Technical capabilities and the success of startups

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Dissertação de Mestrado

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Mestrado Integrado em Engenharia e Gestão Industrial

2021-06-21

“The value of an idea lies in the using of it.”

\- *Thomas Edison*

Resumo

Devido à crescente globalização dos mercados, existe uma maior necessidade de as empresas procurarem a inovação de forma a prosperarem. O mercado das startups de base tecnológica é cada vez maior, mais competitivo e um importante factor de crescimento económico para as sociedades. Assim, perceber quais os factores e como estes influenciam o sucesso destas startups é do interesse da comunidade científica e de todo o ecossistema. Sendo que a criação e o desenvolvimento destas startups requerem não só a ideia, mas também as capacidades técnicas para o fazer, é objetivo da presente dissertação explorar a importânica destas capacidades para o sucesso deste tipo de empresas. Adicionalmente, pretende-se também perceber qual é a relevância dada pelos investidores e pelas aceleradoras a estas capacidades na seleção de startups para os seus portfólios.

Esta análise foi realizada sobre um programa de aceleração, BGI Accelerator, de uma única aceleradora de startups, Building Global Innovators (BGI). A BGI é uma aceleradora de startups sedeada em Lisboa, criada há 11 anos com o objetivo de promover a investigação sobre inovação tecnológica, através de uma parceria entre o Massachusetts Institute of Technology (MIT) e o governo português. Pelo BGI Accelerator, o seu principal programa de aceleração e objeto deste estudo, já passaram 147 startups, que constituíram a amostra utilizada para a análise quantitativa deste projeto.

Sendo que não existe consenso sobre a definição de sucesso de uma startup, foi realizado um estudo qualitativo no qual se procedeu à condução de entrevistas com investidores de Venture Capital e colaboradores da BGI, e a uma revisão cuidada da literatura. Foram identificados 3 indicadores de sucesso comuns: alcançar uma receita significativa, obter financiamento e sobreviver. De seguida, foram recolhidos dados sobre as startups e sobre as capacidades técnicas das equipas que as constituíam. Estes dados foram submetidos a uma análise quantitativa através um modelo de regressão logística para estimar cada um dos 3 indicadores de sucesso. Por fim, realizou-se uma análise qualitativa de modo a complementar os resultados obtidos.

Concluindo, uma startup de base tecnológica ideal deve ter duas capacidades técnicas presentes na sua equipa fundadora: ciências empresariais e engenharia. Contudo, a presença de mais do que um colaborador qualificado na área de ciências empresarias pode ser prejudicial e as startups com grandes equipas estão em desvantagem. Concluiu-se, ainda, que as áreas de ciências físicas e de artes mostraram um impacto negativo significativo na sobrevivência das startups. Além disso, no setor de dispositivos médicos e saúde, as startups que tinham algum fundador com qualificações na área da saúde apresentaram pior desempenho do que as que não tinham. Através das entrevistas, foi possível concluir que a capacidade técnica dos membros da equipa tem um impacto muito grande no sucesso das startups.

Technical capabilities and the success of startups

Abstract

Due to the increasing globalization of markets, there is a greater need for companies to seek innovation in order to prosper. The technology-based startups market is becoming bigger, more competitive and an important economic growth factor for societies. Thus, understanding which are the factors and how they influence the success of these startups is in the interest of the scientific community and the entire startup ecosystem. Since the creation and development of these startups requires not only the idea, but also the technical skills to do so, the aim of this dissertation is to explore the importance of these skills for the success of this type of companies. Additionally, it is also intended to understand the relevance given by investors and accelerators to these capabilities in the selection of startups for their portfolios.

This analysis was performed on an acceleration program, the BGI Accelerator, from a single startup accelerator, Building Global Innovators (BGI). BGI is a Lisbon-based startup accelerator, created 11 years ago with the aim of promoting research on technological innovation, through a partnership between the Massachusetts Institute of Technology (MIT) and the Portuguese government. 147 startups have already passed through the BGI Accelerator, its main acceleration program and object of this study, which constituted the sample used for the quantitative analysis of this project.

Since there is no consensus on the definition of a startup's success, a qualitative study was carried out, in which interviews were conducted with Venture Capital investors and BGI employees and a careful review of the literature was performed. 3 common success indicators were identified: achieving significant revenue, obtaining financing and surviving. Then, data was collected on the startups and on the technical capabilities of their entrepreneural teams. This data was subjected to quantitative analysis using a logistic regression model to estimate each of the 3 success indicators. Finally, a qualitative analysis was carried out in order to complement the results obtained.

In conclusion, an ideal technology-based startup in technology must have two technical skills present in its entrepreneurial team: business sciences and engineering. However, the presence of more than one qualified collaborator in the field of business science can be detrimental and startups with large teams are at a disadvantage. It was also concluded that the areas of physical sciences and arts showed a significant negative impact on the survival of startups and that startups in the medical device and health sector that had a founder with qualifications in the health area in the team performed worse than the ones that did not. Through the interviews, it was possible to conclude that the technical capabilities of the entrepreneural teams have a very big influence on the success of startups.

Acknowledgements

I would like to thank the BGI team for the opportunity to develop this project, the freedom and independence to do so and for all the knowledge transmitted, always with great availability. Namely, to Beatriz Riscado for her support and for putting me in contact with the people I needed. Also, to Tomé Canas, my supervisor at BGI who suggested the project and provided the necessary support. I would also like to thank all those interviewed, both from BGI and from VC companies, for their availability and valuable help.

I would also like to thank Professor José Pedro Coelho Rodrigues for his tireless support at all times, during the project and the elaboration of the dissertation. I have also to thank Professor António Miguel da Fonseca Fernandes Gomes for his help, when required.

I would like to thank my family and, in a very special way, my parents who made this journey possible, through their endless and unconditional support.

Finally, to my friends who made this journey incredible.

Contents

Acronyms and Symbols

AI – Artificial Intelligence

BGI – Building Global Innovators

BGI, S.A – Building Global Innovators, Sociedade Anónima

CVs - Curricula Vitae

DGES – Direção-Geral do Ensino Superior

EIT - European Institute of Innovation and Technology

EPV – Events per Variable

MIT – Massachusetts Institute of Technology

MVP – Minimum Viable Product

ROI – Return on Investment

VC – Venture Capital

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1 Introduction

"If you want something new, you have to stop doing something old."

- Peter F. Drucker

As of June 2021, there were 708 unicorn companies with a total cumulative valuation of $2.319B, which at the conversion rate of 14/06/2021 were worth about €1.916B. A unicorn startup is a private company valued at over $1B. Examples of former unicorns are Facebook, Airbnb and Google, companies that are now a part of the everyday life of most people and are now worth billions of dollars.[1] Every investor's dream is to invest as early as possible in one of these companies. However, finding these unicorns can prove to be a difficult task, since 90% of startups end up failing.[2]

The main goal of this project is to evaluate possible relations between the technical capabilities of the team and startup success to assist investors and accelerators in investment decisions, decreasing the risk and improving the return on investment (ROI). Furthermore, this project aims to help entrepreneurs build their teams to optimise their chances of success.

1.1 Project background and motivation

This project took place at BGI - Building Global Innovators, legally registered as BGI S.A. Created in 2013, this company is a deep tech accelerator. It is presented in more detail in section 1.2.

BGI runs several acceleration programs, for which it must select the startups most likely to succeed. For that reason, it is important, not only to BGI, but also to investors, to know which factors most influence the success of an enterprise. Therefore, this dissertation emerges to tackle one specific factor, to assess the importance of technical skills of the entrepreneurial team in the success of a startup. Consequently, the theme of this dissertation is the importance of the technical skills of the entrepreneurial team to the success of a startup.

[1] "The Complete List Of Unicorn Companies." Accessed June 14, 2021. https://www.cbinsights.com/research-unicorn-companies.

[2] "Startup Failure Rate: Ultimate Report + Infographic [2021]." Accessed June 14, 2021. https://www.failory.com/blog/startup-failure-rate.

1.2 The BGI Accelerator at BGI

As mentioned earlier, this project was developed in BGI. This company is a deep tech innovation global accelerator headquartered in Lisbon (Portugal) with operations in Cambridge, Massachusetts (USA). It was created from the MIT Portugal Innovation and Entrepreneurship Initiative (IEI), launched to support the country's objective to improve its capacity in business education, technological innovation, and entrepreneurship. IEI was born out of a collaboration between MIT Deshpande Centre for Technological Innovation, MIT's School of Engineering, MIT Entrepreneurship Centre and ISCTE-IUL ("Portugal Startup Outlook 2020" 2020).

The case study chosen to analyse was the BGI Accelerator. This program is the main acceleration program provided by BGI and was built based on MIT's methodology. It includes weekly expert mentorship during 2 months, 3 bootcamps with professional coaching and access to a global network of investors, corporate, and partners through invitation only events. Through this program, since 2010, BGI has accelerated 147 startups. From these startups, in 2020, 85 were still alive, meaning a 60% survival rate with a total amount of 263.15M€ of capital raised, with about 80% of these funds being dilutive funding (in exchange for equity) and the remaining 20% non-dilutive funding (grants or awards, with no equity involved) (Macedo 2020; BGI 2019).

Despite the good results achieved by the program, which are especially significant when compared to the 90% failure rate of startups[3], it is important to better these results, not only for BGI, which takes a safe of 3% from its alumni once they are evaluated in 3M€, but also to investors. Therefore, predicting the success of the startups is crucial, and this became an opportunity to study the dependence of said success on the team, particularly, on the technical skills of the team. This program is described further in detail in Chapter 3.

1.3 Project goals

The goal established to this project is to perform an analysis about the influence of the set of technical skills of the entrepreneurial team on the success of the startup. The objective is to provide additional information to accelerators and investors when deciding whether to invest in a new venture or not. It also aims to help founders to design their teams in a way that maximizes their chance of success. The alumni of the BGI Accelerator, an 11-year deep tech international accelerator, were used as case study.

Moreover, this project intends to compare its results with the insights of investors and accelerators and provide a comparison between what role investors expect accelerators to have in the development of the startups and what roles accelerators aim to have.

1.4 Method followed on the project

The elaboration of this dissertation is based on the analysis of a particular acceleration program, the BGI Accelerator. The intention is to try to establish a relation between the skillset of the team and the success of the startup.

First, a review of the existing literature was performed, in order to provide a context for the project and gather what is already established on the subject. To help understand the general perceptions about the subject some interviews were conducted, since they allow for the

[3] "Startup Failure Rate: Ultimate Report + Infographic [2021]." Accessed June 14, 2021. https://www.failory.com/blog/startup-failure-rate.

extraction of the whole and coherent storyline from each actor, as well as the assessment of implicit nonverbal communication.

The alumni of the BGI Accelerator were established as the sample group to be studied. The information about these startups and their teams was obtained through company documents and the missing information was secured through LinkedIn and direct contact with team members.

Finally, 3 different success indexes were built, and a logistic regression was carried out to evaluate a possible correlation between the independent variables and the success of the startups. The indexes were built with the help of the interviewees, who were asked about how they evaluate whether a startup is successful or not. A complementary analysis was performed to support and add to the quantitative analysis.

The method used is further described in detail in Chapter 3.

1.5 Dissertation structure

Firstly, a review of the literature is presented in Chapter 2 to provide the theoretical background of the work performed and reported in this dissertation. It will start with the dissection of the broader concept of innovation and end with a review on the team profile and its influence on startup success.

With this basis, in Chapter 3 the methodology used is described in detail, starting with a comprehensive description of the BGI Accelerator, and followed by the description of the qualitative and quantitative methods used.

In Chapter 4 the results of the project are presented and analysed.

Finally, Chapter 5 elaborates on the conclusions of this dissertation and provides some baselines for further research.

2 Literature Review

This chapter defines the background concepts related with this dissertation and reviews the literature that provides the theoretical background for the work performed. Firstly, a review about the broader concept of innovation is provided, followed by the presentation of the definitions of Startup, Accelerator, Venture Capital (VC) and Startup Ecosystem. This provides the clarification needed to ensure a common ground for the reading of the rest of this dissertation. Then, the notion of success for a startup is addressed. Finally, the relation between the profile of the entrepreneurial team and the probability of success of the startup is assessed, as well as the methods used to establish this association.

2.1 Innovation

Shane (2009) defines innovation as “the process of using knowledge to solve a problem”. The simplest definition of innovation is, perhaps, its definition on the dictionary. According to the Merriam-Webster dictionary, innovation is “a new idea, method, or device”[4]. It is important to note that innovation is not the same as invention. According to the same source, invention is “a device, contrivance, or process originated after study and experiment”[5]. Grasty (2012) takes an interesting analogy to differentiate these two concepts, arguing that invention is like a pebble being thrown into a pound and generating ripples while innovation is the actual amplification and monitorization of those ripples. The one who tossed the pebble is the inventor and the entrepreneur is the one who understands those ripples so well that can predict ‘the next big wave’ (Grasty 2012).

According to Schumpeter (1942), innovation can be a new process, a new product, the use of new materials, a new combination of materials or a new form of organization. Moreover, the innovative entrepreneur is the central economic agent who can introduce new goods to the market through more efficient combinations of production factors, practical implementation of some invention or technical advancement, or even a shift in a production process.

Schumpeter (1942) proposed the concept of creative destruction, arguing that firms that do not innovate are replaced by those that do. An innovative firm is one that ceases the available opportunities in its surroundings, mobilizing both physical infrastructure and demand-pull through new business, which is heavily reliant on established knowledge from existing firms.

[4]“Innovation | Definition of Innovation by Merriam-Webster.” 2021. https://www.merriam-webster.com/dictionary/innovation.

[5]“Invention | Definition of Invention by Merriam-Webster.” 2021. https://www.merriam-webster.com/dictionary/invention.

To take advantage of these opportunities, both new and existing businesses must increase their innovation spending in order to generate new sources of spillovers (Leitão 2019).

Schumpeter's (1942) perspective on innovation differed from the one defended by the Neoclassical Theories. The author argued that innovation and progress come from within the organization following the market structure and research and development (R&D) activities, originating the creation of R&D departments responsible for the development of innovation for the organization. This contrasts with the Neoclassical Theories that placed the firm as a passive user of technologies developed outside, pointing to technology and innovation as influences beyond the firm and the economy itself (Leitão 2019).

Schumpeter (1942) also states that innovation is driven by discoveries based on scientific knowledge, creating the well-known technology push or science and technology push. In this case, innovation stems from inventions rather than the market, as would happen in a demand pull or market pull scenario, in which demand serves as the driver of innovation (Nelson 1959).

On the other hand, Schmookler (1966) argued that technological progress responds to various economic and social factors and, for that reason, market opportunities are the most significant factors for technological development.

In the 1970s, a break from the more traditionalist perspective emerged, with a new theory, by Freeman (1979), which sought for the ideal balance between consumer or societal needs, and technological or scientific opportunities. In this new context, innovation is described as an evolutionary process that occurs as a result of the generation of knowledge. Interactions between various actors, as well as the subsequent spread of information, may serve as a lever for development and economic growth when combined (Nelson and Winter 1982; Lundvall 2016).

Therefore, the innovation process is increasingly being viewed as an immersive learning process, made possible by bringing together and combining the interests of various social and economic actors with various forms of access to various types of knowledge and information (Leitão 2019).

According to Chesbrough (2004) collaborative initiatives are compatible with the open innovation paradigm since collaboration is a form of co-creation in this setting. Due to the complexity that arises from including multiple and diverse types of organizations, such projects face several problems. One of the biggest challenges faced in collaborative projects is trust between partners, since they depend on each other. Manning (2017) suggests that forming trust requires learning dynamics and stabilizing teams of collaboration among enterprises from one project to the next. Furthermore, during the project, the organizations in the consortium may need to carefully balance open and closed innovation, as open innovation compromises confidentiality, which may be required for particular innovations (Munkongsujarit and Srivannaboon 2017).

In this way, although organizations need to manage more carefully their collaborations for innovation, they benefit from the advantages of both models, which are presented in schemes proposed by Chesbrough in Figure 1 and Figure 2, useful to understand their differences.

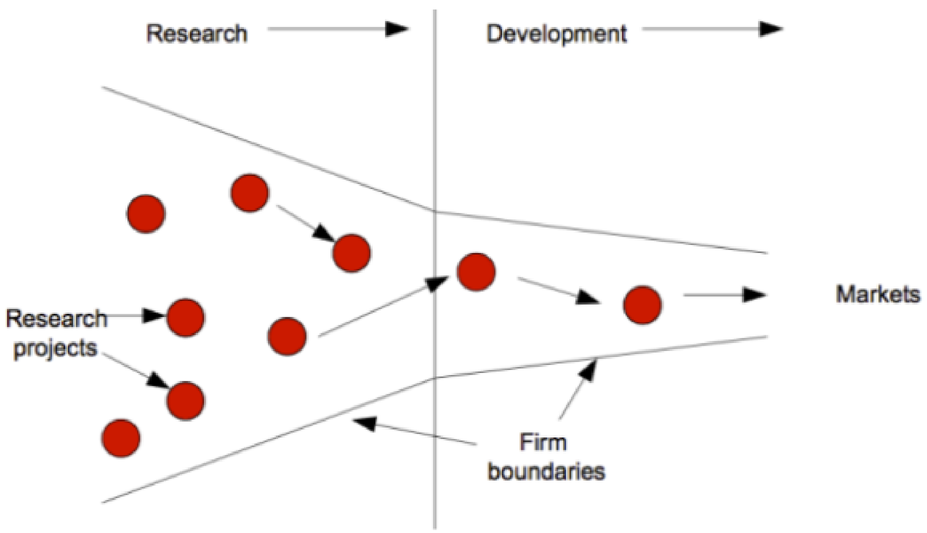

Figure 1 – Closed Innovation Funnel (Chesbrough 2003).

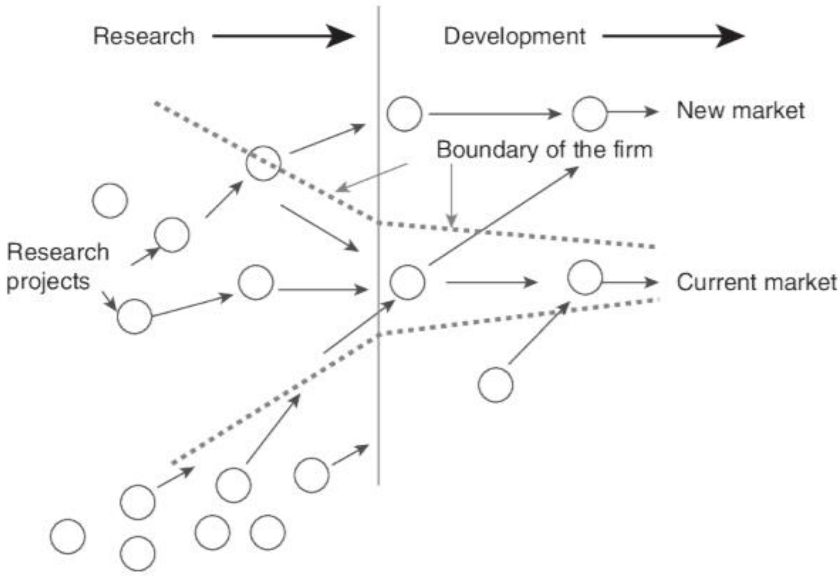

Figure 2 - Open Innovation Funnel (Chesbrough 2003).

2.2 Actors of the innovation process

To establish a common ground and allow a better understanding of the subject under study, the actors involved in the innovation process studied in this dissertation are defined in this section.

Startup

According to Cockayne (2019), there is no scientific agreement on the correct definition of a startup. Following a series of interviews, Cockayne concluded that "startup" is a nebulous term with no clear definition. A common ground is that a startup is a company that is in the initial stages of business. Spender et al. (2017) argue that startups are companies that deliver new ideas into the market and turn them into economically sustainable businesses. Their focus is on the identification and exploration of niche markets that allow for rapid growth. J. Freeman and Engel (2007) point that many startups, an ever-increasing number, are technology-based, created to profit from technological advancements and the market upheavals they frequently cause (Buckley and Prashantham 2018).

Considered the smallest business unit, these companies often start with low levels of capital and resources, high costs and limited revenue, forcing them to look for external partners that can provide them with all these missing points (Spender et al. 2017).

The most common source of capital is the so-called “Family, Friends and Fools” (FFF). Then, startups can look for venture capitals that invest money in the startup in exchange for equity. Other ways of funding can be crowdfunding - which is an open call for funding, allowing a high number of people to invest small amounts of money - and the traditional bank loans that indebt the startup.

Accelerator

Cohen (2013) stated that accelerators, in general, are organizations that assist ventures in defining and building their initial product, identifying promising customer segments, and ensuring resources, such as capital and staff. More specifically, accelerator programs are short-term programs (usually about three months) that assist startup batches with the new venture phase.

These programs also offer a multitude of networking opportunities, with peer ventures and mentors, who can be successful entrepreneurs, program graduates, venture capitalists, angel investors or even corporate executives. Usually, they involve mentoring and bootcamps and end with a big event where startups pitch to a large audience of investors (Cohen 2013).

Venture Capital

According to Zider (1998), Venture capital bridges the gap between the conventional sources of low-cost capital available to ongoing, established businesses and the sources of funds for new ventures (primarily corporations and government agencies).

Venture money is short term money. This money is invested in a company’s balance sheet and infrastructure until it grows and is credible enough to be possible to sell to a corporation or to be possible for institutional public-equity markets can step in and provide liquidity. Essentially, a venture capitalist invests in an entrepreneur's concept, nurtures it for a limited time, and then exits with the assistance of an investment banker.

The context of operations of a venture capital is defined by four main players: entrepreneurs looking for funding; investors aiming for high returns; investment bankers who need companies to sell; and the venture capital firms, who earn money by creating a market for the first three.

Most of venture capital fund investors are very large institutions including financial firms, pension funds, insurance companies, and university endowments, all of which invest a small portion of their total funds in high-risk investments. They aim for a yearly return of 25% to 35% over the lifetime of the investment. Venture capitalists have a lot of latitude because these investments are just a very small part of the institutional investors’ portfolios. Individual investments are not what entices these institutions to invest in a fund, but rather the firm’s overall track record and their faith in the partners themselves. VC firms invest in startups, which, as argued by Schmitt et al. (2017), face a high degree of uncertainty. The lack of tools to support the analysis of these investments often leads to biased decision (Zider 1998; Zhang and Cueto 2017).

Startup Ecosystem

According to Spigel (2017) "entrepreneurial ecosystems are combinations of social, political, economic, and cultural elements within a region that support the development and growth of innovative startups and encourage nascent entrepreneurs and other actors to take the risks of starting, funding, and otherwise assisting high-risk ventures."

A startup ecosystem is formed by people and organizations. The key players are: entrepreneurs, experienced teams running the startups; mentors, experienced leaders that guide entrepreneurs; investors, the sources of money to get the startups going; incubators and accelerators, organizations that allow entrepreneurs to learn from each other; universities, these institutions are a huge source of business ideas; corporations, big companies that invest through VC funds, are potential customers and often the exit for startups; government, in its different levels, it may provide tax benefits for startups and funding; service providers, bankers, lawyers, recruiters, accountants, advisors, agencies, and consultants in the community (Deeb 2019). The composition of a startup ecosystem is schematized in Figure 3.

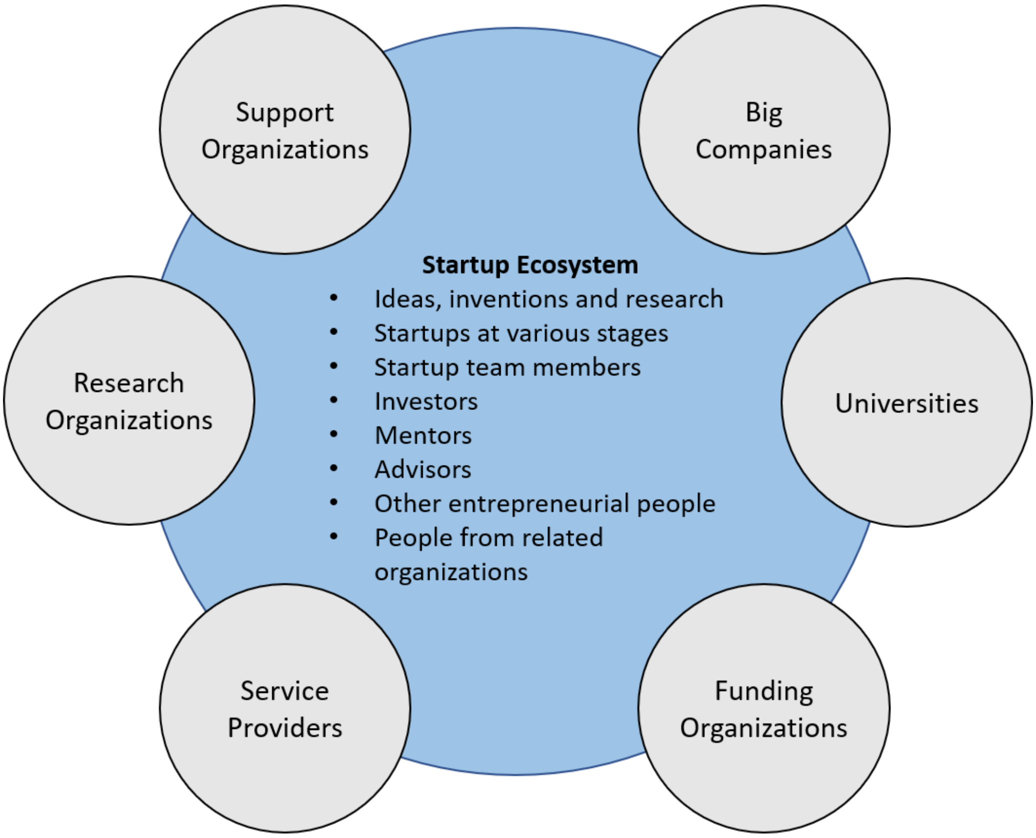

Figure 3 – Startup Ecosystem[6].

[6] "Startup Commons - Startup Commons." Accessed June 26, 2021. https://www.startupcommons.org/.

2.3 Success of Startups

There is currently no consensus in the literature about how to define a technology startup's success. Success, in general, is “the fact that you have achieved something that you want and have been trying to do or get” [7]. Considering this, it is understandable why Santisteban and Mauricio (2017) stated that “success is a term that means different things to different people”. According to the authors, entrepreneurs likely define success differently from a client or an investor (Santisteban and Mauricio 2017).

Numerous studies attempt to define the success of a startup. However, there is no single way of defining it. Success was defined as a “combination of economic and subjective measures” by Hiemstra et al (2006). Rivera-Rodriguez and Restrepo (2008), seem to associate the concept of success with durability, while suggesting that regarding success, survival is a goal for any enterprise, along with profitability and growth. When successful entrepreneurs in Spain were asked about their visions of success, the responses were a combination of economic, social, and personal benefits achieved by their ventures (Alameda 2015).

According to Claire (2012), there are two generational profiles of entrepreneurs with different notions of success. Those born before the mid-20th century adhere to a traditional notion of success, which includes earning money, developing the business by making it more efficient and scalable, and surviving. Later-generation entrepreneurs incorporate more dimensions into their definition of success, mainly regarding personal fulfilment. Moreover, they view success mostly as balancing their personal and working lives, contributing to society, and pursuing their passions.

Nevertheless, Santisteban and Mauricio (2017), in their extensive literature review, concluded that all the definitions have two points in common: “the growth of the company and the number of jobs generated. With respect to growth, it is a validation that the product and/or service offered by startup has the ability to attract users/customers. On the other hand, the creation of jobs is directly influenced by the growth of the company and the growth of the entrepreneurial ecosystem” (Santisteban & Mauricio, 2017, p.9).

On their paper “Econometric estimation of the factors that influence startup success”, Díaz-Santamaría and Bulchand-Gidumal (2021) concluded that “success can be measured in two ways: the startup manages to achieve significant revenue and the startup receives financing”. Regarding financing, the authors did not consider the amount received but instead, only whether financing was obtained or not. Considering revenue, “more than 75% of the entrepreneurs and investors interviewed in the first step of our methodology considered that the figure of EUR 100,000 could be used as a relevant threshold” (Díaz-Santamaría & Bulchand-Gidumal, 2021, p.7).

2.4 Team profile and the startup’s probability of success

As there is no one definition for success, the factors that influence it vary according to the definition applied.

Díaz-Santamaría and Bulchand-Gidumal (2021), regarding the profile of the entrepreneur, analysed the impact of: age; skills, abilities, and previous managerial and commercial experience; training; and previous experience as a founder of other startups. The most relevant influencing success factors were found to be the “Commercial ability”, “Workers” and “Technological training”, being the latter, specifically, the “percentage of partners who

[7] “Success Noun - Definition, Pictures, Pronunciation and Usage Notes | Oxford Advanced Learner’s Dictionary at OxfordLearnersDictionaries.Com.” Accessed May 18, 2021. https://www.oxfordlearnersdictionaries.com/definition/english/success?q=success

have graduate or postgraduate training or an advanced degree in the field of technology”. The impact of these factors was analysed on 2 indicators of success: revenue and the ability to obtain financing. All these factors - the number of workers, the commercial ability, and technological training of the team - were found to have significant influence on success, concerning revenue but no significant correlation with the ability to obtain financing.

According to Khan (1986), a survey conducted to investors indicated that the competence of the entrepreneurs in the field of endeavour has a significant influence in the success of the startup when that success is measured by the profitability of the investment.

Another interesting subject is the profile of the entrepreneur, regardless of the success of his enterprise. Delmar and Davidsson (2000), focusing on the Swedish population, found that only 41.1 % of nascent entrepreneurs had a university degree or were in the process of obtaining one. This is an interesting finding since it means that most of the entrepreneurs in that country, at the time, were not proficient in any of the technical skills considered.

VC’s invest in startups on which they predict, or at least expect success. In general, these firms search for clues as to the quality of a startup in the founder and team characteristics (Macmillan et al 1985). Therefore, it is interesting to understand which are the characteristics of the team that these companies look for when investing on a startup. Some of the factors perceived as good predictors of success are: having more than one founder, previous experience in founding a startup, a complete management team with experience, relevant industry experience, and a higher level of education (Hsu, 2007; Miloud, et all 2012; Sievers et all, 2012; Wasserman, 2017).

Hsu (2007) found that entrepreneurs with past founding experience, particularly those with financial success, are more likely to receive VC funding through a direct linkage and to have better VC valuations. He also suggested that founding teams with at least one member holding a PhD are more likely to receive higher valuations and to get funding via a direct VC tie. Wasserman (2017) also makes this connection between previous funding experience and higher valuations.

From the VC’s point of view, the human and social capital of the startup are important predictors of success and decisive determinants when choosing to invest in a venture and defining its valuation. The sentiment is more positive when the characteristics of the team are perceived to reduce risks (Hsu 2007).

There is a great interest in the scientific community about the startups and which factors lead to their success. However, there is no consensus about the definition of success. It is established that having workers proficient in the field of technology is important, but the other fields of study are yet to be explored. This study aims to define the success of startups and try to fill the existing gap on the impact the different technical capabilities of the entrepreneurial team have on it.

3 Methodology

In this chapter, the methodology used to develop this project is presented. A mixed methodology was used, combining qualitative and quantitative data. Firstly, a qualitative study was performed through interviews, gathering of information available in company files and literature review to find a suitable definition for success. Then, a quantitative study was performed using a logistic regression model to find a relation between the technical capabilities of the entrepreneurial team and startup success. Two main ways of collecting data were used: interviews and company files. Data collection and data analysis are described next.

3.1 The BGI Accelerator

The "BGI Accelerator is a 10 year deep tech international Accelerator – Spin out of MIT Portugal Entrepreneurship Initiative"[8] and is the main acceleration program organized at BGI. It began in 2010 as an innovation and entrepreneurship competition within the MIT Portugal program – a 10-year formal partnership between the Massachusetts Institute of Technology (MIT) and the Portuguese government, aiming at the promotion of the application of technology-based innovation and research through, for instance, university spinouts. Instead of supporting suboptimal and locally protected startup environments, the program aims to quickly facilitate connections and create global networks, providing the accelerated startups with direct access to potential customers, market knowledge, venture capital and relevant initial experience (Amorim 2020), which allows startups to learn from predictable mistakes and accelerate their learning curve.

"Learn from the mistakes of others. You can't live long enough to make them all yourself."

-Eleanor Roosevelt

The BGI Accelerator works with tech-based startups that work towards solving global challenges, with an existence of up to 5 years and less than 2.5M€ in revenue that require significant human and financial capital to achieve full commercialization. Startups eligible to the program must have a working minimum viable product (MVP) in one of 4 verticals:

1. Medical Devices & Health Care;
2. Smart Cities & Industry 4.0;
3. Blockchain Applications & AI;
4. Blue Economy.

[8] "BGI | Takingyoufurther." Accessed May 31, 2021. https://www.bgi.pt/bgi.

The program offers support for 8 months with 3 bootcamps, 2 in Lisbon (Portugal) and 1 in Boston (United States of America), an 8-week mentorship program with industry experts and ad-hoc support for the following 5 years. The chronogram for its 12th edition is depicted in Figure 5.

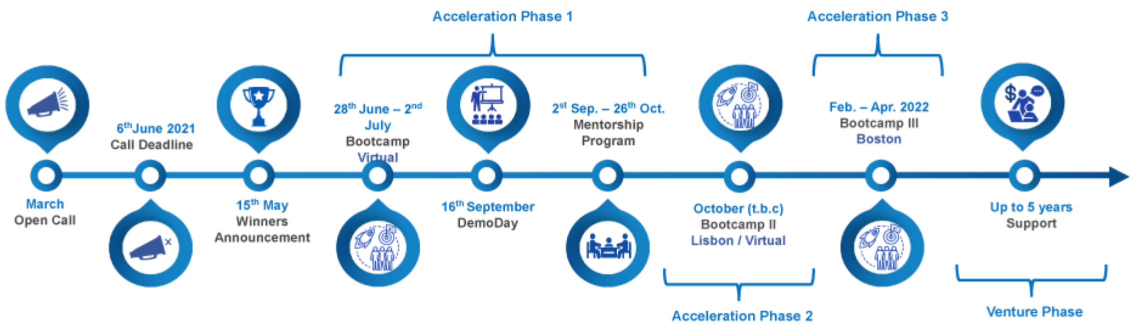

Figure 4 – Chronogram of BGI Accelerator 12th edition[9].

BGI works with a success fee, which means it only gets paid if the startups succeed. The accelerator receives 3% equity if and when the startup reaches a 3M€ Post Money valuation. This equity is transferred when:

- EBITDA (Earnings before interest, taxes, depreciation and amortization) * Industry Coefficient >= 3M €

Or

- Capital Raised >= 3M €

The startups that, at the time of this study, had undergone the program were the chosen sample on which the analysis was conducted. Therefore, it is important to firstly, analyse the metrics that can objectively describe the BGI Accelerator.

Through its main program, until 2020, BGI had received 1044 applications from 2088 entrepreneurs and accelerated a total of 147 startups. 85 of those startups were still operating, meaning a survival rate of 60%. The global dimension of the BGI Accelerator can also be confirmed by the fact that 40% of the applicants were from startups based outside the country where BGI's operations are based, Portugal.

All these startups are profit oriented. Therefore, it is important to understand the financial attractiveness of the program. The startups that had undergone the program raised a total of 272.77M € of which 263.14M € were obtained after the program. 81.7% of the latter were raised in exchange for equity (Dilutive Funding) while the remaining 18.3% were obtained through awards and subventions. On average, startups took 2.5 years to raise an average of 2.93M €. However, the median funding was of a much smaller sum of 430.63k €, meaning that most of the funding was raised by a small number of startups, indicating the occurrence of Pareto's principle that suggests that 80% of the effects come from 20% of the causes (Macedo 2020).

[9]"BGI | Takingyoufurther." Accessed May 31, 2021. https://www.bgi.pt/bgi.

Looking into the program's social impact, it is relevant to look at the direct impact it had on people's lives. The number of jobs created by a startup is one of the ways to measure its success and therefore, it can also represent the success of the acceleration program (Santisteban and Mauricio 2017). According to the available data, 746 highly qualified jobs were created by its alumni[10].

Although all the participants are tech-based, they can be very different since they can operate in any one of the for abovementioned verticals. As shown in Figure 6, "Enterprise IT Blockchain & Artificial Intelligence" and "Smart Cities & Industry 4.0" contribute almost in the same proportion to represent 65% of the startups. Closely behind with 29% is "Smart Cities & Industry 4.0". The least represented vertical, by some margin is "Blue Economy", which only accounts for 6% of all the participants.

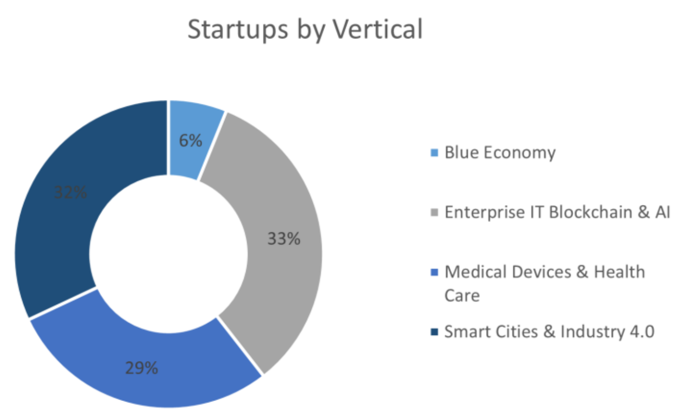

Figure 5 – Startups by vertical.

3.2 Interviews

To collect the existing perspective about the influence that technical skills have on the success of the startup, some interviews were conducted with the relevant actors. Accordingly, 9 interviews were conducted. The criteria to choose the interviewees was to be involved in the selection process of the startups, either to participate in the BGI Accelerator or to invest capital, and/ or to have some capital at stake.

There were 4 collaborators representing BGI, namely the CEO, the Head of Operations, the Head of Open Innovation, and the Head of Business Development. To collect the perspective of the Venture Capital firms, 5 representatives from 5 of the biggest VCs operating in Portugal were interviewed.

All the interviews had 4 main objectives:

1. Understand how startups are evaluated – How the selection process is conducted, what is the criteria and the relevance of the different factors evaluated, and the existence of a protocol.

[10] "BGI | Takingyoufurther." Accessed May 31, 2021. https://www.bgi.pt/bgi.

2. Understand the most valuable technical skills on a startup team – How relevant are the technical skills, which ones are scouted for and what is the ideal combination.
3. Understand what technical skills are better developed during the BGI acceleration program – How BGI works to improve in the startups and what are the expectations investors have.
4. Understand the definition of success and its perceived dependence on the technical skills of the team – Gather information on what metrics should be used to evaluate success and obtain a percentage of the success might be explained by the technical skillset of the team leading the venture.

Additionally, interviewees were also questioned about the importance of soft skills on the success of the startup.

To comply with these objectives, two scripts were written: one for the representatives of BGI and another for the representatives of the VC companies. These scripts can be found in the Appendix A. The interviews were structured with predefined questions so objective information could be retrieved. Yet, some additional questions were done when relevant or necessary, and interviewees were allowed to roam and address other subjects related to the topic.

The interviews were designed to last between 20 and 30 minutes. However, considering the fact that interviewees were given relative freedom to explore their answers, there were very different times, with some interviews taking only 16 minutes and other more than 1 hour. In the end, it took a total of 4 hours and 12 minutes to conduct all the 9 interviews, resulting in an average time of 28 minutes per interview. The interviews could not be recorded without the permission of the VCs and because of that, the relevant information gathered was registered when provided.

3.3 Data analysis

To study the influence that the technical skill set of the team has on the success of the startup, was first determined how to measure the success of the startups through a review of the existing literature and interviews with collaborators of BGI and investors from 5 different Venture Capital firms.

3.3.1 Measuring Success

All the people interviewed had a role in evaluating startups. The interviewees from BGI had an active role in selecting startups for the acceleration programs, namely, for the BGI Accelerator, whereas the interviewees from the Venture Capital firms chose which startups is the fund to invest in.

A few indicators were unanimous concerning the definition of success. All the interviewees agreed that good indicators of success were the financing obtained and the revenue generated. During some interviews, other indicators were also mentioned, such as: profit margin, market share and number of jobs created.

The concern when defining success, was to use metrics that could be transversal to all areas. For example, a startup developing a new treatment for cancer probably needs more financing than one developing an app for shared rides, since health startups, generally, need a lot of money to develop their research and take more time in turning that investment into return. This is due to the necessity of approval from regulators to ensure the safety of the proposed solution.

To tackle this issue, an extensive review of the literature was done in order to establish the metrics for success, combining the information obtained through the interviews and the data available.

3.3.2 Database

To try to measure the influence of technical skills on the success of the startups, a database with data regarding the startups had to be built. At the time this dissertation was conducted, there was no unique or official database containing all the startups, their founders and their performance. For this reason, this research started with the construction of a database with startups from one particular accelerator program for which there was some data available, the BGI Accelerator.

At the time of this study, the program had 147 alumni, which were all defined as units of analysis for this study. The information regarding funding and revenue was obtained from a previous study already mentioned in this paper, conducted at BGI - (Macedo 2020). Macedo created a database with all the startups that had gone through the aforementioned program. In his work, all the startups that had gone through the program were asked to fill a Google form document with some information such as its basic information about the company (company designation, headquarters country, place of origin, year of creation, legal designation, VAT number, and vertical), its valuation, the number of jobs created, its revenues and funding received.

Almost all the information from the database created by Macedo was transposed to the database created to run the statistical model. The information harnessed that is most relevant to this work is shown in Table 1.

Table 1 – Description of relevant variables.

Variable	**Definition**
Status	3 level variable : 1. Non-Active - No longer exists 2. Active - Operating 3. Exit[1] – BGI has divested from the startup
Total Turnover	Total revenues obtained during the startup's lifetime
Total Funding (Pre and After BGI)	Total funding obtained during the startup's lifetime
Total Jobs	Total jobs secured during the startup's lifetime

It is important to note that all the information is referring to 2020, when the forms were sent to the startups and Macedo's database was built. Then, it was necessary to add information regarding the team responsible for the development of the startup. For this purpose, internal files from BGI were used. To ensure coherence, the team considered was the one operating when the startup applied for the program. Regarding some ventures, the *curriculum vitae* of all the members of the team was available while for others it was not. For the cases where the information was not available in the company files, a search through LinkedIn was done. When it was not possible to get the details through the social network, the founders of the team were directly contacted via phone or email.

The factor to be addressed is the technical skill set of the team developing the business. A team member was considered to have a determined technical capability when meeting one of these two criteria:

1. Had a college degree in the area.
2. Had extensive work experience in the area (over 5 years).

Being that there are over 1800 college majors, it is impossible, or, at the very least, not practical, useful, or easy to study their individual influence on the success of a startup[11]. To tackle this issue, the technical capabilities were divided according to the fields of education provided by Direção-Geral do Ensino Superior (DGES)[12]. All higher education courses in Portugal are grouped according to these areas of study. The areas that had representation within the startups considered are presented in Table 2 with the links to all the corresponding majors.

Table 2 – Links for the courses in each area.

Area	**Correspondent courses**
Training of Teachers / Trainers and Educational Sciences	https://www.dges.gov.pt/guias/indarea.asp?area=14
Arts	https://www.dges.gov.pt/guias/indarea.asp?area=21
Humanities	https://www.dges.gov.pt/guias/indarea.asp?area=22
Social and Behavioural Sciences	https://www.dges.gov.pt/guias/indarea.asp?area=31
Information and Journalism	https://www.dges.gov.pt/guias/indarea.asp?area=32
Business Sciences	https://www.dges.gov.pt/guias/indarea.asp?area=34
Law	https://www.dges.gov.pt/guias/indarea.asp?area=38
Natural Sciences	https://www.dges.gov.pt/guias/indarea.asp?area=42
Physical Sciences	https://www.dges.gov.pt/guias/indarea.asp?area=44
Mathematics and Statistics	https://www.dges.gov.pt/guias/indarea.asp?area=46
Computing	https://www.dges.gov.pt/guias/indarea.asp?area=48
Engineering and Related Techniques	https://www.dges.gov.pt/guias/indarea.asp?area=52
Architecture and Construction	https://www.dges.gov.pt/guias/indarea.asp?area=58
Agriculture, Forestry and Fisheries	https://www.dges.gov.pt/guias/indarea.asp?area=62

[11] "List of College Majors." Accessed June 2, 2021. https://www.mymajors.com/college-majors/.

[12] "Acesso Ao Ensino Superior 2021 - Índices de Cursos (Por Área de Estudos e Curso)." Accessed June 2, 2021. https://www.dges.gov.pt/guias/indarea.asp.

Health	https://www.dges.gov.pt/guias/indarea.asp?area=72
Personal Services	https://www.dges.gov.pt/guias/indarea.asp?area=81

Apart from the ones represented in Table 2, there are 6 other areas categorized by DGES:

1. Industries
2. Veterinary Sciences
3. Social Services
4. Transportation Services
5. Environmental Protection
6. Security Services

These areas of study were also considered when collecting the data about the teams. However, none of the 147 startups had collaborators with technical skills in these fields so these were not considered when performing the statistical analysis.

To fairly evaluate the number of skills available to the enterprise, every time a team member was found to have a skill, the number of persons with that skill would be incremented by one.

3.3.3 Logistic Regression

After the data was collected and properly organized, a decision about the method used for the quantification of the relation between the technical capabilities and startup success had to be made.

The overall idea of a regression falls in one of two categories:

1. How well does a set of predictor variables predict the dependent variable;
2. Which variables are significant predictors of the dependent variable and how big is their impact.

Therefore, a regression was chosen as the tool to reach the objectives of this dissertation of quantifying the impact the different technical capabilities have on startup success.

A multiple linear regression is used when the dependent variable is continuous and there are multiple independent variables. However, the variables chosen to measure success are categorical (these are described with more detail in Chapter 4). A logistic model is used to model the probability of contrary events, such as success/ fail and since this study included 3 variables being used as metrics of success, and all 3 were coded as binary variables, 3 logistic regressions were performed.

A generally used rule to guide the appropriate size of the sample in order to perform a logistic regression on a dataset is the “one in ten rule”, which states that these models should be applied to samples where there are at least 10 events per variable. However, according to Vittinghoff and McCulloch (2007) this rule is to conservative and 5 to 9 events per variable (EPV) is a good size and that only minor problems can occur, which were also seen in samples with 10 to 16 events per variable. Since the sample size used in this project is of 147 and there are 16 independent variables, there are 9.19 EPV, which is appropriate. All the models and tests were conducted for a confidence interval of 95%. Table 3 presents the variables used in the model and their main descriptive statistics. These results show that the typical entrepreneurial team is made of 2 people skilled in “Engineering and Related Techniques” and 1 person skilled in “Business Sciences”.

Table 3 – Descriptive statisticts.

Predictor	Type of Variable	Mean	Std. Dev	Min.	Max.
Training of Teachers / Trainers and Educational Sciences	Independent	0.01361	0.11624	0	1
Arts	Independent	0.19048	0.52777	0	3
Humanities	Independent	0.05442	0.36607	0	4
Social and Behavioural Sciences	Independent	0.18367	0.42233	0	2
Information and Journalism	Independent	0.04082	0.23047	0	2
Business Sciences	Independent	0.7619	0.93144	0	5
Law	Independent	0.04762	0.29455	0	3
Natural Sciences	Independent	0.21088	0.66447	0	4
Physical Sciences	Independent	0.17007	0.62345	0	4
Mathematics and Statistics	Independent	0.04082	0.28375	0	3
Computing	Independent	0.05442	0.22762	0	1
Engineering and Related Techniques	Independent	2.17007	1.66912	0	8
Architecture and Construction	Independent	0.02041	0.18392	0	2
Agriculture, Forestry and Fisheries	Independent	0.0068	0.08248	0	1
Health	Independent	0.18367	0.59703	0	4
Personal Services	Independent	0.03401	0.21629	0	2
Revenue Success	Dependent	0.17007	0.37698	0	1
Funding Success	Dependent	0.55102	0.49909	0	1
Survival Success	Dependent	0.60544	0.49043	0	1

3.4 Complementary Analysis

As a complement to the logistic regression, a qualitative analysis of the survival of the startup was performed. Startups were divided into "non-active" and "active". It is important to note that, to maintain coherence with the quantitative analysis, the startups from where BGI had already exited were considered "active" since they had not gone out of business.

Then, the composition of the typical startups for both scenarios ("active" and "non-active") was provided, using the average quantity of each skill present in each scenario. Initially, this comparison was made disregarding any segmentation. Then, both statuses were compared between verticals. This means that 5 comparisons were made: 1 global and 1 for each of the 4 verticals.

An analysis on the team size was also performed, by ensuring the same separation regarding survival and comparing team sizes. In this case, the tool chosen was the boxplot as it provides a visual summary of the data and enables the quick identification of mean values, dispersion of data and signs of skewness. Even though the startups from where BGI had exited from are only 5, they were also analysed in this case. Finally, resourcing to doughnut charts, the distribution of the different technical skills in the dataset was explained.

4 Results and Discussion

4.1 Interviews

The first step of this project was interviewing some of the key players in the BGI Accelerator ecosystem in order to get their perspective on the topic of this dissertation so it could serve as a starting point and comparison to the quantitative analysis.

One of the goals of this project, as previously mentioned, is to understand how accelerators and investors make their decision of which ventures to support and invest in, and how to help them with that process. From the interviews it was possible to understand that BGI and most venture capital firms have a protocol to help them with that decision.

Even though a protocol exists in the majority of cases, most of the time the choice of whether to invest or not ends up being subjective and is heavily influenced by the personal perspective of the person making the evaluation. In an attempt to decrease this bias, most companies have the decision made by more than one person.

BGI conducts segmented acceleration programs for the European Institute of Innovation and Technology (EIT) as well as its own acceleration program, the BGI Accelerator. The EIT was created in 2008 by the European Union to improve the continent's ability to innovate. Therefore, the EIT is the European reference for innovation.

In the acceleration programs developed by BGI for the EIT, there are several juris, from the different accelerators organizing the programs around Europe. All these juris make their evaluation following some guidelines provided by the EIT and giving scores to the different factors being evaluated. The process for the BGI Accelerator is similar: a group of BGI collaborators build an individual assessment based on some topics and then make a joint decision.

Regarding Venture Capital firms, usually someone from the company, an analyst or an associate does the scouting. This scouting is performed by having close contact with accelerators, innovation initiatives and events. Then, an initial evaluation is performed following a protocol to check whether the startup fills the requirements defined by the fund. VC firms often manage more than one fund, each fund having a different goal and a different vertical associated. After this initial evaluation is performed, it is brought to a group of decision makers and the decision of making the investment or not is defined.

Despite some structural differences in the selection process, both accelerators and VCs, evaluate the same factors, which are described in Table 4.

Table 4 - Evaluated factors – based on the interviews and EIT Health Bridgehead[13] assessment form.

Factor	Description
Innovativeness of the idea	Uniqueness of the product/project and difficulty to replicate Progress achieved beyond the state of the art and the uniqueness of the advantages provided by the product/solution Long term impact
Team and management capabilities	Capability of the team to develop the company and handle associated risks Balanced experience in business and technology Motivation of the team
Market opportunity and traction	Existence of a clear market for the solution Traction of the company
Business model and development strategy	Solidity of the revenue model Identification of the development barriers and validity of the mitigation measures Scalability

Another objective of the interviews was to understand how these decision makers perceive technical skills and their importance to startup success. Analysing data collected from the interviews, it was possible to develop the characterization of the "ideal" team to develop a startup, in these initial stages. The consensus was that more than one person should be responsible for the venture. To tackle the problems that will most certainly appear it is important to have more than a single perspective. The ideal team should have at least someone with business knowledge and experience in the industry and someone responsible for the technical development of the startup, being it a medical doctor if the solution is a new drug or a software developer if the solution is a new app. It was also agreed that this is somewhat a utopian idea since it is, rarely or almost never the case. In some interviews it was also noted that marketing, operations and finance are also good skills to have on the team. The general idea is that, after the core technical and business skills, the more multidisciplinary the team is, the better. Another point taken is that to much industry experience can be harmful. This is due to the disruptive nature of startups that requires new thinking, detached form the common routines of established companies.

To try to measure how the technical skills of a team of entrepreneurs influence the probability of success of the startup, interviewees were asked the percentage of success they attribute to these technical skills. The responses from the 9 interviewees were very similar, ranging from 70-80%.

The interviews also provided some insights on why investors value acceleration programs. Concerning the BGI Accelerator, investors view it as a quality stamp, valuing the fact they were selected for the program. It is also expected that alumni startups know how to present their business idea and have already identified the barriers to success and developed the solutions. The key advantages of the program, according to investors are:

1. Creates a network;
2. Improves communication;

[13] https://eithealth.eu/bridgehead/

3. Helps to develop the Go-to-market plan.

These same advantages were recognized as the goal for the program by BGI collaborators.

Finally, the interviews also provided a guideline for the quantitative study. Investors and BGI collaborators were asked about the indicators that measure the success of a startup. The key metrics identified were:

1. Revenue;
2. Funding raised;
3. Growth rate;
4. Market share;
5. Profitability;
6. Number of jobs created;
7. Return on investment.

4.2 Quantitative Analysis

From the responses obtained in the interviews and the literature review, it was concluded that success can be measured in two ways:

1. Achieving significant revenue (>100k€);
2. Obtaining financing.

This was the same approach taken by Díaz-Santamaría & Bulchand-Gidumal (2021), which also performed a logistic regression to establish a relation between different factors and startup success.

Data reveals that from the 147 startups, only 25 have reached a revenue equal or bigger than 100k€ and 81 startups obtained financing. The scarcity of success regarding revenue is probably due to two factors:

1. Data was obtained through a Google forms document which was filled by startups. Several fields were left in blank because startups were reluctant to provide some information.
2. Startups usually take some time to start selling, and most startups in this case study did entered the program less than 5 years ago.

To overcome this issue, a 3rd indicator was used. According to Restrepo Puerta & Rivera Rodriguez (2008), survival is a goal for any enterprise and an indicator of success, and, therefore, the status of the startup was used as the third indicator. Bellow, Table 5 presents the frequency of success for all three indicators.

Table 5 - Frequencies of success.

	Revenue Success	Financing Success	Survival Success
N	25	81	89
%	17%	55%	61%

The first dependent variable was based on revenue. This variable was coded as 1 for startups that obtained a revenue greater than 100k€ and 0 for the ones that did not. To get to the results presented in Table 6, the functional form described in expression (4.1) was used.

$$\text{Revenue success}_i = \beta_0 + \beta_1 \text{ Training of Teachers / Trainers and Educational Sciences}_i + \beta_2 \text{ Arts}_i + \beta_3 \text{ Humanities}_i + \beta_4 \text{ Social and Behavioural Sciences}_i + \beta_5 \text{ Information and Journalism}_i + \beta_6 \text{ Business Sciences}_i + \beta_7 \text{ Law}_i + \beta_8 \text{ Natural Sciences}_i + \beta_9 \text{ Physical Sciences}_i + \beta_{10} \text{ Mathematics and Statistics}_i + \beta_{11} \text{ Computing}_i + \beta_{12} \text{ Engineering and Related Techniques}_i + \beta_{13} \text{ Architecture and Construction}_i + \beta_{14} \text{ Agriculture, Forestry and Fisheries}_i + \beta_{15} \text{ Health}_i + \beta_{16} \text{ Personal Services}_i \quad (4.1)$$

Where:

β_m, is the regression coefficient (m=1, … ,16)

To evaluate the regression model presented, there are some values that must be analysed. For this model predicting revenue, the Chi-square presented a p-value of 0.412, meaning that this model has no statistical significance, because p-value is superior to 0.05. The coefficient of determination, R^2, describes the amount of variance in the dependent variable associated with the independent variables in a linear regression model, with bigger R^2 values suggesting that the model can explain more variation, up to a maximum of 1. Because it is not possible to construct a single R^2 statistic that includes all of the characteristics of R^2 in the linear regression model for regression models with a categorical dependent variable, other approximations are used instead. The one chosen to evaluate was the Nagelkerke R^2, since it is an adjusted version of the Cox & Snell R-square that adjusts the scale of the statistic to be scaled from 0 to 1, as the commonly used R^2 for continuous dependent variables. The Nagelkerke R^2 for this model was of 0.178, which may mean that the model is not very good at explaining the variation of the dependent variable. Regarding the Hosmer and Lemeshow Test, the Chi-square has a significance of 0.728, meaning there is no proof that the model is not a good fit. The tables showing these values are all depicted in Appendix B.

Table 6 – Estimate of achieving significant revenue.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Step 1[a]	Training of Teachers / Trainers and Educational Sciences	-18,678	25702,012	,000	1	,999	,000	,000	.
	Arts	-,221	,443	,250	1	,617	,801	,336	1,910
	Humanities	-18,594	10618,421	,000	1	,999	,000	,000	.
	Social and Behavioural Sciences	-1,037	,811	1,636	1	,201	,354	,072	1,737
	Information and Journalism	-18,959	14794,465	,000	1	,999	,000	,000	.
	Business Sciences	-,460	,304	2,286	1	,131	,631	,348	1,146
	Law	,079	,846	,009	1	,926	1,082	,206	5,681
	Natural Sciences	-,241	,363	,440	1	,507	,786	,386	1,601
	Physical Sciences	-,317	,441	,518	1	,472	,728	,307	1,727
	Mathematics and Statistics	-18,362	13330,405	,000	1	,999	,000	,000	.
	Computing	-19,314	13130,684	,000	1	,999	,000	,000	.
	Engineering and Related Techniques	-,106	,166	,412	1	,521	,899	,650	1,244
	Architecture and Construction	-9,704	15114,433	,000	1	,999	,000	,000	.
	Agriculture, Forestry and Fisheries	-20,554	40192,970	,000	1	1,000	,000	,000	.
	Health	-,521	,511	1,042	1	,307	,594	,218	1,616
	Personal Services	-19,105	14732,730	,000	1	,999	,000	,000	.
	Constant	-,436	,599	,531	1	,466	,646		

a. Variable(s) entered on step 1: Training of Teachers / Trainers and Educational Sciences, Arts, Humanities, Social and Behavioural Sciences, Information and Journalism, Business Sciences, Law, Natural Sciences, Physical Sciences, Mathematics and Statistics, Computing, Engineering and Related Techniques, Architecture and Construction, Agriculture, Forestry and Fisheries, Health, Personal Services.

The results indicate that no technical skill was found to have significant impact on the dependent variable of obtaining a revenue greater than 100k€. Even when considering a confidence level of 90%, no independent variable shows a significant impact on the dependent variable. Therefore, it is not possible to prove that any of the different technical capabilities has a significant impact in the ability to obtain significant revenue.

The second dependent variable to be analysed concerns financing. This variable was coded as 1 for startups that could gather some kind of funding and 0 for the ones that did not. To obtain the results presented in Table 7, the functional form described in expression (4.2) was used.

$$\text{Financing success}_i = \beta_0 + \beta_1 \text{ Training of Teachers / Trainers and Educational Sciences}_i + \beta_2 \text{ Arts}_i + \beta_3 \text{ Humanities}_i + \beta_4 \text{ Social and Behavioural Sciences}_i + \beta_5 \text{ Information and Journalism}_i + \beta_6 \text{ Business Sciences}_i + \beta_7 \text{ Law}_i + \beta_8 \text{ Natural Sciences}_i + \beta_9 \text{ Physical Sciences}_i + \beta_{10} \text{ Mathematics and Statistics}_i + \beta_{11} \text{ Computing}_i + \beta_{12} \text{ Engineering and Related Techniques}_i + \beta_{13} \text{ Architecture and Construction}_i + \beta_{14} \text{ Agriculture, Forestry and Fisheries}_i + \beta_{15} \text{ Health}_i + \beta_{16} \text{ Personal Services}_i \quad (4.2)$$

Where:

β_m, is the regression coefficient (m=1, … ,16)

The fitness of the model, as for revenue the Chi-square of the model showed a p-value of 0.592, meaning that this model has no statistical significant. Regarding the Nagelkerke R, the value is 0.122, meaning a low explanation of the variation of the predictor variable through the model. Looking at the Hosmer and Lemeshow Test, the Chi-square shows a significance of 0.728, signifying that there is no proof that the model is not a good fit. The tables showing these values are all depicted in Appendix C.

Table 7 – Estimate of obtaining financing.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Step 1[a]	Training of Teachers / Trainers and Educational Sciences	21,503	27533,012	,000	1	,999	2181506417	,000	.
	Arts	-,228	,342	,445	1	,505	,796	,408	1,555
	Humanities	-,281	,537	,274	1	,601	,755	,263	2,165
	Social and Behavioural Sciences	-,266	,437	,371	1	,543	,766	,325	1,806
	Information and Journalism	-,175	,770	,052	1	,820	,839	,185	3,800
	Business Sciences	-,202	,195	1,075	1	,300	,817	,558	1,197
	Law	,340	,683	,248	1	,619	1,405	,368	5,358
	Natural Sciences	,319	,312	1,048	1	,306	1,376	,747	2,533
	Physical Sciences	,061	,301	,042	1	,838	1,063	,589	1,920
	Mathematics and Statistics	,311	,661	,222	1	,638	1,365	,374	4,988
	Computing	-,993	,898	1,223	1	,269	,371	,064	2,153
	Engineering and Related Techniques	-,094	,117	,644	1	,422	,911	,724	1,145
	Architecture and Construction	,208	,973	,046	1	,830	1,232	,183	8,295
	Agriculture, Forestry and Fisheries	-21,622	40192,970	,000	1	1,000	,000	,000	.
	Health	,216	,339	,405	1	,525	1,240	,639	2,409
	Personal Services	-,966	1,149	,707	1	,400	,380	,040	3,616
	Constant	,607	,443	1,876	1	,171	1,834		

a. Variable(s) entered on step 1: Training of Teachers / Trainers and Educational Sciences, Arts, Humanities, Social and Behavioural Sciences, Information and Journalism, Business Sciences, Law, Natural Sciences, Physical Sciences, Mathematics and Statistics, Computing, Engineering and Related Techniques, Architecture and Construction, Agriculture, Forestry and Fisheries, Health, Personal Services.

The results show that the scenario is similar to the one concerning revenue. None of the predictive variables show a significant impact on the predictor variable, whether a significance of 5% or 10% is considered. Therefore, it is not possible to prove that any of the different technical capabilities has a significant impact in the ability to obtain significant revenue.

As mentioned in the methodology section, in a later stage of this project a third measure of success was included: the survival of the startup. To do this, the variable status of the dataset was used, coding as 1 the startups that were “active” or where an “exit” was done and as 0 the startups with a “non-active” status. To obtain the results presented in Table 8, the functional form described in expression (4.3) was used.

$$\text{Survival}_i = \beta_0 + \beta_1 \text{ Training of Teachers / Trainers and Educational Sciences}_i + \beta_2 \text{ Arts}_i + \beta_3 \text{ Humanities}_i + \beta_4 \text{ Social and Behavioural Sciences}_i + \beta_5 \text{ Information and Journalism}_i + \beta_6 \text{ Business Sciences}_i + \beta_7 \text{ Law}_i + \beta_8 \text{ Natural Sciences}_i + \beta_9 \text{ Physical Sciences}_i + \beta_{10} \text{ Mathematics and Statistics}_i + \beta_{11} \text{ Computing}_i + \beta_{12} \text{ Engineering and Related Techniques}_i + \beta_{13} \text{ Architecture and Construction}_i + \beta_{14} \text{ Agriculture, Forestry and Fisheries}_i + \beta_{15} \text{ Health}_i + \beta_{16} \text{ Personal Services}_i \quad (4.3)$$

Where:

β_m, is the regression coefficient (m=1, … ,16)

Looking into the fitness tests performed in this model, it performed much better than the other two. The Chi-square of the model showed a p-value of 0.014, which is smaller than 0.05, meaning that the logistic regression model is significantly better that the null model, with a confidence level of 95%. The Nagelkerke R^2 was also greater for this model, with a value of 0.257, showing that the technical skills have better explanatory capacity when predicting survival than revenue or financing. Regarding the Hosmer and Lemeshow Test, the Chi-square shows a significance of 0.728, signifying that there is no proof that the model is not a good fit. The tables showing these values are all depicted in Appendix D.

Table 8 – Estimate of surviving.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	Training of Teachers / Trainers and Educational Sciences	21,595	27695,127	,000	1	,999	2390872994	,000	.
	Arts	-1,004	,391	6,588	1	,010	,367	,170	,789
	Humanities	,470	,625	,564	1	,453	1,600	,470	5,449
	Social and Behavioural Sciences	,153	,482	,101	1	,751	1,166	,453	2,999
	Information and Journalism	,209	,803	,068	1	,795	1,232	,256	5,940
	Business Sciences	-,672	,220	9,294	1	,002	,511	,332	,787
	Law	-,750	,684	1,202	1	,273	,472	,124	1,805
	Natural Sciences	,168	,339	,245	1	,620	1,183	,609	2,297
	Physical Sciences	-,643	,331	3,766	1	,052	,526	,275	1,006
	Mathematics and Statistics	-,248	,684	,131	1	,717	,781	,204	2,985
	Computing	-1,255	,944	1,766	1	,184	,285	,045	1,815
	Engineering and Related Techniques	-,183	,128	2,040	1	,153	,832	,647	1,071
	Architecture and Construction	18,321	20223,474	,000	1	,999	90545779,90	,000	.
	Agriculture, Forestry and Fisheries	19,814	40192,969	,000	1	1,000	402903141,5	,000	.
	Health	-,403	,320	1,585	1	,208	,668	,357	1,252
	Personal Services	-1,700	1,306	1,692	1	,193	,183	,014	2,366
	Constant	1,756	,512	11,747	1	,001	5,787		

a. Variable(s) entered on step 1: Training of Teachers / Trainers and Educational Sciences, Arts, Humanities, Social and Behavioural Sciences, Information and Journalism, Business Sciences, Law, Natural Sciences, Physical Sciences, Mathematics and Statistics, Computing, Engineering and Related Techniques, Architecture and Construction, Agriculture, Forestry and Fisheries, Health, Personal Services.

Examining the results for the logistic regression model for the survival of the startup, it is possible to conclude that this model is better than the previous two. As shown in Table 8, there are two areas of knowledge with an impact on survival with a significance of 5%: “Arts” and “business sciences”. If the confidence interval is decreased to 90%, “Physical Sciences” also has significant impact in the dependent variable. This model suggests that startups where team members have technical skills in these three fields of study are more likely to be non-active. “Physical Sciences” and “Business Sciences” have a similar impact on the predictor variable while “Arts” has the biggest negative significant impact. This model showed global significance and the independent variables have an explanatory capacity of 26.3%.

4.3 Complementary Analysis

A relation between the different technical capabilities and the success of the enterprise could only be verified using quantitative methods when this success concerned survival. Therefore, to complement this analysis, a qualitative analysis was performed on the data.

Intuitively, one may presume that different technical skills are required for different startups. It is easy to assume that a startup emerging in the healthcare sector may be more in need of a medical doctor than a startup exploring AI.

Firstly, to have a base for comparison, the composition of the typical “active” and “non-active” startup, disregarding the vertical, was analysed. As shown in Table 9, the typical startup team, successful or not, has 2 people skilled in “engineering and related techniques” and 1 in “business sciences”.

Table 9 – Average composition of “active” an “non-active” startups.

	Non-Active	Active
Business Sciences	1	0.61
Engineering and Related Techniques	2.24	2.12

When looking at startups from the different verticals, there is a difference between what a successful team looks like. Regarding survival, the average successful startup has a different composition than an unsuccessful one.

Regarding startups in the “blue economy” vertical, as shown in Table 10 the average active startup is composed by 1 member with knowledge in “business sciences”, 1 proficient in the area of “natural sciences” and 2 in “engineering and related techniques” while “non-active” startups were composed by 3 people with skills in “business science” and 4 in “engineering and related techniques”. This suggests that startups in this vertical need members proficient in these 3 fields of study but regarding business sciences and engineering and related techniques, an excess of these skills might be harmful.

Table 10 - Average composition of “active” an “non-active” startups in the “blue economy” vertical.

Blue economy	Non-Active	Active
Business Sciences	2.67	0.5
Natural Sciences	0	0.83
Engineering and Related Techniques	4	2.33

When looking at startups focused on “enterprise IT blockchain & AI”, the typical active startup is created by 1 person with skills in “business sciences” and 2 in “engineering and related techniques”. The same goes to startups that have gone out of business, with the difference that those startups have a team member proficient in “arts”, suggesting a negative impact of this field of studies, corroborating the findings of the logistic regression. Results are showed in Table 11.

Table 11 - Average composition of “active” an “non-active” startups in the “enterprise IT blockchain & AI” vertical.

Enterprise IT Blockchain & AI	Non-Active	Active
Arts	0.62	0.13
Business Sciences	0.92	0.65
Engineering and Related Techniques	2.27	2.43

The third vertical accelerated in the BGI Accelerator is “medical devices & health care”. These were the most surprising results since an average active startup was composed by two people with skills in “enterprise IT blockchain & AI”. The startups that were out of business, were much more multidisciplinary, including team members with skills in business sciences, natural sciences, physical sciences, engineering and related techniques, and health. The most notorious fact is that “active” startups, contrarily to the ones that were not, on average, did not have anyone proficient in “health”. “Business sciences” and “natural sciences” were also not represented in the successful startups. However, the numbers were rounded half to even and as it can be seen in Table 12, the averages are not very far off being rounded up to one. This suggests that these skills are not crucial to success, but do not have a clear negative impact in the survival of the startups. The exception is “physical sciences” which is clearly closer to 0 in the “active” startups, indicating a significant difference when comparing to the “non-active” and, therefore, suggesting a negative impact in the startup success.

Table 12 - Average composition of “active” an “non-active” startups in the “medical devices & health care” vertical.

Medical Devices & Health Care	Non-Active	Active
Business Sciences	0.8	0.47
Natural Sciences	0.6	0.47
Physical Sciences	0.7	0.19
Engineering and Related Techniques	1.9	1.94
Health	0.9	0.44

The last vertical is “smart cities & industry 4.0”. In this group of startups, as shown in Table 13, both “active” and “non-active” had a typical team of 1 person proficient in “business sciences” and 2 in “engineering and related techniques”.

Table 13 - Average composition of “active” an “non-active” startups in the “smart cities & industry 4.0” vertical.

Smart Cities & Industry 4.0	Non-Active	Active
Business Sciences	0.95	0.75
Engineering and Related Techniques	2.11	2.04

Looking at these results, there is a common ground independently of the vertical of the startup: a typical “active” startup has someone with attributes in “engineering and related techniques” and “business sciences”, adding to the results of the interviews and the quantitative analysis. The exception is the Medical Devices & Health Care sector, whose standard “active” startup did not have any team member proficient in “business sciences”. However, as previously explained, the average was close to rounding up to one.

The skills of “engineering and related techniques” do not seem to have a differentiating impact on success, since both “active” and “non-active” ventures had this field of study in its skillset in the same quantity. The exception was “blue economy”. However, it is to be taken into account that this vertical was poorly represented in the dataset, with only 9 startups competing in this segment. This omnipresence may be explained by the fact that the BGI Accelerator is a deep tech accelerator, meaning that all solutions must be tech based, and that, as stated by one of the investors interviewed, in-house development is mostly preferred.

Another verified tendency, supported by the logistic regression, is that while present in most startups, “business sciences” seems to have a negative impact when more than one collaborator is proficient in this skill. This situation can be partly explained by the implications team size has on this indicator of success, alongside the fact that “business sciences” is one of the most present technical capabilities.

When comparing the team sizes between startups, a trend can be identified. As shown in Figure 6, the overall average team size is 3.72, being the biggest team composed of 8 people, and the smallest being a single-person team. It is also interesting to note that 50% of the startups were developed by 3 to 5 people. When considering the status of the startups, smaller teams meant more successful startups. The average size was 4.2 for non-active startups, 3.5 for active startups.

It can be argued that the average is sensitive to extreme values, but as it can be seen in the Figure 7 and Figure 8, the interquartile range varies between the different status which means the middle 50% scores vary. Data shows that these middle 50% in the non-active startups have between 3 and 5 team members and in the active startups between 2 and 4.

At least from BGI’s point of view, the most successful alumnis are the ones where an exit was achieved. This is corroborated by the responses to the interviews where ROI was said to be a good measure of startup success. Therefore, as a complement, startups from where BGI was able to divest were also analysed. It is shown in Figure 9, that these companies were developed by teams with 2 to 3 people and the median value was of 2.6. This supports the argument that there is, to some degree, an inverse relation between team size and the success of the startup, at least from the point of view of survival. The negative impact may be caused by the difficult task of aligning different visions from different people. The bigger the team, the more challenging this is, as Mol (2019) argued, aligned goals are very important to communicate efficiently and share knowledge.

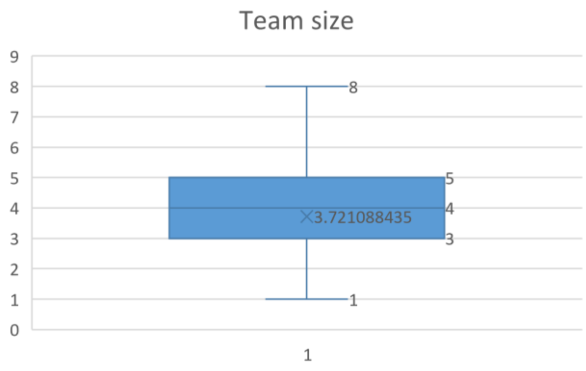

Figure 6 – Size of the teams.

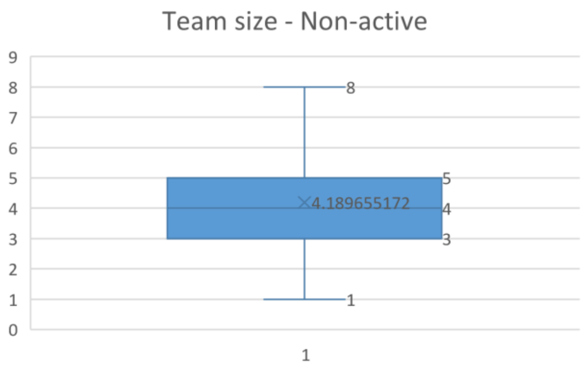

Figure 7 – Size of the teams (non-active startups).

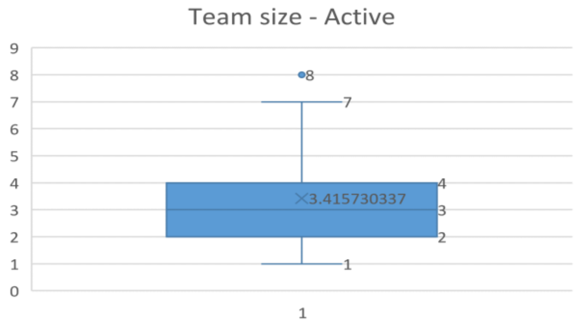

Figure 8 – Size of the teams (active startups).

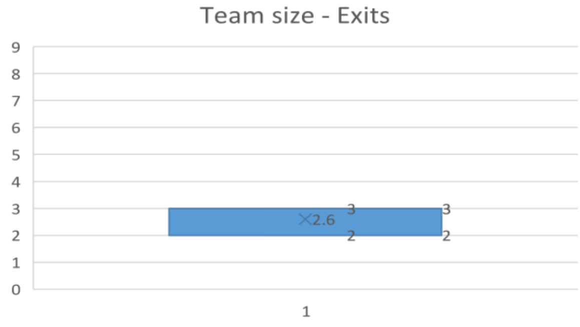

Figure 9 – Size of the teams (exits).

It is also relevant to characterize the skills of the startups. Because of the way data was organized for this study, the number of skills in a startup can be bigger than the number of people that compose the team. In fact, this is the case in 34% of the considered startups. One example of this situation is a very common case: when a founder has a degree in engineering and later in his career also completes a Master of Business Administration degree, commonly known as MBA, to help turn his technical expertise into a successful business.

Even though this study focuses on revenue and financing as metrics of success, it is undeniable that the status of the startup is also an indicator of its success. Naturally, a startup which is no longer active is less successful than one that is still alive. It can also be assumed, that a startup where an exit occurred is successful since it means it has reached a Post Money valuation of 3M €, was bought by an investor and BGI was able to sell its position in the enterprise, which is the accelerator's main goal.

One might feel tempted to assume that a startup where this is the case has a competitive advantage. However, it might not be the case. As shown in Figure 11, 44% of these startups were non-active, which is a bigger percentage when compared to the opposite case depicted in Figure 10, where each team member ensured one or no technical skill to team, which has 37% of non-active startups. The percentage of exits is very similar, being 4% and 3% respectively. Although these results may not be significative, it is interesting to note that, in this particular sample, startups where there are multiskilled collaborators are more likely to be out of business.

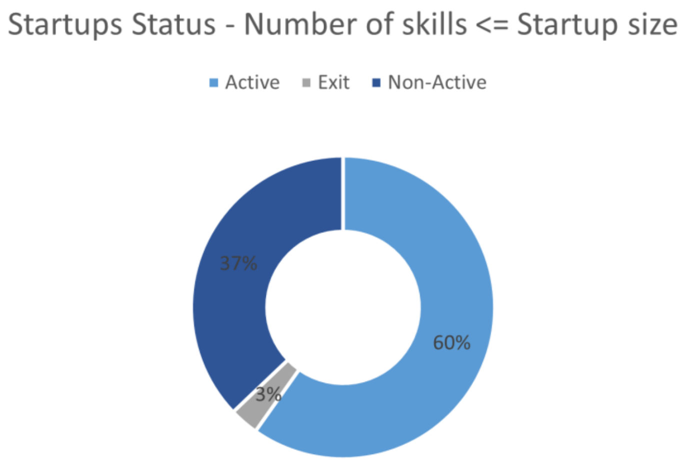

Figure 10 – Status of the startups where the number of skills is lower than the size of the team.

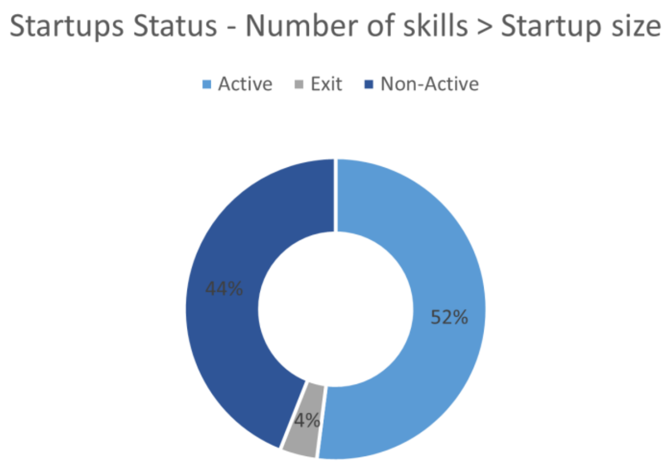

Figure 11 - Status of the startups where the number of skills is greater than the size of the the team.

A total of 547 people were involved in the development of the startups. All these entrepreneurs together had a total of 615 technical skills. As explained above, this is due to the fact that one team member can be trained in more than one area of studies.

The most represented area, by some margin, is Engineering and Related Techniques. This was expected since the startups are only eligible to the BGI Accelerator if they are tech-based. Nevertheless, not all startups had someone trained in engineering in their team. In fact, 20% of the startups did not have this skill in their skillset.

As it is shown in Figure 12, from the 615 technical skills identified, 52% were of Engineering and Related Techniques, 18% of Business Sciences and the remaining 30% were distributed between the remaining areas of study.

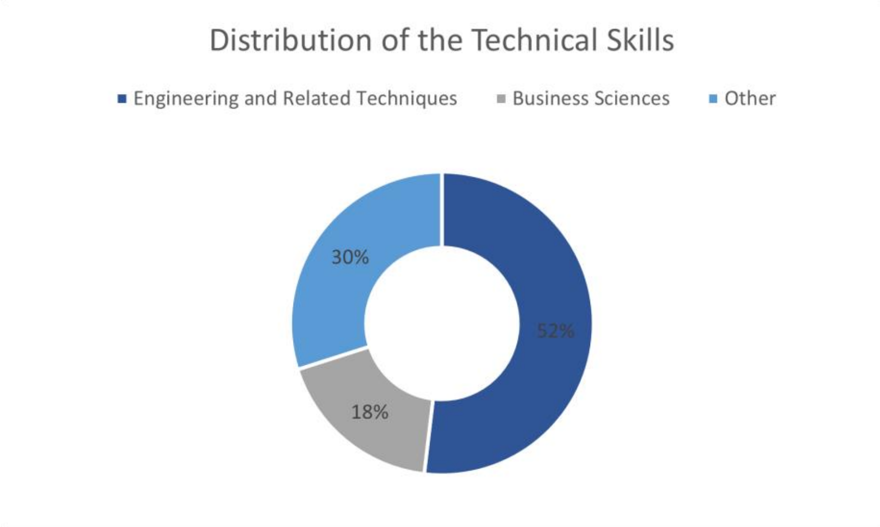

Figure 12 – Distribution of the technical skills.

5 Conclusions

This work was focused on studying the influence of the set of technical capabilities of the entrepreneurial team on the success of the startup. To provide the theoretical background on the subject, Chapter 2 presents the concept of innovation and its evolution from Schumpeter's Creative Destruction Theory and the conventional closed innovation model to the more recent open innovation model. Then, the actors were defined to ensure a common language, followed by review about the established scientific bases on startup success and the influence of the entrepreneurial team profile on it, particularly the technical capabilities.

To understand the key actors' perspectives about the topics addressed, some interviews were conducted. These interviews were done to collaborators from BGI who had a role in the selection of the startups to participate in the BGI Accelerator and join the accelerators' portfolio, and with investors from VC firms. Some interesting insights, especially concerning the Portuguese startup ecosystem, were revealed. Both the VC firms and BGI have a similar selection process. Firstly, some scouting is performed to find promising startups. Then, a collaborator evaluates these leads following some established criteria and presents its evaluation to a board that will make the final decision on whether to invest or not. Data collected from the interviews also revealed that the same factors were considered by both the accelerator and VC investors, but with different criteria suiting the interests of the investors.

The case study for this work was the BGI Accelerator, BGI's main acceleration program. A database was built with information from the 147 startups and the 547 entrepreneurs that had participated in the program up to its 10^{th} edition. The data about entrepreneurs was obtained through the analysis of their Curricula Vitae (CVs). Investors expect this program to help startups develop a solid business plan, to improve communication and to create and facilitate contact between all the stakeholders of the startup ecosystem.

Then, an analysis on this data was performed. This study used 3 possible indicators of success: significant revenue (>100k€), securing funding, and surviving. These indicators were all validated with interviews and the review of the scientific literature available.

To analyse the data and investigate possible relations, a quantitative methodology already tested in the literature was used: a logistic regression was applied to test these relations. Regarding revenue and funding, no relation between different technical capabilities and startup success was found. There are different possible explanations for this. First, it might be that there is no relation, even though it is an unlikely scenario. It may also be due to the data collection method used. These KPIs – revenue and funding – were provided by the startups and some entrepreneurs are not very willing to provide financial data. However, when the measure used for success was survival, the model proved to be a good predictor and some relations were found. The fields of study of arts, business sciences and physical sciences have significant negative impact on the success of the startup with arts having a particularly significant impact. No significant impact was found in the remaining areas of study.

To support and improve the results of this model, a qualitative analysis was performed to the data. To decrease the bias that could emerge from comparing startups from different market segments, these ventures were separated by vertical (area of activity) and the successful startups were compared. It was possible to conclude that engineering did not have a differentiating impact in this sample since both successful and unsuccessful startups showed an equal presence of that technical capability in their skillset. This is probably because of the technological nature of all the startups eligible to the program. Entrepreneurs proficient in business sciences were also a big and constant presence in the program. A typical successful startup would have one team member with knowledge in business sciences but more than one evidenced to harm the venture chances of success.

These findings led to the investigation of the influence of the size of the startup. An inverse relation between the size of the team and the success of the startup was observed, with active startups showing a smaller average team size than the ones that have gone out of business.

Summarizing, an ideal tech-based startup must have two technical capabilities in its skillset: business sciences and engineering. However, more than one collaborator skilled in business might be harmful and startups with big teams are at a disadvantage. Physical sciences and arts showed a significative negative impact in the survival of the startup and startups in the medical devices and health care sector that did have someone proficient in the field of health on the team showed poorer performance than the ones that did not. Through interviews, it was possible to conclude that the technical capabilities of team members do have a very big impact on the success of the startups.

This research presents some limitations that can suggest future lines of research. First, this analysis was conducted in a sample of startups from one specific accelerator, the BGI Accelerator. Therefore, all startups were subject to a similar evaluation and fulfilled the same criteria. Moreover, this accelerator focuses in technological startups, meaning that the conclusions of this study may not be applicable to all types of startups. Consequently, the extension of this study to startups from different accelerators would be valuable. Furthermore, the startups analysed had different lifetimes and operated in 4 different verticals. Due to the size of the sample, it was not possible to perform a quantitative analysis comparing startups from the same vertical. This analysis would be important to compare with the results provided by the complementary analysis. Finally, considering that there is no consensus in the literature about the definition of startup success, this work could be extended by exploring different definitions.

In the very risky world of startups, where there is great uncertainty, the conclusions drawn from this project can support accelerators and investors in their investment decisions. They can also be used to help design the entrepreneurial teams: assisting entrepreneurs in building their teams and helping accelerators and VCs to advise the startups in their portfolios.

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APPENDIX A: Scripts used to guide the interviews

BGI Interviews

Objectives:

- Understand how startups are evaluated;
- Understand the most valuable technical skills on a startup team;
- Understand what technical skills are better developed during the BGI acceleration program;
- Understand the definition of success and its perceived dependence on the technical skills of the team.

Questions:

1. How does the evaluation process of a startup work?
2. Which are the main evaluated criteria?
3. What is the importance of the technical skills of the team?
4. Which are the technical skills that add more value to a team?
5. In your opinion, which are the most valued soft skills? How can you identify them in the recruitment process?
6. Do you believe that diverse academic backgrounds add value to a team?
7. In the acceleration programs developed by BGI, in which technical skills is the training more focused on?
8. What do you define as success for a startup? Which are the metrics you use to evaluate it?
9. How do you think the technical skills of a team of entrepreneurs influence its probability of success?

Investors Interviews

Objectives:

- Understand how startups are evaluated;
- Understand the most valuable technical skills on a startup team;
- Understand what technical skills are better developed during the BGI acceleration program;
- Understand the definition of success and its perceived dependence on the technical skills of the team.

Questions:

1. How does the evaluation process of a startup work?
2. Which are the main evaluated criteria?
3. What is the importance of the technical skills of the team?
4. Which are the technical skills that add more value to a team?
5. In your opinion, which are the most valued soft skills? How can you identify them in the recruitment process?
6. Do you believe that diverse academic backgrounds add value to a team?
7. How valuable do you think the BGI acceleration program is for a startup? What are the areas of knowledge you think are best addressed in these programs?
8. What do you define as success for a startup? Which are the metrics you use to evaluate it?
9. How do you think the technical skills of a team of entrepreneurs influence its probability of success?

APPENDIX B: Logistic regression - Revenue

Table 1 – Case processing summary.

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	147	99,3
	Missing Cases	1	,7
	Total	148	100,0
Unselected Cases		0	,0
Total		148	100,0

a. If weight is in effect, see classification table for the total number of cases.

Table 2 – Dependent variable encoding.

Dependent Variable Encoding

Original Value	Internal Value
0	0
1	1

Block 0: Beginning Block

Table 3 – Classification table.

Classification Table[a,b]

Observed			Predicted: Revenue 0	Predicted: Revenue 1	Predicted: Percentage Correct
Step 0	Revenue	0	122	0	100,0
		1	25	0	,0
	Overall Percentage				83,0

a. Constant is included in the model.

b. The cut value is .500

Table 4 – Variables in the equation.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-1,585	,220	52,134	1	,000	,205

Table 5 – Variables in the equation.

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	Training of Teachers / Trainers and Educational Sciences	,415	1	,519
		Arts	,101	1	,750
		Humanities	,670	1	,413
		Social and Behavioural Sciences	1,828	1	,176
		Information and Journalism	,951	1	,329
		Business Sciences	1,425	1	,233
		Law	,020	1	,887
		Natural Sciences	,008	1	,928
		Physical Sciences	,196	1	,658
		Mathematics and Statistics	,628	1	,428
		Computing	1,734	1	,188
		Engineering and Related Techniques	,132	1	,717
		Architecture and Construction	,373	1	,541
		Agriculture, Forestry and Fisheries	,206	1	,650
		Health	,345	1	,557
		Personal Services	,750	1	,386
	Overall Statistics		9,988	16	,867

Block 1: Method = Enter

Table 6 – Omnibus tests of model coefficients.

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	16,597	16	,412
	Block	16,597	16	,412
	Model	16,597	16	,412

Table 7 – Model summary.

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	117,466[a]	,107	,178

a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

Table 8 – Hosmer and Lemeshow test.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	5,278	8	,728

Table 9 – Hosmer and Lemeshow test.

Contingency Table for Hosmer and Lemeshow Test

		Revenue = 0		Revenue = 1		
		Observed	Expected	Observed	Expected	Total
Step 1	1	15	15,000	0	,000	15
	2	15	14,850	0	,150	15
	3	13	13,713	2	1,287	15
	4	16	13,906	0	2,094	16
	5	12	12,509	3	2,491	15
	6	9	10,307	4	2,693	13
	7	10	11,517	5	3,483	15
	8	13	11,888	3	4,112	16
	9	11	10,478	4	4,522	15
	10	8	7,833	4	4,167	12

Table 10 – Classification table.

Classification Table[a]

			Predicted		
			Revenue		Percentage Correct
	Observed		0	1	
Step 1	Revenue	0	122	0	100,0
		1	25	0	,0
	Overall Percentage				83,0

a.

b. The cut value is .500

APPENDIX C: Logistic regression - Funding

Table 1 – Case processing summary.

Unweighted Cases		N	Percent
Selected Cases	Included in Analysis	147	99,3
	Missing Cases	1	,7
	Total	148	100,0
Unselected Cases		0	,0
Total		148	100,0

a. If weight is in effect, see classification table for the total number of cases.

Table 2 – Dependent variable encoding.

Dependent Variable Encoding

Original Value	Internal Value
0	0
1	1

Block 0: Beginning Block

Table 3 – Classification table.

Classification Table[a,b]

Observed			Predicted Funding 0	Predicted Funding 1	Percentage Correct
Step 0	Funding	0	0	66	,0
		1	0	81	100,0
	Overall Percentage				55,1

a. Constant is included in the model.

b. The cut value is .500

Table 4 – Variables in the equation.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	,205	,166	1,525	1	,217	1,227

Table 5 – Variables not in the equation.

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	Training of Teachers / Trainers and Educational Sciences	1,652	1	,199
		Arts	,586	1	,444
		Humanities	,410	1	,522
		Social and Behavioural Sciences	,547	1	,459
		Information and Journalism	,049	1	,825
		Business Sciences	1,439	1	,230
		Law	,417	1	,519
		Natural Sciences	2,196	1	,138
		Physical Sciences	,352	1	,553
		Mathematics and Statistics	,166	1	,684
		Computing	1,060	1	,303
		Engineering and Related Techniques	,950	1	,330
		Architecture and Construction	,099	1	,754
		Agriculture, Forestry and Fisheries	1,236	1	,266
		Health	1,320	1	,251
		Personal Services	1,823	1	,177
	Overall Statistics		12,203	16	,730

Block 1: Method = Enter

Table 6 – Omnibus tests of model coefficients.

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	14,095	16	,592
	Block	14,095	16	,592
	Model	14,095	16	,592

Table 7 – Model summary.

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	188,157[a]	,091	,122

a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

Table 8 – Hosmer and Lemeshow test.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	4,356	8	,824

Table 9 – Contingency table for Hosmer and Lemeshow Test.

Contingency Table for Hosmer and Lemeshow Test

		Funding = 0		Funding = 1		
		Observed	Expected	Observed	Expected	Total
Step 1	1	10	10,902	5	4,098	15
	2	9	8,357	6	6,643	15
	3	8	7,218	6	6,782	14
	4	4	5,880	8	6,120	12
	5	6	6,046	7	6,954	13
	6	9	6,635	6	8,365	15
	7	7	5,873	7	8,127	14
	8	6	5,916	9	9,084	15
	9	4	5,241	11	9,759	15
	10	3	3,934	16	15,066	19

Table 10 – Classification Table.

Classification Table[a]

			Predicted		
			Funding		Percentage
Observed			0	1	Correct
Step 1	Funding	0	26	40	39,4
		1	16	65	80,2
	Overall Percentage				61,9

a. The cut value is .500

APPENDIX D: Logistic regression - Survival

Table 1 – Case processing summary.

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	147	99,3
	Missing Cases	1	,7
	Total	148	100,0
Unselected Cases		0	,0
Total		148	100,0

a. If weight is in effect, see classification table for the total number of cases.

Table 2 – Dependent variable encoding.

Dependent Variable Encoding

Original Value	Internal Value
0	0
1	1

Block 0: Beginning Block

Table 3 – Classification table.

Classification Table[a,b]

Observed			Predicted: Active/Not active 0	Predicted: Active/Not active 1	Predicted: Percentage Correct
Step 0	Active/Not active	0	0	58	,0
		1	0	89	100,0
	Overall Percentage				60,5

a. Constant is included in the model.

b. The cut value is .500

Table 4 – Variables in the equation.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	,428	,169	6,438	1	,011	1,534

Table 5 – Variables no in the equation.

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	Training of Teachers / Trainers and Educational Sciences	1,321	1	,250
		Arts	4,976	1	,026
		Humanities	,286	1	,593
		Social and Behavioural Sciences	,292	1	,589
		Information and Journalism	,073	1	,787
		Business Sciences	6,302	1	,012
		Law	1,655	1	,198
		Natural Sciences	1,163	1	,281
		Physical Sciences	1,946	1	,163
		Mathematics and Statistics	,048	1	,826
		Computing	1,881	1	,170
		Engineering and Related Techniques	,176	1	,675
		Architecture and Construction	1,188	1	,276
		Agriculture, Forestry and Fisheries	,656	1	,418
		Health	,146	1	,702
		Personal Services	2,519	1	,112
	Overall Statistics		27,020	16	,041

Block 1: Method = Enter

Table 6 – Omnibus tests of model coefficients.

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	30,903	16	,014
	Block	30,903	16	,014
	Model	30,903	16	,014

Table 7 – Model summary.

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	166,295[a]	,190	,257

a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

Table 8 – Hosmer and Lemeshow test.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	11,058	8	,198

Table 9 – Contingency table for Hosmer and Lemeshow test.

Contingency Table for Hosmer and Lemeshow Test

		Active/Not active = 0		Active/Not active = 1		
		Observed	Expected	Observed	Expected	Total
Step 1	1	13	12,158	2	2,842	15
	2	12	9,790	3	5,210	15
	3	4	7,701	11	7,299	15
	4	5	6,643	10	8,357	15
	5	7	5,645	8	9,355	15
	6	4	5,241	12	10,759	16
	7	4	4,105	11	10,895	15
	8	4	2,692	8	9,308	12
	9	5	2,889	10	12,111	15
	10	0	1,137	14	12,863	14

Table 10 – Classification Table.

Classification Table[a]

			Predicted		
			Active/Not active		Percentage
Observed			0	1	Correct
Step 1	Active/Not active	0	28	30	48,3
		1	11	78	87,6
	Overall Percentage				72,1

a. The cut value is .500