								-38,6302		131,9354	0,45098	0,203383	0,293484	0,02480514	16,06464	258,0727	10,85%
abr/21	26	231		171,3306								-40,4635		130,867	0,560811	0,314509	-0,11576	0,45775241	100,133	10026,61	43,35%
mai/21	27			172,0956								-52,7969		119,2987							
jun/21	28			172,8606								-52,7135		120,1471							
jul/21	29			173,6256								74,07813		247,7038							
ago/21	30			174,3907								73,32813		247,7188							
set/21	31			175,1557								-8,75521		166,4005							
out/21	32			175,9207								43,34896		219,2697							
nov/21	33			176,6857								4,703125		181,3888							
dez/21	34			177,4507								73,41146		250,8622							
jan/22	35			178,2158								-9,08854		169,1272							
fev/22	36			178,9808								-66,4219		112,5589							

ME	MSE	MAPE
7,351133	1219,894	11,80%

Figure 2 - FASHION sales forecast corrected values

Intercept	63,29817
Slope	-0,44515

U
0,635186

Correlação entre Erros			
Lim Inf	r	Lim Sup.	> r está dentro dos limites,
-0,5658	-0,12866064	0,565803	não há correlação dos erros

date	t	Zt	Mt (N=12)	Tt	Ct	dt	S't	stdev	Lim inf	Lim sup	OK?	St	Et	Z^t	VRR	VRR^2	VRP	(VRR-VRP)^2	E^t	E^t2	APE
mar/19	1	17		62,85302			-53,8333					-51,691		11,16205					5,83795	34,08166	34,34%
abr/19	2	13		62,40788			-47,6667					-45,5243		16,88357	-0,23529	0,055363	-0,00685	0,05218725	-3,88357	15,08212	29,87%
mai/19	3	8		61,96273			-48,0833					-45,941		16,02176	-0,38462	0,147929	0,232443	0,38076083	-8,02176	64,34858	100,27%
jun/19	4	14		61,51758			-52,125					-49,9826		11,53494	0,75	0,5625	0,441868	0,09494537	2,465056	6,076503	17,61%
jul/19	5	45		61,07244			-44,3333					-42,191		18,88146	2,214286	4,903061	0,348676	3,48049969	26,11854	682,1779	58,04%
ago/19	6	36		60,62729			-39,8333					-37,691		22,93632	-0,2	0,04	-0,4903	0,08427645	13,06368	170,6598	36,29%
set/19	7	76	61,58333	60,18214	1,40119	14,41667	14,14583	0,383016	13,39512	14,89655	OK	16,28819	-1,87153	76,47034	1,111111	1,234568	1,124176	0,00017069	-0,47034	0,221217	0,62%
out/19	8	156	60,66667	59,737	0,92967	95,33333	98,52083	4,507806	89,68553	107,3561	OK	100,6632	-5,32986	160,4002	1,052632	1,108033	1,110529	0,00335209	-4,40019	19,36168	2,82%
nov/19	9	125	60,41667	59,29185	1,124817	64,58333	64,58333					66,72569	-2,14236	126,0175	-0,19872	0,039489	-0,1922	4,2546E-05	-1,01754	1,035396	0,81%
dez/19	10	153	60	58,8467	1,153297	93	93					95,14236	-2,14236	153,9891	0,224	0,050176	0,231913	6,2608E-05	-0,98906	0,978248	0,65%
jan/20	11	76	58,16667	58,40156	-0,23489	17,83333	17,83333					19,97569	-2,14236	78,37725	-0,50327	0,253279	-0,48773	0,00024142	-2,37725	5,651323	3,13%
fev/20	12	28	55,91667	57,95641	-2,03974	-27,9167	-27,9167					-25,7743	-2,14236	32,1821	-0,63158	0,398892	-0,57655	0,00302805	-4,1821	17,49	14,94%
mar/20	13	1	54,83333	57,51126	-2,67793	-53,8333	-53,8333					-51,691	-2,14236	5,820292	-0,96429	0,929847	-0,79213	0,02963675	-4,82029	23,23521	482,03%
abr/20	14	7	54,66667	57,06612	-2,39945	-47,6667	-47,6667					-45,5243	-2,14236	11,54181	6	36	10,54181	20,6280532	-4,54181	20,62805	64,88%
mai/20	15	8	56,08333	56,62097	-0,53764	-48,0833	-48,0833					-45,941	-2,14236	10,68	0,142857	0,020408	0,525714	0,14657942	-2,68	7,182392	33,50%
jun/20	16	4	56,125	56,17582	-0,05082	-52,125	-52,125					-49,9826	-2,14236	6,193185	-0,5	0,25	-0,22585	0,07515721	-2,19319	4,810062	54,83%
jul/20	17	11	55,33333	55,73068	-0,39734	-44,3333	-44,3333					-42,191	-2,14236	13,53971	1,75	3,0625	2,384926	0,40313148	-2,53971	6,450104	23,09%
ago/20	18	16	55,83333	55,28553	0,547802	-39,8333	-39,8333					-37,691	-2,14236	17,59456	0,454545	0,206612	0,599505	0,02101337	-1,59456	2,542618	9,97%
set/20	19	70	56,125	54,84038	1,284615	13,875	13,875					16,28819	-2,41319	71,12858	3,375	11,39063	3,445536	0,00497535	-1,12858	1,273691	1,61%
out/20	20	158	56,29167	54,39524	1,896429	101,7083	101,7083					100,6632	1,045139	155,0584	1,257143	1,580408	1,21512	0,00176588	2,941567	8,652819	1,86%
nov/20	21	157		53,95009								66,72569		120,6758	-0,00633	4,01E-05	-0,23623	0,05285405	36,32421	1319,449	23,14%
dez/20	22	122		53,50495								95,14236		148,6473	-0,22293	0,049698	-0,0532	0,02880762	-26,6473	710,0789	21,84%
jan/21	23	88		53,0598								19,97569		73,03549	-0,27869	0,077667	-0,40135	0,01504545	14,96451	223,9365	17,01%
fev/21	24	28		52,61465								-25,7743		26,84035	-0,68182	0,464876	-0,695	0,00017366	1,159654	1,344796	4,14%
mar/21	25	8		52,16951								-51,691		0,478533	-0,71429	0,510204	-0,98291	0,07215875	7,521467	56,57246	94,02%
abr/21	26	4		51,72436								-45,5243		6,200053	-0,5	0,25	-0,22499	0,07562867	-2,20005	4,840235	55,00%
mai/21	27			51,27921								-45,941		5,33824							
jun/21	28			50,83407								-49,9826		0,851427							
jul/21	29			50,38892								-42,191		8,197947							
ago/21	30			49,94377								-37,691		12,2528							
set/21	31			49,49863								16,28819		65,78682							
out/21	32			49,05348								100,6632		149,7167							
nov/21	33			48,60833								66,72569		115,334							
dez/21	34			48,16319								95,14236		143,3055							
jan/22	35			47,71804								19,97569		67,69373							
fev/22	36			47,27289								-25,7743		21,49859							

ME	MSE	MAPE
1,411897	131,0831	45,63%

Figure 3 - FASHION sales forecast for boots values

Intercept	42,662
Slope	1,792674

U
0,443965

Correlação entre Erros			
Lim Inf	r	Lim Sup.	> r está dentro dos limites,
-0,5658	-0,6301821	0,565803	não há correlação dos erros

date	t	Zt	Mt (N=12)	Tt	Ct	dt	S't	stdev	Lim inf	Lim sup	OK?
mar/19	1	77		44,45467			-38,125				
abr/19	2	76		46,24734			-16,2083				
mai/19	3	126		48,04002			18,375				
jun/19	4	109		49,83269			20,375				
jul/19	5	168		51,62537			125,1667				
ago/19	6	73		53,41804			116,1667				
set/19	7	27	62,625	55,21071	7,414286	-35,625	-20,7292	21,06589	-62,0183	20,55998	OK
out/19	8	3	59,75	57,00339	2,746612	-56,75	-65,4792	12,34491	-89,6752	-41,2832	OK
nov/19	9	6	57,29167	58,79606	-1,5044	-51,2917	-51,2917				
dez/19	10	28	55,04167	60,58874	-5,54707	-27,0417	-27,0417				
jan/20	11	42	55,54167	62,38141	-6,83974	-13,5417	-13,5417				
fev/20	12	40	61,54167	64,17408	-2,63242	-21,5417	-21,5417				
mar/20	13	30	68,125	65,96676	2,158242	-38,125	-38,125				
abr/20	14	54	70,20833	67,75943	2,448901	-16,2083	-16,2083				
mai/20	15	89	70,625	69,55211	1,072894	18,375	18,375				
jun/20	16	92	71,625	71,34478	0,28022	20,375	20,375				
jul/20	17	197	71,83333	73,13745	-1,30412	125,1667	125,1667				
ago/20	18	188	71,83333	74,93013	-3,09679	116,1667	116,1667				
set/20	19	70	75,83333	76,7228	-0,88947	-5,83333	-5,83333				
out/20	20	10	84,20833	78,51548	5,692857	-74,2083	-74,2083				
nov/20	21	9		80,30815							
dez/20	22	49		82,10082							
jan/21	23	26		83,8935							
fev/21	24	56		85,68617							
mar/21	25	110		87,47885							
abr/21	26	175		89,27152							
mai/21	27			91,06419							
jun/21	28			92,85687							
jul/21	29			94,64954							
ago/21	30			96,44222							
set/21	31			98,23489							
out/21	32			100,0276							
nov/21	33			101,8202							
dez/21	34			103,6129							
jan/22	35			105,4056							
fev/22	36			107,1983							

date	St	Et	Z^t	VRR	VRR^2	VRP	(VRR-VRP)^2	E^t	E^t2	APE
mar/19	-40,3021		4,152587					72,84741	5306,746	94,61%
abr/19	-18,3854		27,86193	-0,01299	0,000169	-0,63816	0,39083724	48,13807	2317,274	63,34%
mai/19	16,19792		64,23793	0,657895	0,432825	-0,15476	0,66041424	61,76207	3814,553	49,02%
jun/19	18,19792		68,03061	-0,13492	0,018204	-0,46007	0,10572506	40,96939	1678,491	37,59%
jul/19	122,9896		174,6149	0,541284	0,292989	0,601972	0,00368299	-6,61495	43,75756	3,94%
ago/19	113,9896		167,4076	-0,56548	0,319763	-0,00353	0,31578796	-94,4076	8912,799	129,33%
set/19	-22,9063	-12,7188	32,30446	-0,63014	0,397073	-0,55747	0,00528004	-5,30446	28,13734	19,65%
out/19	-67,6563	10,90625	-10,6529	-0,88889	0,790123	-1,39455	0,2556936	13,65286	186,4006	455,10%
nov/19	-53,4688	2,177083	5,327312	1	1	0,775771	0,05027875	0,672688	0,452509	11,21%
dez/19	-29,2188	2,177083	31,36999	3,666667	13,44444	4,228331	0,31546687	-3,36999	11,35681	12,04%
jan/20	-15,7188	2,177083	46,66266	0,5	0,25	0,666524	0,0277301	-4,66266	21,7404	11,10%
fev/20	-23,7188	2,177083	40,45533	-0,04762	0,002268	-0,03678	0,00011753	-0,45533	0,207329	1,14%
mar/20	-40,3021	2,177083	25,66467	-0,25	0,0625	-0,35838	0,0117469	4,335325	18,79504	14,45%
abr/20	-18,3854	2,177083	49,37402	0,8	0,64	0,645801	0,02377748	4,625984	21,39973	8,57%
mai/20	16,19792	2,177083	85,75002	0,648148	0,420096	0,587963	0,00362221	3,249977	10,56235	3,65%
jun/20	18,19792	2,177083	89,5427	0,033708	0,001136	0,006098	0,00076232	2,457303	6,038339	2,67%
jul/20	122,9896	2,177083	196,127	1,141304	1,302576	1,131816	9,0036E-05	0,872962	0,762063	0,44%
ago/20	113,9896	2,177083	188,9197	-0,04569	0,002087	-0,04102	2,1796E-05	-0,91971	0,845869	0,49%
set/20	-22,9063	17,07292	53,81655	-0,62766	0,393957	-0,71374	0,00741014	16,18345	261,904	23,12%
out/20	-67,6563	-6,55208	10,85923	-0,85714	0,734694	-0,84487	0,00015067	-0,85923	0,73827	8,59%
nov/20	-53,4688		26,8394	-0,1	0,01	1,68394	3,18244199	-17,8394	318,2442	198,22%
dez/20	-29,2188		52,88207	4,444444	19,75309	4,875786	0,18605555	-3,88207	15,0705	7,92%
jan/21	-15,7188		68,17475	-0,46939	0,220325	0,391321	0,74082023	-42,1747	1778,709	162,21%
fev/21	-23,7188		61,96742	1,153846	1,331361	1,383362	0,0526777	-5,96742	35,61013	10,66%
mar/21	-40,3021		47,17676	0,964286	0,929847	-0,15756	1,25853289	62,82324	3946,759	57,11%
abr/21	-18,3854		70,8861	0,590909	0,349174	-0,35558	0,89584326	104,1139	10839,7	59,49%
mai/21	16,19792		107,2621							
jun/21	18,19792		111,0548							
jul/21	122,9896		217,6391							
ago/21	113,9896		210,4318							
set/21	-22,9063		75,32864							
out/21	-67,6563		32,37131							
nov/21	-53,4688		48,35149							
dez/21	-29,2188		74,39416							
jan/22	-15,7188		89,68684							
fev/22	-23,7188		83,47951							

ME	MSE	MAPE
9,624886	1522,195	55,60%

Figure 4 - FASHION sales forecast for sandals values

APPENDIX D: FINTECH orders dashboard on Power BI

Figure 1 - FINTECH orders dashboard dedicated to orders

Figure 2 - FINTECH orders dashboard dedicated to buyers

Figure 3 - FINTECH orders dashboard dedicated to buyers of paid orders

APPENDIX E: FINTECH regression studies

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,926463143
R Square	0,858333956
Adjusted R Square	0,858039432
Standard Error	70,0836701
Observations	483

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	14314272,33	14314272,33	2914,309031	2,9722E-206
Residual	481	2362537,712	4911,720815		
Total	482	16676810,04			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	-50,18104975	4,934831545	-10,16874625	3,92755E-22	-59,87754054	-40,48455895	-59,87754054	-40,48455895
btc	10,19314838	0,188816762	53,98434061	2,9722E-206	9,822140779	10,56415597	9,822140779	10,56415597

Figure 1 - FINTECH regression with all data set

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,948301478
R Square	0,899275693
Adjusted R Square	0,897201004
Standard Error	65,80946639
Observations	483

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	18637272,01	18637272,01	4303,339452	4,3879E-242
Residual	482	2087486,988	4330,885867		
Total	483	20724759			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
btc	7,515983522	0,114573193	65,59984338	2,1803E-242	7,290858897	7,741108146	7,290858897	7,741108146

Figure 2 - FINTECH regression with cancelled orders only

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,91074931
R Square	0,829464305
Adjusted R Square	0,827389617
Standard Error	14,37627324
Observations	483

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	484531,574	484531,574	2344,387762	4,7054E-187
Residual	482	99618,42596	206,6772323		
Total	483	584150			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
btc	1,211869035	0,025028854	48,41887816	2,9383E-187	1,162689893	1,261048177	1,162689893	1,261048177

Figure 3 - FINTECH regression with paid orders only

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,958347907
R Square	0,918430711
Adjusted R Square	0,909810022
Standard Error	133,6678986
Observations	117

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	23336297,57	23336297,57	1306,103859	1,26703E-64
Residual	116	2072584,427	17867,10713		
Total	117	25408882			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
btc	9,150365364	0,253191767	36,14005893	5,69472E-65	8,648887168	9,651843561	8,648887168	9,651843561

Figure 4 - FINTECH regression with 2021 orders only