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The Most Influential Team Attributes When Predicting Start-up Success

A quantitative study of 25 430 European new ventures

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by

Johan Torssell

Master of Science Thesis TRITA-ITM-EX 2022:165
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SE-100 44 STOCKHOLM

De Mest Inflytelserika Team-attribut vid Prediktion av Framgång hos Start-ups

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Examensarbete TRITA-ITM-EX 2022:165
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Abstract

Digitisation, quantitative analysis, and data-driven methods have been used for investment decision support for more than two decades within the finance sector, however there are great differences of its adoption in different parts of the financial market. One part of the market that has not yet achieved a high level of adoption is the Venture capital (VC) industry. In this study, quantitative analysis will be applied to a dataset of 25430 early stage start-ups in Europe to determine which characteristics of a founder and executive team are most influential when predicting start-up success. This study is part of an effort towards the digitisation of the industry, enlightening quantitatively robust insights into evaluating the teams of new ventures, and reducing bias in the venture capital investment process. It is also part of an effort in bringing insights to current and aspiring entrepreneurs about the most important start-up team characteristics, something that could be used to become a better entrepreneur or build a more efficient and well balanced entrepreneurial team.

Keywords - Venture Capital; Entrepreneurship; Team Attributes; Start-ups

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De Mest Inflytelserika Team-attribut vid Prediktion av Framgång hos Start-ups</td></tr>
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Sammanfattning

Digitalisering, kvantitativ analys, och datadrivna metoder har använts som support vid investeringsbedömning i mer än två decennier inom finanssektorn. Emellertid finns stora skillnader mellan dess adaption in olika delar av finansmarknaden. En del av marknaden som ännu inte uppnått en hög grad av adaption är riskkapitalindustrin (VC). In denna studie kommer en kvantitativ analys genomföras av 25430 nystartade företag i Europa för att dra slutsatser kring vilken karakteristik hos grundare och chefsteamet som har störst inverkan vid prediktion av vidare företaget blir framgångsrikt eller inte. Studien är en del av en satsning mot att digitalisera industrin, belysa kvantitativt robusta insikter i utvärderingen av start-up-team, och minska bias i investeringsprocessen. Arbetet är också en del av en satsning att bidra med insikter till befintliga och aspirerande entreprenörer om vilken karakteristik som är viktigast för att grunda ett framgångsrikt företag, något som kan användas för att bli en bättre entreprenör eller för att bygga ett mer effektivt och välbalanserat team.

Nyckelord - Venture Capital; Entreprenörskap; Team-attribut; Start-ups

Contents

Foreword

Thank you to Andre Retterath and Earlybird Venture Capital for providing data, support, and valuable insights into the venture capital industry. Also thank you Terrence Brown for providing general and specific feedback throughout the writing of this thesis.

Disclosure

The following parts have been written in collaboration between Johan Torssell and Ludvig Wärnberg Gerdin as part of an internship at Earlybird Venture Capital.

- 1 Introduction
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1 Introduction

Data-driven methods have been used for investment decision support for more than two decades within the finance sector. There are, however, great differences in the adoption of data-driven methods in different parts of the financial market. On the one hand, equity funds such as Renaissance Technologies and Bridgewater Associates have leveraged such methods, an important contributor to the consistent returns that they have been able to generate (Brewster, 2008; "Renaissance Technologies", n.d.). These companies emphasised the use of technical solutions with a great focus on mathematical and statistical methods to gather such achievements. On the other hand, Venture capital (VC) firms have not achieved the same adoption of quantitative analysis and data-driven investment decisions. However, despite having traditionally slow and qualitative methods, VC firms - in contrast to mutual fund managers - are able to sustain the performance of their funds over time and between different funds, making it an attractive alternative investment source for institutional investors and wealthy individuals (Harris et al., 2020). Given the attractiveness of the area, the inflow of money has significantly increased during the previous years. Globally, the total deal value reached a record $476bn in the first three quarters of 2021, up from $314bn in 2020 (Preqin, n.d.). In the European market alone, the total deal value reached €102.9bn in 2021, up from €46.8bn in 2020, representing an increase of around 120% (Gabbert et al., 2020).

Part of the reason behind the lack of adaptation of data-driven methods in the VC industry is due to the focus on relationships, lack of data, and lack of knowledge in computer science by the traditional venture capitalist. Now, with a constantly growing amount of available data, even within private markets, data-driven methods using statistical analysis could enable higher efficiency and accuracy in the VC investment process, as well as reduce the human bias inherent in the traditional deal-flow (Retterath, 2020a). Indeed, efforts from both research and industry indicates that the belief that data-driven methods could improve VC operations and deal-flow has grown stronger. In fact, research in the space is not only claiming that available data can be used to predict future venture success but also that machine learning models and advanced software can beat the human investor (Retterath, 2020b). From an industry perspective, this has resulted in both established and new VC-firms adapting quantitative methods for investment decision support (Martin, 2022; "Moonfire, Philosophy", n.d.; Retterath, 2020a).

A first step in the digitisation of the industry and transition towards data-driven methods is to quantitatively analyse available data to provide insights for venture capitalists. These analyses could include the founder and executive team, company traction and market conditions. To maximise the impact of the conclusions and to complement existing research, this project will focus on analysing which characteristics of the founder and executive team are most influential when predicting start-up success as well as how predicted venture performance is affected by different values of each respective variable.

The project aims to fill a gap in current research of the influence of founder and executive team characteristics on predicted start-up success. The filling of the gap is of great value both for research and practical applications. The findings can validate or undermine already existing research as well as serve as a base for future qualitative research explaining the reason behind the results. In practice, the results can be used by the venture accelerator and venture capital industries to improve the team evaluation and decrease bias in the investment decisions. The research can furthermore support in the research around and practical development of data-driven models predicting future venture success, something part of a general venture capital digitisation and the rise of a data-driven venture capital investment process.

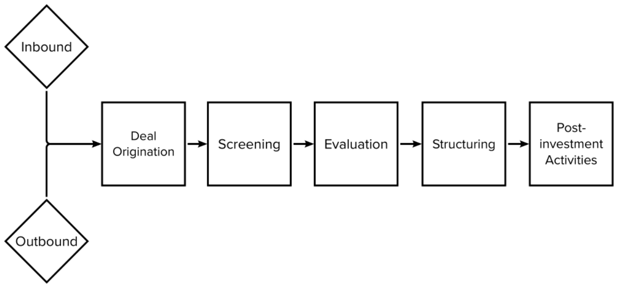

Figure 1: Traditional VC process as described by Tyebjee and Bruno (1984).

1.1 Background

1.1.1 Traditional VC Investment Process

One of the most widely cited processes is that described by Tyebjee and Bruno (1984). The authors outlined the investment process in five stages, as illustrated in Figure 1. Firstly, the venture capitalist recognises a possible investment opportunity in the deal origination phase. The channels through which deals are originated are categorised as either inbound or outbound. Inbound investment opportunities represent those in which the investee reaches out to the investor, for example when the investee cold emails the investor or applies for funding through forms. Outbound investment opportunities represent those in which the investor reaches out to the investee, for example through referrals. In the screening phase, venture capitalists reduce the number of investment opportunities to a manageable number of deals, applying "hard" criteria such as geography, and "soft" criteria such as feeling for the team. Those managing to fulfil the required criteria are then evaluated on the basis of risk and reward in the evaluation phase. If favorable return with respect to the risk it adds to the portfolio, the venture capitalist focuses on outlining favorable terms for a particular deal, for example the ticket size and share that the venture capitalist would own post-investment. If the deal closes, post-investment activities are initiated. The focus of the VC-firm in the post investment phase is company monitoring, exit handling, and general support, such as aiding in key hires (Tyebjee & Bruno, 1984).

1.1.2 Data-driven Venture Capital

Weibl and Hess (2019) uses the outline of the venture capitalist investment process described by Tyebjee and Bruno in order to describe how each stage can and has been transformed by data-driven methods. Weibl and Hess interviewed 13 venture capitalists from 13 different firms, inquiring their view on how their deal funnel has changed because of the availability of data. The following list summarises the findings for each phase:

- **Deal origination phase**: Weibl and Hess explain that the deal origination phase has radically changed. Data sources such as Crunchbase, Pitchbook, and LinkedIn allow the venture capitalist to source potential deals on a larger scale and from a wider range of sources more efficiently, whereas sources such as Statista enables the analyst to assess whether or not the market conditions are right for investing into that particular industry and start-up.

- **Screening phase**: Again, using sources such as Crunchbase and LinkedIn, Venture capitalists can extract information about executive team education, corporate, and entrepreneurial experience as well as social media presence in order to predict whether or not the firm will be successful or not. Using the calculated probability of success based on aforementioned data, the venture capitalist can scrutinize among venture options found in the deal origination phase.
- **Evaluation phase**: Weibl and Hess describes the evaluation phase as not being significantly affected by the availability of data. The assessments made in the evaluation phase are mainly based on qualitative factors rather than on quantitative data, as in the screening phase.
- **Structuring phase**: Structuring is made on a case-by-case basis and is negotiated between the venture capitalist and the start-up team, leading to the data tools and data availability having less impact on the traditional way of handling deals in this phase.
- **Post-investment phase**: Parts of the activities post-investment can be made more efficient with data. For instance, access to platforms for comparison of portfolio companies to their peers was previously a more difficult process. The authors describe that VCs might build internal platforms for comparisons among portfolio companies. However, activities post-investment are mainly done manually and has not changed significantly in the data-driven era.

1.2 Purpose & Research Question

When initiating the project, I went under the belief there would be plenty of research on the topic of team attributes contributing to company success. However, whilst performing the literature review, sufficient research for many personal and team attributes was not found, especially for quantitative studies utilising larger datasets. A potential reason for lack of quantitative research on the topic could be the lack of data and the belief of niche applications of the results, namely within the venture acceleration and venture capital industry. Furthermore, as the venture capital investment process traditionally has been based on relationships and been comprised of business oriented personnel, quantitative methods and data-driven solutions have not yet penetrated the industry. The addition of quantitative research on the topic could easily be applied in the existing VC investment process by guiding analysts on which attributes to focus on, what attributes that increase the probability of success, and which attributes are complementary in a team. In the long run, the conclusions can be utilised in a future data-driven VC investment process by guiding the development of such a solution and serving as a benchmark for validating the prediction models.

In addition to the value of the research for venture acceleration and venture capital industry, the research have the potential to bring value to entrepreneurs and aspiring entrepreneurs. This is not only it's future potential indirect effects of an unbiased data-driven investment process but also a direct effect by the insights into the important attributes of successful founding and executive teams. This information could guide entrepreneurs and aspiring entrepreneurs into which skill set and experience to pursue to increase their probability of founding a successful venture. Furthermore, while conducting the research, there has been an increasing interest in the findings from a recruitment and human resources perspective. More specifically, the findings can be of great help when recruiting new team members by looking at what attributes of the existing team currently are holding them back. The findings can in this scenario serve as a guideline on what attributes to look for in a new team member to complement the existing team and maximise the potential performance.

In light of this research gap and the potential impact of filling it would have on the venture capital industry and society as a whole, the research question has been phrased as follows:

Which characteristics of a founder and executive team are most influential when predicting start-up success?

1.3 Expected Results

The expected results include an understanding of what characteristics of founder and executive teams are most influential when predicting start-up success on three levels:

1. The general importance of founder and executive teams' characteristics when evaluating start-ups. For example that age, team size and diversity would be the most influential factors
2. The impact of the actual feature value on the predicted probability of success. For example what team size yields the highest predicted probability of success
3. The importance of different team attributes in specific company predictions. For example that the academic background of the founders is considered to reduce their predicted probability of success

1.4 Sustainability

This research's impact on sustainable development will be grounded in the UN 2030 Agenda for Sustainable Development (United Nations, n.d.-b). The agenda has the purpose to serve as a "blueprint for peace and prosperity for people and the planet, now and into the future" (United Nations, n.d.-a). The core of the agenda is 17 Sustainable Development Goals (SDGs) which broadly can be categorised into people, planet, prosperity, peace, and partnership (United Nations, 2015). Of these categories, the research has the potential to impact people and prosperity, and more specifically the goals of promoting inclusive and sustainable economic growth (8) and reducing inequality (10). The reasoning behind this is that a lack of quantitative studies on the area risks leading to biased decision making by venture capitalists. These decisions could be based on stereotypes, relationships or simply the venture capitalists ability to see a young self in the founders they invest in (Corea et al., 2021). Therefore, filling this gap could directly reduce bias in the investment decision process (SDG 10) (Corea et al., 2021). Reduced bias will in this case practically reduce inequalities of outcome and promote equal opportunity, as included in the targets connected to SDG 10 (United Nations, 2015). This is in turn connected to efficient capital allocation and SDG 8 as reduced bias would result in investments being made in start-ups with the highest potential to bring value to the world rather than to the most connected entrepreneurs (Retterath, 2020a). Moreover, the research is also in line with the target of SDG 8 to support entrepreneurship and innovation by providing valuable insights to existing and aspiring entrepreneurs (United Nations, 2015).

1.5 Disposition

The report is comprised of four main sections followed by a conclusion. In the first section, 2 Attributes of Successful Founding Teams, the existing literature on start-up performance is presented within the areas of demographics and personal attributes, academic experience, and professional experience, as these are deemed to be the most impactful categories when evaluating teams in the context of new venture success (Schjoedt & Kraus, 2009). This review includes both qualitative and quantitative studies from the fields of management and psychology research. The second section 3

Method walks through the entire methodology used in this research, from determining which attributes to include in the study to the implementation of machine learning models and the evaluation of the importance of the team attributes on the predicted probability of success. The third section, 4 Results presents the key findings of the analysis, mostly through visualisations of the impact different attributes and metric values have on the predicted probability of success. In the final section 5 Discussion, the results of the analysis will be connected to existing research either undermining or strengthening the results of previous studies. The discussion will also hypothesise around the results and present potential explanations where existing research is lacking, something that can serve as a platform for future research.

2 Attributes of Successful Founding Teams

The following section presents the relations between team attributes and new venture success as found by existing research. Following Schjoedt and Kraus (2009), the team-attributes most impactful when evaluating new venture success has been split up into the categories demographics and personal attributes, academic experience, and professional experience. The following review includes both qualitative and quantitative studies and is not limited by geography, industry, or research field.

2.1 Demographics & Personal Attributes

Azoulay et al. (2020) study the relationship between founder age and company success. The presented key arguments for youth being a beneficial founder trait is cognitive abilities, less distracted by family and responsibilities, and more capable of disruptive ideas (Planck's Principle). However, they might have difficulties managing efficient R&D due to insufficient knowledge, especially within deeptech. Older founders have the key benefits of human, social and financial capital. The findings of the study is that the average age of founders of companies hiring at least one person is 42 years at the time of starting the company. Furthermore, the average age increases to 45 years for companies with the top 0.1% highest employee growth rate. In terms of company success predictability, Azoulay et al. (2020) finds that there is an increased likelihood of achieving the top 0.1% growth rate or a successful exit up to 60 years of founder age. An explanation behind the correlation between age and high-growth start-ups could be a significant impact of industry experience. Moreover, a relation was found between prior salaries and start-up success, more specifically that the most successful entrepreneurs typically have had high prior salaries. This is explained partly by skills, and partly due to the higher barriers of entry resulting from higher opportunity costs meaning worse ideas never get tested (Azoulay et al., 2020).

Dai et al. (2019) investigate how gender and functional diversity is related to innovation of new ventures in traditionally male-dominated industries. In the study, innovation performance is defined as the internally perceived newness of the offered products/services, the speed of development and the number of introduced products/services to the market. The main finding is a positive and significant relation between gender diversity, functional diversity, and innovation performance. A possible explanation behind the results is a difference in cognitive approach to opportunity identification between males and females (DeTienne & Chandler, 2007). Furthermore, Dai et al. (2019) explain that the relation between gender diversity and innovation performance is not linear. The reasoning behind this is that a greater presence of females allows other female employees to express their perspectives in innovation management, something that in turn increases the innovation performance of the firm.

Considering behavioural diversity, Fuel et al. (2021) investigate the behavioural diversity of the team using a DISC analysis and how different combinations affect the performance of the venture. A total of 245 entrepreneurs from 109 companies where surveyed for both personal, team, and company information. This included questions about socio-demographics, motivation, team members' respective competencies, and venture performance. The questionnaire also included a DISC assessment used for categorising behavioural types. The findings include that the dominance dimension (D) of the DISC assessment was more present in successful start-ups than unsuccessful ones. This means that teams with a general orientation towards results and risk taking historically have performed better. The authors mention that the dominance still requires complementary profiles to form a high performing team. According to the study, a good complement to the dominance dimension is steadiness (S) as the team would be competitive and socially balanced. Assessing teams only with steadiness profiles, no major impact on the performance was found. According to the study, the conscientiousness dimension (C) could be counterproductive for the venture as an excessive attention to detail could reduce the pace of expansion. However, the authors comes to conclude that a certain degree of conscientiousness could benefit the firm (Fuel et al., 2021).

Mueller et al. (2017) analyse the relationship between developer passion, self-regulatory mode, grit, and venture performance. The findings include a positive and significant relationship between grit, the "perseverance toward long-term goals", and venture performance. The relation is explained by the entrepreneur's ability to consistently and passionately work towards long-term goals whilst the entrepreneur with less grit would get discouraged by setbacks and challenges (Duckworth et al., 2007). Furthermore, Mueller et al. (2017) finds a positive relationship between the self-regulatory mode locomotion and grit, that is, the focus on achieving goals and moving forward. The self-regulatory assessment, the focus on reflection and evaluation of possible pathways and goals, was found to be negatively related to grit.

Regarding the team size, multiple studies finds there is a homogeneous, positive and significant correlation between venture performance and management team size (Lechler, 2001; Song et al., 2007). This is supported empirically by Miloud et al. (2012) claiming new ventures founded by a team of founders achieve higher valuations than those with one founder. Furthermore, Miloud et al. (2012) support claims by Roure and Keeley (1990) that having a complete and balanced team are of high importance for new venture valuations. More specifically that teams with filled key positions such as CEO, VP of sales and VP of engineering, have a higher likelihood of receiving funding at higher valuations and achieving higher growth.

Abebe et al. (2020) is presenting a meta-analysis of the effects on firm performance of having a founder CEO versus a non-founder CEO. According to the analysis, existing empirical evidence is inconsistent. A number of studies concludes a positive relationship between having a founder CEO and firm performance. The main supportive arguments are that founder CEOs' often are more highly motivated in their position due to their unique relationship to the firm. This is partly due to the firm being the person's life achievement but also due to a likely significant equity ownership in the firm. Furthermore, a founder CEO usually have significant industry- and firm-specific knowledge and skills acquired throughout the the life of the company (Abebe et al., 2020).

On the contrary, some research argues that the performance of non-founder CEOs could be valuable for the firm, especially in firms which recently experienced excessive growth. The rationale is that companies in these scenarios could outpace the capabilities of their CEO therefore requiring professional CEOs with experience leading larger companies. Another argument is that non-founder CEOs can bring in new and objective perspectives to the company (Abebe et al., 2020).

2.2 Academic Experience

Colombo and Grilli (2005) investigate the effects of founders' human capital when growing new technology-based ventures. The study finds that the total years of education has a positive and significant relation to the likelihood of raising capital. However, there is no significant relation between total years of education and venture growth. When breaking down the metric, the study concluded a positive significant relation between education in economics and managerial fields and venture growth, which also applies for technical and scientific education but to a lesser extent. Connected to the total years of education, Hsu (2007) found a negative correlation between founders with a PhD and receiving VC funding in established industries and a positive correlation in emerging industries. This is explained respectively by the personal characteristics of the average PhD recipients and the signaling of the degree (Hsu, 2007).

Following this research, Kalyanasundaram et al. (2021) finds that higher levels of education within the team contribute positively to the probability of survival. The reasoning behind the result is that higher levels of education support technology creation and diffusion as well as indicating a higher level of maturity resulting in the team being better prepared for excessive challenges.

Sunesson (2009) evaluate the probability of investment, acquisition and IPO based on whether the entrepreneur and venture capitalist have a shared academic background or not. The findings show that there is a 57% increased likelihood of an investment taking place when the entrepreneur and venture capitalist attended the same academic institution. This effect is especially strong for smaller and younger VC firms and for non-Ivy League universities. Furthermore, it is shown there is a 42% increase in the likelihood of reaching an acquisition or IPO when the entrepreneur and venture capitalist attended the same top three academic institution. The reasoning behind the results is grounded in information asymmetry. The author claims that the fear of information gaps prevents potentially profitable transactions and that shared social networks, such as having attended the same education, reduce this fear. With a reduced information asymmetry, more efficient capital allocation can be achieved (Sunesson, 2009).

In a study of the founding team composition and early stage performance of university spin-offs, Visintin and Pittino (2014) utilise the data from 103 start-ups in Italy. The study reports that integrated differentiation within the founding team between academic and non-academic members have a positive effect on growth. The reasoning behind this is that the university spin-offs often are based on emerging scientific research and therefore are exposed to the scientific-technological uncertainties but still requires business skills for commercialisation. To cover both areas, both research and business profiles are needed. Furthermore, the profiles are considered highly complementary as academics due to their educational specialisation often lack business skills and seldom belong to relevant business and finance social networks (Visintin & Pittino, 2014). This finding is in line with Roininen and Ylinenpää (2009) which concludes ventures spinning off from academia often utilises a technology-push requiring change in consumer behaviour while non-academic based start-ups rather employ a market-pull strategy where existing market opportunities are identified and satisfied. Visintin and Pittino (2014) also concludes that differentiated teams can generate destructive separation effects which highlight an importance of efficient integration between team members with different profiles. This means that heterogeneity is beneficial to the extent that it brings new perspectives to the decisions by stimulating healthy debate, encourage learning, and support problem solving. The likelihood of achieving an efficient integration and create productive collaboration between team members of different background is higher in smaller teams due to the higher degree of interactions between team members (Visintin & Pittino, 2014).

The conclusions around education heterogeneity are also concluded to hold in new ventures independent on being university spin-offs or not. In a study by Amason et al. (2006), empirical evidence shows a negative relationship between education heterogeneity and firm performance. The reasoning is similar to that of Visintin and Pittino (2014), that homogeneous teams will be more well integrated resulting in valuable informal and frequent discussions. The study furthermore admits there might be benefits of heterogeneity in the team but suggests the costs may outweigh the benefits, especially in novel, new ventures requiring a high level of integration and close interaction (Amason et al., 2006). Schjoedt and Kraus (2009) concludes efficient teams to have heterogeneity in human capital such as experience, knowledge and skills while being homogeneous in their ways of working to enable efficient and agile operations.

2.3 Professional Experience

Spanjer et al. (2017) examine the relation between skill set diversity and entrepreneurial performance. The main finding is that there is a positive relation between diversity in experience and entrepreneurial performance, in line with Dai et al. (2019). The study also finds that experience deteriorates over time resulting in older experience relating to decreased entrepreneurial performance while recent experience increases performance. This is explained by entrepreneurs with a less recent variety of experience potentially having outdated information or an inaccurate memory from the experience leading to incorrect conclusions. The relation between skill set diversity and entrepreneurial performance is in line with Lazear (2005) theory that entrepreneurs must be ”jacks-of-all-trades” rather than specialists in one specific area. The reasoning behind this is that the entrepreneur, rather than conducting the specialised work, must be able to spot and combine skills to drive successful operational and recruiting efforts. These findings are supported by Carpenter and Fredrickson (2001) which investigate top management teams of major US industrial companies and their diversity's impact on global expansion. Even though the study only concerns major US industrial companies, the findings are of long-term relevance also for smaller firms and newly started ventures. The main findings are that heterogeneity in international work experience, education and firm tenure has a positive and significant relation to global expansion whilst functional heterogeneity has a negative. The presented explanation for this is that functional heterogeneity could reduce the cohesiveness of the team and increase the degree of disagreement. This could in turn result in a more defensive expansion strategy and difficulties reaching agreements and a common commitment for global expansion (Carpenter & Fredrickson, 2001).

Even though skill set variety has been shown to improve venture performance, related industry experience has been shown to increase the likelihood of success (Azoulay et al., 2020; Colombo & Grilli, 2005; Kalyanasundaram et al., 2021; Miloud et al., 2012; Siegel et al., 1993; Song et al., 2007) and that the entrepreneur achieves or exceeds their own expectations (Cassar, 2014). Beyond the obvious reasons, Cassar (2014) explains this to be due to superior forecasting abilities that comes with industry experience. On the other hand, Marino and Noble (1997) finds no empirical evidence that industry experience impact venture growth therefore challenging the current research consensus.

Additionally, Marino and Noble (1997) finds no empirical evidence that prior start-up experience significantly impact venture growth. However, Colombo and Grilli (2005), Gompers et al. (2008), and Miloud et al. (2012) finds performance persistence in entrepreneurship showing that teams with prior founding experience have a significantly higher probability to succeed in subsequent ventures, especially when the previously founded companies have been successful. The explanation behind the results is split down into two factors; (1) market timing skill, and (2) entrepreneurial management skills. The research concludes the market timing skill is the most significant indicator of performance persistence and that there is no relation between managerial skills and market timing abilities. Another possible explanation is the perception of performance persistence, both by venture capital firms and potential customers. Given this perceptions, VCs are more likely to fund serial entrepreneurs, and customers and incumbent firms are more likely to collaborate or purchase goods and services from entrepreneurs with a track record (Gompers et al., 2008).

Part of these findings are supported and complemented by Hsu (2007) which investigate the relationship between valuation of start-ups, funding likelihood and prior founding experience. The study found that entrepreneurial teams with a higher degree of experience starting companies achieve higher company valuations. The impact is especially significant for entrepreneurs previously starting successful companies, something that resulted in a 39% higher pre-money valuation compared to entrepreneurs failing in their prior ventures. Furthermore, the study finds that previous founding experience lead to an increased likelihood of receiving funding from direct social ties to venture capitalists and that they rely more on their own network when recruiting executives than on the network of the VC-firm (Hsu, 2007).

Kirschenhofer and Lechner (2012) supports the findings of performance persistence in entrepreneurship in their study about performance drivers of serial entrepreneurs. In addition to what was presented in previously mentioned research, Kirschenhofer and Lechner (2012) reasons that the performance persists also due to experienced entrepreneurs' ability to build effective diverse teams. On the contrary of performance persistence, they find that repeated partnership, i.e founding a company with people the entrepreneur previously worked with, is detrimental to start-up performance. The reasoning behind these findings is that previous partners might be brought into the team for other reasons than being a good fit with the industry and overall company goals. Groups working together for longer amounts of time also have a tendency to form similar opinions and think as a group which creates a more homogeneous team. This will in turn lead to less questioning and worse discussions (Kirschenhofer & Lechner, 2012).

Evaluating management skills' impact on the probability of new ventures' probability of receiving funding at high valuations, Miloud et al. (2012) and Beckman et al. (2007) finds that start-ups where the founding team has previous top management experience has a higher probability of raising funds, receive higher valuations, and achieve an IPO. Gimeno et al. (1997) supports this claiming prior management experience is also positively related to new ventures' economic performance. General human capital, such as management skills, is however related to a higher threshold of expected performance which in turn could lead to entrepreneurs switching to other opportunities. This is explained by the wider knowledge and the broader number of outside opportunities (Gimeno et al., 1997).

Gimeno et al. (1997) also address the affect of the number of prior employments on new venture performance and likelihood of leaving the venture. It is presented that entrepreneurs with few prior jobs have lower general human capital due to less experience. However, a large number of prior jobs might also signal lower general human capital with the reasoning that the person frequently have switched jobs due to insufficient performance. Furthermore, entrepreneurs with more prior jobs might be less willing to tolerate low performance and therefore show a lower degree of grit and a higher likelihood of exiting the venture when things don't go as planned. The study found that two to four prior jobs are optimal for maximising general human capital and reduce the risk of quitting (Gimeno et al., 1997).

Regarding common team experience, Roure and Keeley (1990) finds a positive, but not with major significance, relation between venture success and having prior joint experience within the team. In the study, prior joint experience is defined as having worked in the same organisation for at least six months. Additionally, Roure and Keeley (1990) finds that areas in which the team might be weak in can be offset by strengths in another, at least concerning the three areas management, industry, and strategy.

3 Method

To enable a rigorous quantitative analysis of how different attributes of founder and executive teams impact the predicted probability of start-up success, the entire process from feature engineering and data sourcing to machine learning model implementation and evaluation will be conducted. All analysis will be conducted in `Python` (Van Rossum & Drake, 2009), using mainly the `pandas`, `numpy` and `scikit-learn` packages. Below the entire 11-step process is covered.

3.1 Research Philosophy

The research is grounded in a post-positivist worldview where the world is considered to only be possible to observe imperfectly (Creswell, 2009). The reason for a post-positivist worldview in this study is its suitability in quantitative studies and that the data used only gives us insights into the attributes covered by the data (Creswell, 2009). Because of this and to increase the objectivity of the results, there will be a focus on presenting potential biases and their effects as well as perspectives on validity and reliability. Aligned with the post-positivist worldview, data and logical considerations will be used to reach objective results and form conclusions (Creswell, 2009). The body of the research has an inductive approach using real world observations as a base to find patterns and to form a theory. This means that the source data will drive the results entirely without being influenced by existing research or hypotheses formed by the researcher (Azungah, 2018). There will also be a deductive component based on existing research with the purpose of undermining or further strengthening current theories. This deductive component will further strengthen the validity of the research by highlighting potential biases and alternative explanations where the results are not in line with existing research (Creswell, 2009). This will be conducted quantitatively by analysing data, but also include a qualitative element where existing research (both quantitative and qualitative) will be considered and compared to the quantitative results.

3.2 Feature Engineering

The feature engineering will be conducted with an iterative approach. The initial iteration will only be based on the previous knowledge of the author and conducted unstructured as a brainstorming. The reasoning behind this approach is to avoid bias from existing literature on the topic. In further iterations, existing literature will be considered and experts consulted to ensure maximum coverage. Throughout the project, especially in the model performance evaluation and improvement phase, the features will be revisited and evaluated based on their marginal impact on the predictions.

3.3 Data Sourcing

Data-driven venture success prediction, in a productionalised environment, is highly dependent on the data available to semi- or fully-programmatically fetch. Considering the broad coverage and ease of access to Crunchbase data, this will be used as the primary venture and team information source for this study. Table 1 presents all sources from which data is fetched. Based on the literature review, Crunchbase is the most widely used database for data-driven start-up evaluation due to the company coverage and number of data points (Arroyo et al., 2019; Corea et al., 2021; Glupker et al., 2019; Gupta et al., 2015; Krishna et al., 2016; Ross et al., 2021). It is also concluded in Retterath and Braun (2020) that Crunchbase together with Pitchbook and VentureSource[1] are the most extensive company databases for information about the company, founders, and funding rounds. At the time

[1] Acquired by CB Insights 2020 (CB Insights, 2020)

Table 1: Data sources.

Data sources	Description	Included data
Crunchbase	Person and company database	• Basic company information • Person background • Funding round data • Acquisitions and IPOs
QS University World Ranking	University and ranking database	• University ranking per subject
Fortune Global 500	Ordered list of the 500 largest companies based on revenue	• Company ranking based on revenue
Fortune most admired companies	Ordered list of the 333 most admired companies to work for	• Company ranking based on prestige
Forbes most valuable brands	Ordered list of the 100 most valuable brands	• Company ranking based on brand value

of the study, Crunchbase was considered the second best database for founder information, that includes coverage, education accuracy and completeness accuracy.

The final data used for the analysis is including companies started between 2007-05-29 and 2017-05-11 and fetched from Crunchbase 2022-01-24.

3.4 Data Pre-Processing

Four steps are essential to the data-preprocessing: removing look-ahead bias, selecting a subset of ventures based on founding date, extracting ventures from relevant industries and geographies, and only extracting features for venture executives and founders.

Firstly, the look-ahead bias is reduced. Only information before a pre-determined date, henceforth referred to as the cutoff-date, is extracted for each venture. The cutoff date represents the point in time at which the venture capitalist would have evaluated the start-up. For instance, consider Apple which was founded in 1976 and assume the venture capitalist to be an early-stage investor. The investor would have most likely considered an investment in Apple a period after its founding date, say at the end of 1977. The cutoff date is therefore set to 1997-12-31, and only information available at 1997-12-31 is considered as input to the prediction model in the model development. Without the cutoff date, current information about the company would be considered, information that the venture capitalist would not have access to at the time of making an investment decision.

Here, the date will be set to be two months before the date of the company's seed round being announced. If the organisation did not raise a seed round, the date will be assigned to be the 80th percentile of the number of days before raising seed, calculated based on how many days it took for past companies to raise a seed round.

Secondly, only a subset of ventures were extracted from the Crunchbase dataset. Two filters were applied. First, only ventures founded after the initiation of the Crunchbase dataset were considered. It is feasible that the data coverage and data reliability is low for the companies founded before the Crunchbase database was created. Therefore, to reduce the bias in the sample, those ventures where completely removed. Second, only ventures founded before the date 2022-05-05 minus five years were considered. The rationale is to ensure that all ventures in the sample will have had time to mature.

Thirdly, only European ventures within the technology space were considered.

Fourthly, only characteristics of founders and executives for each start-up will be calculated. The rationale for doing so is two-fold. First of all, most members at a start-up, especially early-stage start-ups targeted in this study, will be attributed an executive role. Therefore, the study cover characteristics of the majority of the team. Second of all, the characteristics of the founding and executive team is presumably the most influential in determining the success of the venture on a short- to mid-term basis - again, especially in early-stage start-ups, considering that it is the founding and executive team that makes the strategic decisions (Hambrick & Mason, 1984).

The definition of an executive is that the person is either tagged as an executive in Crunchbase or that the person is considered to have a leadership role. The leadership roles considered were C-suite executives, presidents, and vice presidents.

3.5 Feature Calculation

Features are grouped in three main categories: demographics, academic experience, and professional experiences (Schjoedt & Kraus, 2009). Demographics variables include gender and age, academic experiences include for example the number of unique subjects in their education (for example applied mathematics and physics), and professional experience include variables such as the number of industries that the person has worked in.

The calculation is conducted in two steps. Firstly, the variables will be calculated on an individual level. For instance, It will be determined whether or not the person is a serial entrepreneur, defined as whether the person has founded companies previous to the current one. The variables calculated on an individual level will in turn be utilised to calculate features on a team level. Team-level metrics include for instance the number of serial entrepreneurs in the founding team. The team-level metrics will be calculated for the founder, and executive teams separately (See section 3.4). That is, the number of serial entrepreneurs in the executive team and the number of serial entrepreneurs in the founding team will be used as separate features.

3.6 Descriptive Analysis

The pre-processing of the data and the selection of the machine learning model is highly dependent on the features and the nature of the data. Therefore, an exploratory data analysis will be conducted and used to optimise data pre-processing and model selection. In practice, this will include an exploratory analysis of the sparsity and distribution of the individual features as well as correlations between them.

3.7 Target Extraction & Definition of Success

The end target for an investor in VC is a major exit, either through acquisition or IPO. However, as there is only a very low number of ventures achieving a major exit, the target will be significantly imbalanced. Due to the sparsity of major exits, we will instead evaluate the models ability to predict whether or not a venture will reach a post-seed investment. Reaching a post-seed investment can be seen as a proxy as to whether or not the company will be "successful", especially for investors focusing on early-stage start-up investments (pre-seed and seed investments). It is, however, important for the venture capitalist that the start-up is able to raise a post-seed investment within a reasonable amount of time from the founding date, partly due to the fund duration and partly because it shows the continued momentum and growth of the start-up. Therefore, the post-seed investment is constrained to have to happen within five years from the founding date of the venture. The rationale of choosing five years is based on the the 80th percentile of the time it takes for a venture to raise a seed investment, plus a reasonable amount of time from a seed investment to a series A investment round.

3.8 Pre-Processing

Many of the variables considered will suffer from significant sparsity. Therefore, as a final preparation, the variables with more than 90% missing values will be dropped from the feature set.

Furthermore, even when using post-seed investment within five years, there is a significant class imbalance in the dependent variable. Therefore, random under-sampling in combination with the Synthetic Minority Oversampling TEchnique (SMOTE) will be utilised. The rationale for conducting random under-sampling in combination with SMOTE is that, in the original paper, the combination was shown to perform better than solely using SMOTE (Chawla et al., 2002).

3.9 Modelling

The machine learning models and associated pipeline/s will be selected based on the features, exploratory data analysis and target. The model that will be used is the Gradient Boosting Machines algorithm LightGBM due to its superior performance predicting start-up success (Retterath, 2020b).

3.10 Model Evaluation

The performance of the model will be evaluated using cross-validation where a number of metrics could be used. Such metrics include precision, recall and AUC-ROC. Precision represents the potential cost savings the VC-firm could make when employing the algorithm by reducing the amount of time analysts have to spend evaluating ventures with low potential for future success. Recall is representing a the likelihood of missing out on potentially successful deals and will be of higher focus due to the nature of venture capital and the search for unicorns. Recall is defined as,

$$\begin{aligned}\text{Recall} &= \frac{\text{True positives } (TP)}{\text{True positives } (TP) + \text{False Negatives } (FN)} \\ &= \frac{\text{"Predicted Series A" and "Reached Series A"}}{\text{"Predicted Series A" and "Reached Series A"} + \text{"Predicted flop" and "Reached Series A"}}\end{aligned}$$

As there is only a limited amount of potential unicorns and as VC-firms only look for companies with the potential to return the entire fund, the model can not risk turning down potentially highly successful ventures. That is, the model should predict a low number of FP's and that recall therefore will be used.

3.11 Cross-validation & Hyper-Parameter Tuning

The dataset is initially split into two partitions, one training and one holdout partition. The model is developed on the training partition whereas the testing of its performance is conducted on the holdout partition. To develop the model, the optimal hyper-parameters for the model will be determined empirically using the `Optuna` package. Using the best performing setting of hyper-parameters, the model will be re-trained on the full training partition. Finally, the performance of the model will be recorded on the holdout partition.

3.12 Feature Importance Calculation

The feature importance is calculated using the package SHAP (Shapley Additive exPlanations) utilising Shapley values explained in Lundberg et al. (2017).

Shapley values is a method based on coalition game theory that can be used for explaining individual machine learning predictions. This is accomplished by breaking down the overall prediction into how much each feature contributed to the value of the prediction. A feature's Shapley value is calculated by making the model prediction using all possible permutations of feature sets and then calculating the average difference in the prediction when the feature is in the set and when it is not. This means that the greater a feature's impact on the prediction, the larger its Shapley value is, and that negative Shapley values represent a reduction in the predicted value and the positive Shapley values an increase (Molnar, 2022).

The main benefits of using Shapley values for the individual prediction feature influence is that it satisfies the following four properties and therefore can be considered fair and fully explainable:

- Efficiency: The sum of all features' Shapley values equals the difference between the predicted value and the expected value with no known information (often average value)
- Symmetry: Two features' Shapley values are the same if they contribute the same to the overall prediction in all possible feature coalitions
- Dummy: Features with no marginal contribution to the overall prediction has Shapley value zero
- Additivity: The sum of Shapley values of feature sub-sets equals the Shapley values for the whole feature set

The main drawback of the method is that it does not build a prediction model explaining how changes in the feature values would affect the prediction. Another drawback of using Shapley values is that the complexity scales exponentially with the number of features meaning exact values seldom can be calculated in practice. To overcome this, various sampling methods or approximations are applied in practical implementations (Molnar, 2022).

Due to the minor relevance of the difference between Shapley and SHAP values in this paper, the two can be interpreted as synonymous.

3.13 Validity & Reliability

Considering the validity of the findings, the most significant factors are the data quality and the method used to calculate the attributes' impact on the predicted probability of success. The data can be evaluated from perspectives of coverage and quality, meaning how large part is covered of all companies and information about them, and how accurate the available information is. As presented in 3.3 Data Sourcing, the primary data source for this study is Crunchbase. As also presented, Retterath and Braun (2020) concludes Crunchbase to be the second most extensive company database in terms of coverage and quality of founder information. To take precautions against lacking data quality and avoid look ahead bias, only companies founded within Crunchbase's existence are considered in this study, as described in 3.4 Data Pre-Processing.

On the other hand, the dataset could indirectly be biased. A successful start-up is in this study defined as one that has received follow on funding, as the decision whether to invest in a particular start-up or not is affected by bias, the success metric is by nature biased. However, as the success metric of receiving follow on funding is related to other start-up success metrics and widely used in other research, the used definition of success is considered the least biased and most accurate one.

Considering the method used to calculate the attributes' impact on the predicted probability of success, namely Shapley values, the validity is considered high. The concept used Shapley values earned Lloyd Shapley a Nobel prize in economic sciences and is now considered an established method for feature importance (Molnar, 2022; NobelPrize.org, 2022).

Considering the reliability of the study, the most significant factors are the data and the machine learning model implementation and optimisation. As the data sources are well described under 3.3 Data Sourcing, the data can be fetched retroactively given that the data is stored by Crunchbase. The data pre-processing and model implementation is also described in the method but minor details not included in the report could result in slight differences to the end result when trying to replicating the study. The most difficult part to exactly replicate will be the hyperparameter-tuning as it includes a random factor to it. Despite that it might be difficult to exactly replicate the environment in which the analysis was made, it should be fairly straight forward to arrive at the conclusions presented in this report.

4 Results

Table 2 reports the final features used for evaluating the most influential team attributes when predicting start-up success. The final dataset included a total of 25430 companies evaluated on 58 variables.

The results of the study are divided into three parts. Part one, 4.1 Global Feature Importance, presents the features with highest mean Shapley values meaning the team characteristics mostly influential for predicting company success. Part two, 4.2 Feature Value Impact on Prediction, presents the impact different feature values have on the predicted probability of success. Part three, 4.3 Prediction Specific Feature Importance, presents the feature value impact on specific predictions. Most results are measured in SHAP values which can be interpreted as follows:

- The larger the SHAP value, the greater the impact on the predicted probability of receiving follow on funding
- Positive SHAP values increase the predicted probability of raising follow on funding
- Negative SHAP values decrease the predicted probability of raising follow on funding

Table 2: Final features and their summary statistics.

		Missing	Overall
n			25430
age_at_started_on_mean_founders, mean (SD)		21476	31.6 (8.0)
age_at_cutoff_mean_founders, mean (SD)		21476	33.4 (8.1)
fraction_missing_gender_founders, mean (SD)		7625	0.0 (0.1)
fraction_female_founders, mean (SD)		7625	0.1 (0.3)
fraction_male_founders, mean (SD)		7625	0.9 (0.3)
fraction_other_founders, mean (SD)		7625	0.0 (0.0)
age_at_started_on_mean_executives, mean (SD)		19586	32.4 (8.4)
age_at_started_on_std_executives, mean (SD)		19586	0.0 (0.0)
age_at_cutoff_mean_executives, mean (SD)		19586	34.2 (8.5)
age_at_cutoff_std_executives, mean (SD)		19586	0.0 (0.0)
fraction_missing_gender_executives, mean (SD)		77	0.0 (0.1)
fraction_female_executives, mean (SD)		77	0.1 (0.3)
fraction_male_executives, mean (SD)		77	0.9 (0.3)
fraction_other_executives, mean (SD)		77	0.0 (0.1)
founder_is_ceo, n (%)	False	12546	3570 (27.7)
	True		9314 (72.3)
founder_left_company, n (%)	True	0	351 (1.4)
	missing		25079 (98.6)
tech_roles_count, mean (SD)		20201	1.1 (0.3)
business_roles_count, mean (SD)		6530	1.3 (0.8)
other_roles_count, mean (SD)		15774	1.3 (0.6)
fraction_tech_roles, mean (SD)		20201	0.5 (0.3)
fraction_business_roles, mean (SD)		6530	0.8 (0.3)
executives_count, mean (SD)		895	1.6 (1.1)
founders_count, mean (SD)		895	1.0 (0.9)
team_founders_in_executives, mean (SD)		895	0.6 (0.4)
individual_location_count_mean_founders, mean (SD)		19907	0.7 (0.7)
individual_industry_count_mean_founders, mean (SD)		21861	3.4 (2.2)
individual_startup_founder_count_mean_founders, mean (SD)		22526	1.4 (0.9)
individual_startup_founder_duration_sum_mean_founders, mean (SD)		22526	2145.2 (2546.2)
individual_startup_founder_duration_max_mean_founders, mean (SD)		22526	1715.3 (1578.5)
individual_startup_founder_duration_max_max_founders, mean (SD)		22526	1776.1 (1661.4)
individual_startup_founder_raised_amount_sum_mean_founders, mean (SD)		22526	263635.4 (9453796.4)
individual_startup_founder_raised_amount_sum_max_founders, mean (SD)		22526	267689.8 (9457556.1)
individual_startup_founder_funding_round_sum_mean_founders, mean (SD)		22526	0.0 (0.2)
individual_startup_founder_funding_round_sum_max_founders, mean (SD)		22526	0.0 (0.2)
individual_startup_founder_exit_valuation_sum_mean_founders, mean (SD)		22526	55744937.1 (1057412832.8)
individual_corporate_executive_count_mean_founders, mean (SD)		22710	1.4 (0.9)
individual_corporate_executive_duration_sum_mean_founders, mean (SD)		22710	2499.7 (2654.1)
individual_corporate_executive_duration_sum_max_founders, mean (SD)		22710	2612.6 (2825.8)
individual_corporate_executive_duration_mean_mean_founders, mean (SD)		22710	1779.3 (1653.4)
individual_corporate_executive_duration_mean_max_founders, mean (SD)		22710	1841.4 (1712.2)
individual_corporate_business_position_count_mean_founders, mean (SD)		22819	1.6 (1.2)
individual_corporate_business_position_duration_sum_mean_founders, mean (SD)		22819	2398.2 (2801.2)
individual_corporate_business_position_duration_sum_max_founders, mean (SD)		22819	2502.3 (2959.4)
individual_location_count_mean_executives, mean (SD)		21970	0.7 (0.7)
institution_name_nunique_founders, mean (SD)		18006	1.6 (1.1)
institution_name_count_founders, mean (SD)		18006	1.7 (1.3)
subject_aggregated_nunique_founders, mean (SD)		18006	1.3 (0.6)
degree_type_aggregated_nunique_founders, mean (SD)		18006	1.5 (0.9)
degree_type_numeric_mean_founders, mean (SD)		18006	1.3 (0.8)
degree_type_numeric_std_founders, mean (SD)		18006	0.3 (0.5)
degree_type_numeric_max_founders, mean (SD)		18006	1.5 (0.9)
institution_name_nunique_executives, mean (SD)		18006	1.6 (1.1)
institution_name_count_executives, mean (SD)		18006	1.7 (1.3)
subject_aggregated_nunique_executives, mean (SD)		18006	1.3 (0.6)
degree_type_aggregated_nunique_executives, mean (SD)		18006	1.5 (0.9)
degree_type_numeric_mean_executives, mean (SD)		18006	1.3 (0.8)
degree_type_numeric_std_executives, mean (SD)		18006	0.3 (0.5)
degree_type_numeric_max_executives, mean (SD)		18006	1.5 (0.9)
follow_on, n (%)	False	0	23171 (91.1)
	True		2259 (8.9)

4.1 Global Feature Importance

The global feature importance reports the mean absolute SHAP value for each feature over all companies in the dataset and is reported in figure 2. The significantly most impactful features are regarding the number of executives in the team, whether the CEO is also one of the founders, and the fraction of the team members in business roles. Other top 20 most impactful features with research attention include gender diversity (`fraction_male_founders`) and academic experience (`degree_type_numeric_mean_founders`). The variables with the suffix `missing_flag` are indicators for data missing for the original variable and will not be considered in the analysis but presented under 6.3 Limitations.

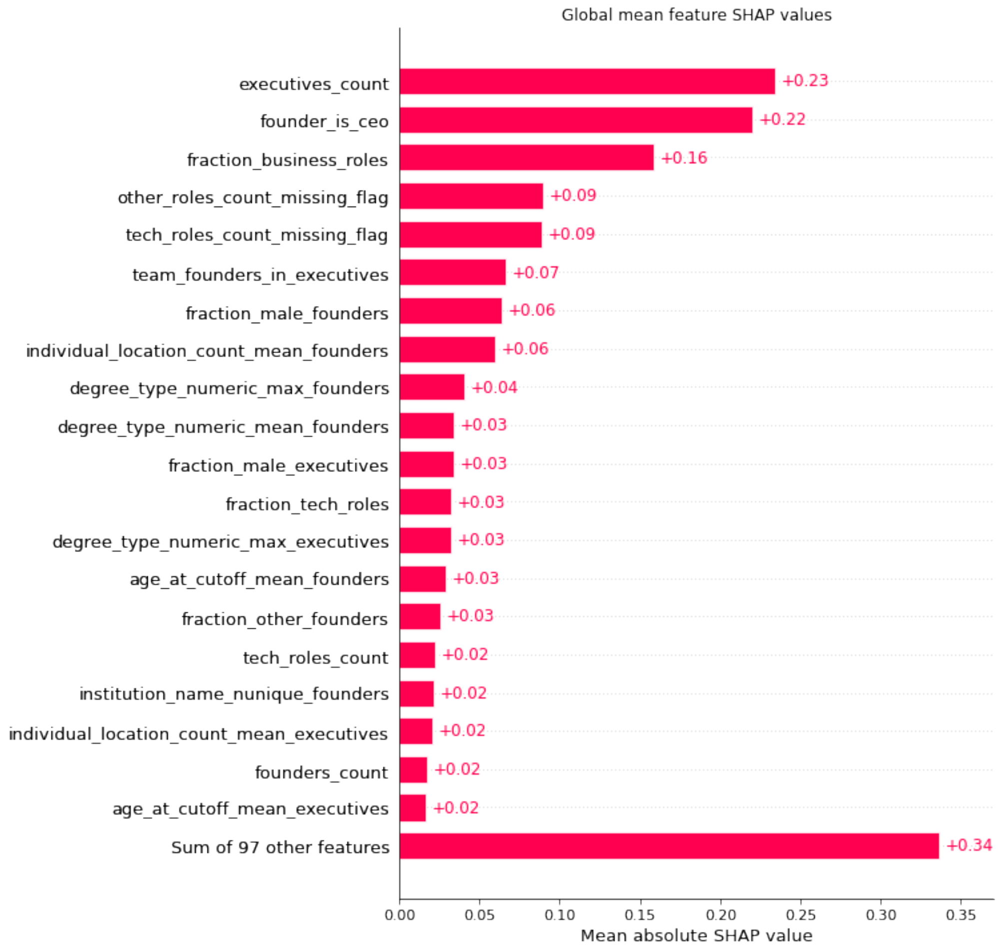

Figure 2: The 20 features with highest mean SHAP Values, and therefore predictive power, in the dataset.

4.2 Feature Value Impact on Prediction

Figures 3 to 8 show the impact on the SHAP values for different feature values. The figures should be interpreted as follows:

- Each dot in the scatter plot represent one company in the dataset
- The light background histogram represents the density of data points
- Negative SHAP values reduce the predicted probability of success and positive SHAP values increase it

Figure 3 shows a significant increase in SHAP value up to three executives and with as stable SHAP value between three and six executives. Beyond that, no significant patterns can be identified due to the low density.

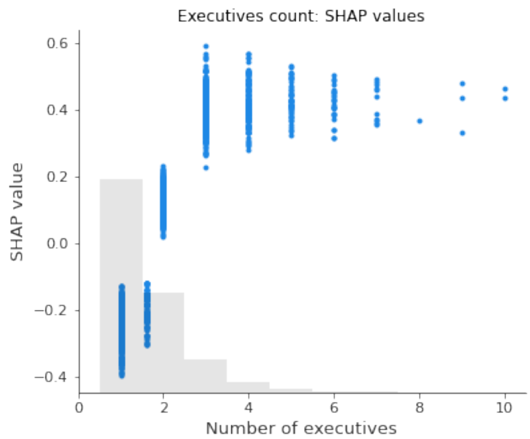

Figure 3: Impact on the SHAP value of the number of executives.

As seen in figure 4, there is a clear difference in SHAP value between teams with a CEO that also is a founder and the teams with an external CEO.

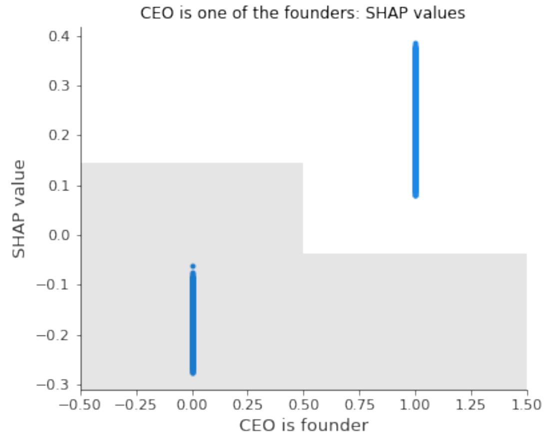

Figure 4: Impact on the SHAP value of whether the CEO also is a founder.

From figure 5, the results show higher SHAP values for teams where up to 75% of the team members have business roles. Teams with higher fraction of business roles is generally considered to negatively impact the probability of success.

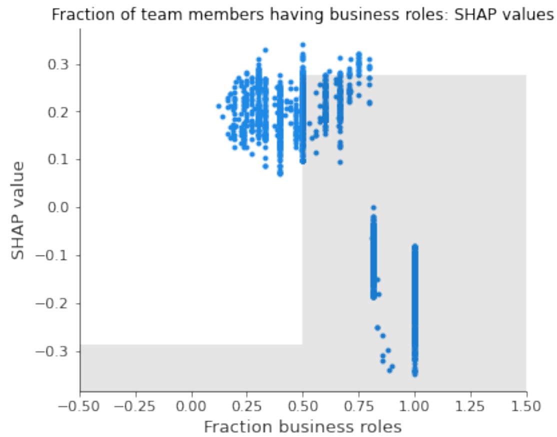

Figure 5: Impact on the SHAP value of fraction of team members with business roles.

Figure 6 shows a peak in SHAP value at 50% founders in the executive team. The highest density is at 100% founders in the team for which the average SHAP value is negative.

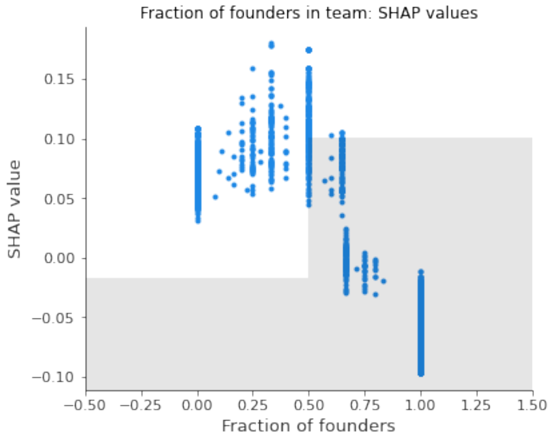

Figure 6: Impact on the SHAP value of fraction of founders in the executive team.

The impact of gender diversity on the predicted probability of success is shown in figure 7 which claims male founding teams has the highest density, SHAP value, and lowest spread.

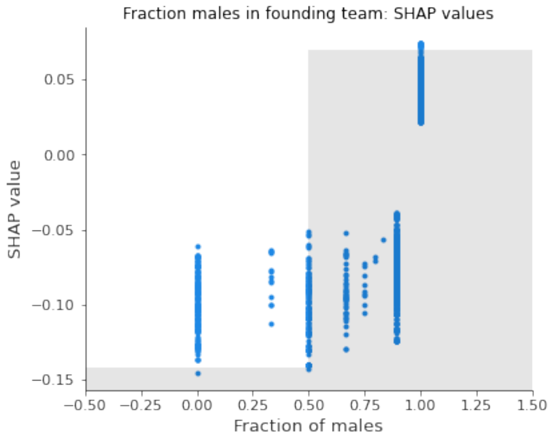

Figure 7: Impact on the SHAP value of the founding teams' fraction of males.

For mean age of executives at the time of starting the company (figure 8), there is an upwards trend in SHAP value and decrease in spread up to 27 years of age after which the SHAP value is slightly decreased until 33. At the age of 33, we see the highest density and lowest spread amongst all ages, as well as a local peak. After the age of 33, the SHAP value remains relatively stable, after which we see an increase in SHAP value and spread up to the age of 48.

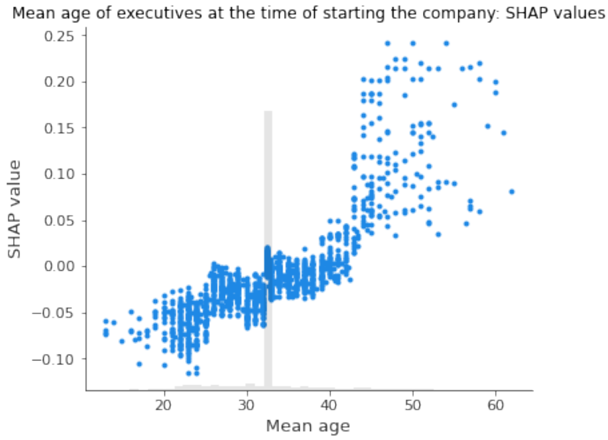

Figure 8: Impact on the SHAP value of the teams members' mean age when starting the company.

4.3 Prediction Specific Feature Importance

In figure 9 and 10, the impact of the feature values is shown on the prediction of certain companies probability of success. Figure 9 shows a company with higher than average predicted probability of success (42% compared to the average of 8%). Key features positively impacting the prediction is the Amount of executives (4), fraction of team members in business roles (75%), that all founders only worked in one country before, and that the CEO also is one of the founders. Figure 10 shows a company with lower than average predicted probability of success (2% compared to the average of 8%). The key features negatively impacting the prediction is that there is a team only consisting of one founder in a business role and that that founder has a bachelor's degree. An attribute positively impacting the predicted probability of success is the age of the founder (36). Figure 11 shows a company with an average predicted probability of success (8%). The most impactful attributes negatively affecting the prediction is the fraction of business roles within the team (100%) and the mean age of the executives at the time of raising seed. The most positively impactful attributes include that the CEO is also one of the founders, the maximum degree of the founders (PhD), and the number of executives (2).

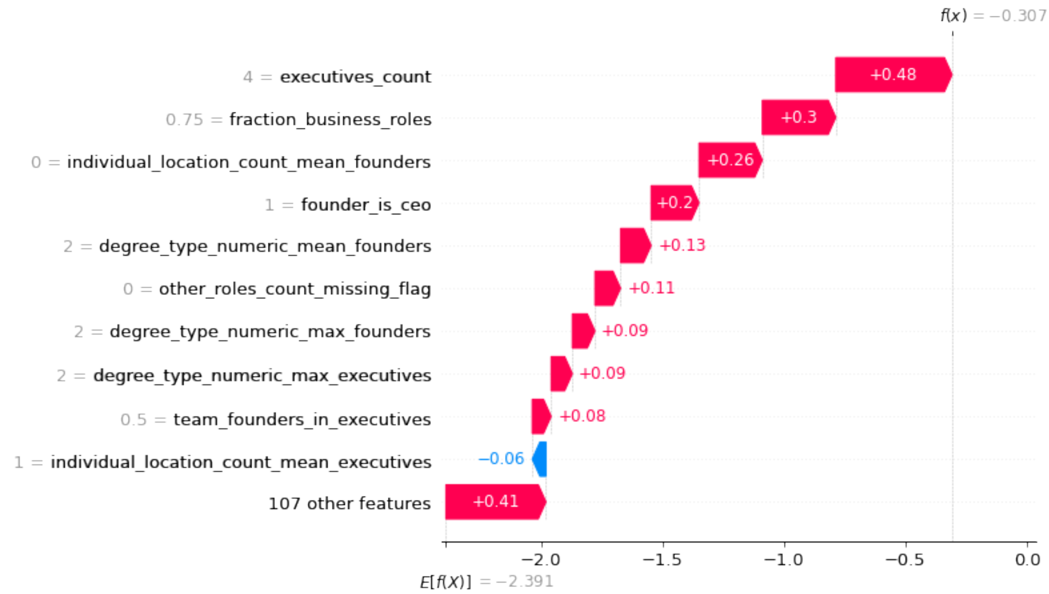

Figure 9: SHAP value per feature for a company from France with an above average predicted probability of success (42%).

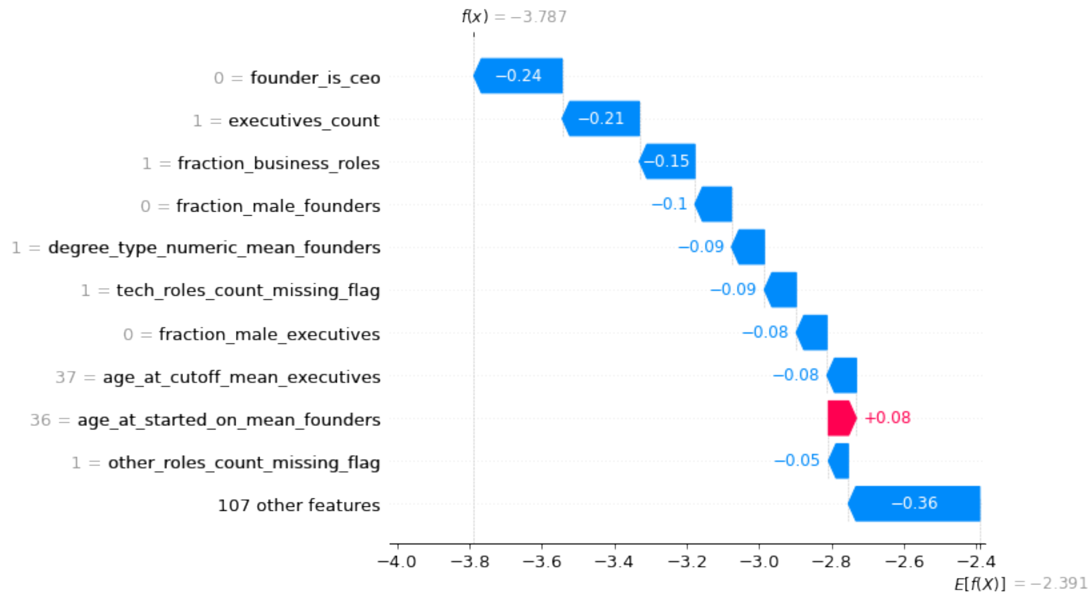

Figure 10: SHAP value per feature for a company from the UK with below average predicted probability of success (2%).

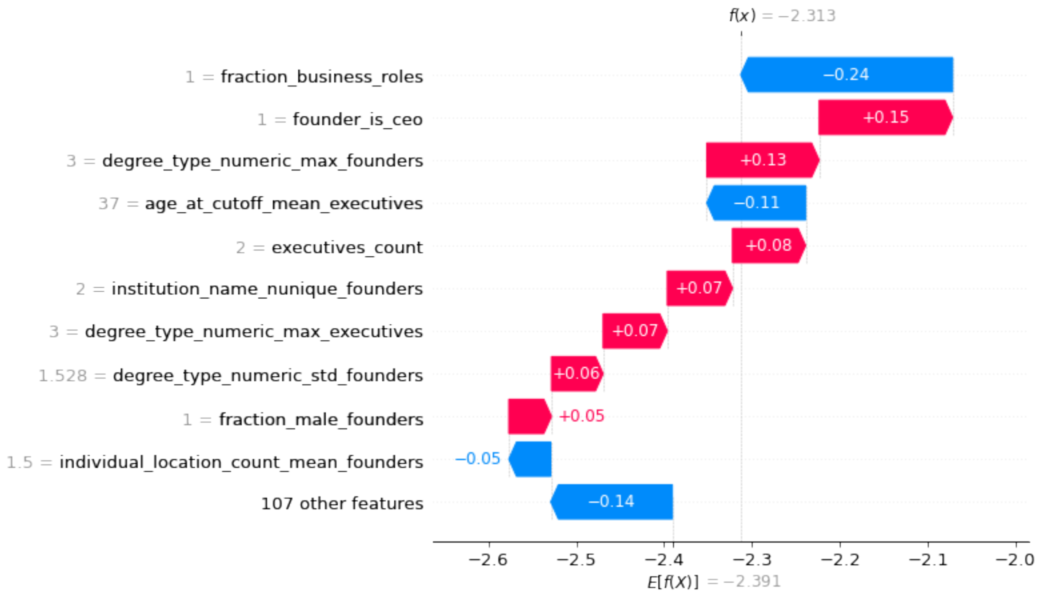

Figure 11: SHAP value per feature for a company from the UK with average predicted probability of success (8%).

5 Discussion

This research investigates which characteristics of a founder and executive team are most influential when predicting start-up success. Given the trend of digitisation in general and specifically within the venture capital industry, there is lack of research on the topic of the most influential team characteristics on new venture performance, especially quantitative research based on large datasets. The following discussion is based on the results of the study and connect it to existing research on the topic. For areas that were not covered in the literature review due to insufficient research, hypotheses will be formed but left for future research to be evaluated.

Executives Count

The study finds that the number of executives in the firm has a comparatively significant impact on the predicted probability of success. Furthermore, the results regarding size of the executive team is in line with Miloud et al. (2012) and Song et al. (2007) showing that single person teams have a significant negative impact on the predicted probability of success whilst teams with three to five members have a significant positive impact (see figure 3).

Team Size

The complementarity of the team members as discussed in Roure and Keeley (1990) is not evaluated in this study. However, given the results regarding team size, a hypothesis can be formed. For larger teams, one can hypothesise a correlation to diversity attributes such regarding gender, educational background, and professional experience. This could in turn foster discussion and increase the number of perspectives considered in strategic decision making. Furthermore, one could argue that small teams (below five members) can achieve higher degrees of agility, something could be beneficial in early stage start-ups. For teams with more than five team members, no hypotheses will be formed due to the small sample size.

Founder CEO

Evaluating the team characteristics of having a founder CEO, the results clearly show a relatively higher influence on the predicted performance than most other team attributes (see figure 2). The results regarding the relationship is also clear where companies with a founder CEO in all cases had a positive effect on the predicted performance (see figure 4). As existing empirical research is inconsistent regarding founder CEOs impact on firm performance and that arguments exists both for and against founder CEOs (Abebe et al., 2020), only an hypothesis can be formed in accordance with the current research setting. In line with the supportive arguments presented in Abebe et al. (2020), a highly motivated and intrinsically driven CEO could be considered being of significant importance in newly started ventures due to the high uncertainty. This intrinsic drive of building a life achievement can be connected to the impact of grit (Mueller et al., 2017) and therefore outweigh the argument in favor of non-founder CEOs. In other words, the objectivity brought in by non-founder CEOs could be a disadvantage for newly started firms as a passion-driven perseverance towards long-term goals might be required to overcome the initial hurdles before success can be achieved (Duckworth et al., 2007). Furthermore, the effect of financial incentives in favour of a founder CEO is most certainly of high significance for the firms in this study due to their early stage (Abebe et al., 2020). That is, a founder CEO would have a significant equity ownership in the firm and therefore financially incentivised whilst direct monetary compensation for a non-founder CEO could be under strict budgetary constraints. The final arguments in favour of a professional CEO regarding the risk of start-ups experiencing excessive growth outpacing the founder CEO's capabilities (Abebe et al., 2020) is of less importance in this study due to its focus on early stage ventures.

Fraction of Team Members in Business Roles

No prior research was found on the part of the executive and founder team being in business roles compared to other roles (technical, marketing, operations, finance, external) and we can therefore only hypothesise the reason behind the results. The results clearly shows a negative impact on the predicted probability of success when the founder and executive team is composed of more than 80% business related roles. There is however no clear patterns between the range of 25-75% business roles. Due to the nature of early stage companies and that business roles in this context are including positions such as CEO, vice president, and partner, it is natural that most teams in the data set have more than 50% of the team being in business positions. It is not surprising that teams are negatively impacted by being entirely consisting of people in business roles due to the decreased functional and skill set diversity compared to more balanced teams (Dai et al., 2019; Spanjer et al., 2017). The findings are also aligned with Visintin and Pittino (2014) regarding product related roles and business related roles complement each other and increase the firm's probability of success.

Fraction Founders

The fraction of founder in the team was considered to be of relatively high importance when predicting the probability of start-up success. The existing research is sparse on this topic but an adoption of the results from Abebe et al. (2020) can be used to form an hypothesis. The basis for such an hypothesis would partly revolve around the industry- and company specific knowledge as well as the high motivation of founders, both intrinsically as creating their life work and in terms of financial compensation tied to the performance of the firm. It is also partly revolved around the value non-founders could provide the firm by balancing the passion of the founders with objectivity and new perspectives (Abebe et al., 2020). Furthermore, a balanced team of both founders and non-founders could indicate a greater diversity in terms of education, professional background, and skills, based on the assumption that founding teams often find each other based on having similar profiles. This increase in diversity would in turn trigger the positive effects described in Spanjer et al. (2017), Dai et al. (2019), and Carpenter and Fredrickson (2001).

Gender Diversity

The findings on the gender diversity in the team is of relatively moderate importance (see figure 2). The findings are not in line with the reviewed literature as there are no explicit indications a more diverse team would perform better than a less diverse team (see figure 7). Furthermore, the non-linearity explained in Dai et al. (2019) is not seen in the results. A reason behind this could be a potential indirect bias in the dataset as discussed under 3.13. This could mean that the model has adapted a bias that has existed in the funding of companies in the dataset which in turn implies there historically could have existed a bias towards funding all male teams.

Executive Team Mean Age

Addressing the results connected to mean age of the executive team, the impact is considered insignificant but considering the trend seen in figure 8, the findings are in line with Azoulay et al. (2020). Reviewing the figure, there are a few patterns that can be seen and hypothesised around beyond what is explained in the literature review. The first one is at the age of 24 where a slight decrease of average SHAP value can be seen. This could be due to graduation from university and hence a decreased attractiveness engaging in entrepreneurial activity for top talents due to alternative employment options within established corporations. The first peak in SHAP value is around the age of 26, an age where one can reason that young professionals have gained their first professional experience. Utilising this experience, the probability of starting a successful company is likely to increase (Azoulay et al., 2020; Gimeno et al., 1997; Miloud et al., 2012). The second peak at age 33, the spread reaches a minimum. After this peak, the SHAP value remains stable until the age of 40. This could be explained by family and relation related activities broadly changing the priorities of entrepreneurs and aspiring entrepreneurs from business to family. Above the age of 40 the sample set is rather small but the general upwards trend could be explained by increased financial and human capital gained from work experience and personal networks (Azoulay et al., 2020). Further hypothesising beyond the literature review, the pattern where stability in SHAP value followed by a rather sudden increase could be caused by children of entrepreneurs and aspiring entrepreneurs reaching an age where they can be more independent and that the entrepreneurs and aspiring entrepreneurs therefore can give more attention to founding companies.

Prediction Specific Feature Importance

Regarding the prediction specific feature importance, figures 9, 10, and 11 demonstrate the difference between the global and local feature importance. That is, the difference between the average absolute impact of the attributes and the specific attribute values' impact on the predicted probability of success for a specific company. For example, the mean degree type amongst founders is rather insignificant on a global level whilst being an important factor in the companies represented by figures 9 and 10. The same goes for the highest degree amongst the founders, this parameter is not of great significance neither on a global level or in the companies represented by figure 9 and 10 but is of great significance in the company represented by figure 11. The reason behind these differences is the interdependence and interaction between the attributes. For example, a more well educated team could be of great benefit in emerging industries but a disadvantage in established (Hsu, 2007).

6 Conclusion

Answering the research question of *which characteristics of a founder and executive team are most influential when predicting start-up success*, this study has taken a quantitative approach analysing 25430 early stage start-ups in Europe. The analysis was conducted on three levels; (1) the mean impact of different team features, (2) the feature value impact on the prediction, and (3) the team feature importance for specific predictions. The three most impactful characteristics were found to be (1) the number of executives in the team, (2) whether the CEO is also one of the founders, and (3) the fraction of the team that are in business roles, indicated by the features' Shapley values. The values of these features are determined to most positively affect the predicted probability of success as follows:

- Number of executives: 3-5
- CEO is one of the founders: Yes
- Fraction of the team in business roles: 25-75%

6.1 Implications For Theory

This research implications on theory is three-fold. Firstly, it uses quantitative methods and large amounts of data to further strengthen the conclusions from existing research. Secondly, the research builds upon the body of knowledge around the most impactful team attributes when predicting early stage start-up success as well as how these values of different team metrics affect the prediction. Thirdly, the findings are derived from data explaining how the predicted probability is affected without explaining why. This means that this study can serve as a base for future quantitative and qualitative research elaborating on the reasons behind the results.

6.2 Implications For Practice

The practical implications can be split up into two dimensions creating four combinations: Direct versus indirect implications and implications for the VC/accelerators or for the start-up. The direct value for venture capital firms and start-up accelerators can be realised by utilising the results from the study in existing deal flow operations. Concretely, this means that the findings can guide investors what team attributes to focus on when evaluating companies as well as how different values on team metrics can affect the probability of achieving follow on funding. This information will enable VC firms and accelerators to reduce bias in their team evaluations by using results from grounded statistical analysis instead of own only experience. Furthermore, the results have the ability to guide entrepreneurs and aspiring entrepreneurs understand important factors in forming an efficient entrepreneurial team and which experienced are most valuable in start-ups. Existing founders can also use the results when hiring new personnel as it provides insights into efficient team compositions such as the balance between business and technical roles. The last practical implication is regarding the digitisation of the VC industry where the results can be seen as the first next step in a larger change towards using data-driven methods for investment decision support.

6.3 Limitations

Most of the limitations of this study are related to the data and the granularity of the results. As the study only evaluates the most influential team characteristics for general start-up success, the study does not consider the different impact of the characteristics in different combinations, industries, and market environments. Furthermore, the findings from the study are reported mostly on an aggregated level meaning they can not be taken as a certainty in all situations. For example, the finding that teams with 100% business roles generally impacted the company's predicted probability of success negatively might be true for the general case but in highly business oriented firms with no technical components, entirely business oriented teams might be of benefit.

In terms of data limitations, the study only use the Crunchbase data for European companies started between 2007-05-29 and 2017-05-11. Even though the Crunchbase database has been shown to be one of the most extensive company databases (Retterath & Braun, 2020), it is limited and certain metrics such as mean team age has to be calculated through proxies. Furthermore, a potential survival bias is likely to exist despite efforts reducing it. For example might companies fail before they are added to the Crunchbase database or successful start-ups be covered more extensively resulting in a survival bias. A significant number of team features, such as experience working in bulge bracket investment banks, had to be dropped from the dataset due to sparsity of more than 90%. The sparsity in certain metrics could pose a risk for the model not being entirely accurate and result in variables such as `other_roles_count_missing_flag` and `tech_roles_count_missing_flag` being deemed some of the most important variables even though they reasonably are not.

The target and definition of success for a firm is in general highly ambiguous and therefore raise a limitation. In this study, the target and definition of success is that the company has raised follow on funding within five years after the venture was founded. The reasoning behind selecting this target is explained under 3.7 Target Extraction & Definition of Success. This target could be considered insufficient as the end goal of the venture capitalist is to achieve a major exit and the end goal of the firm could be to maximise for example growth in terms of sales or number of employees.

As for the final major limitation, the study does not include a perspective on how the importance of team attributes have changed over time. In this study, the entire dataset has been seen as one with no time consideration except for the definition of success and target extraction. It could however be true that the impact of certain attributes are dependent on the general development of the market or other factors that could be captured by including a time perspective.

6.4 Future Research

Potential future research includes similar studies on companies in other parts of the world. Suggested for these studies is to limit them to a certain geography to avoid a bias towards attributes related to certain regions. Furthermore, research exploring the reasons behind the identified patterns would be of value to strengthen the results and expand the understanding around team composition and venture performance. Thirdly, studies covering above mentioned limitations would be of interest. One example is conducting a deeper investigation including additional data sources such as LinkedIn, Product Hunt, and social media. This would reduce the issue of sparse data for certain team metrics and hence increase the validity and granularity of the research. Another example would be an investigation into how different time periods, industries and market environments affect the impact of different team attributes. As a third and final suggestion on future research, a study where different targets and definitions of success are experimented with would be of interest to try to reduce bias caused by biased data.

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