MIND THE GAP: TO WHAT EXTENT DO FASHION ENTREPRENEURS' PERSONAL CHARACTERISTICS AND COMPETENCIES IMPACT THE SURVIVAL OF THEIR RESPECTIVE STARTUPS?

Master Thesis

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Executive Summary

In recent years, the notion of entrepreneurship has gained increased attention in the academic and business circuits, emphasizing the impact of entrepreneurial activity associated with innovation, value generation, and breaking through barriers, whilst putting forward products and services today's generations could not imagine living without. One set of industries, where such entrepreneurial qualities are mirrored are those in close connection to cultural and artistic activity. It is therefore not surprising that entrepreneurial research's focus has been increasingly concerned with the commerce of culture. Aside such growing interest, the literary efforts concerning individual players within the cultural industries, especially the fashion industry, have been scarce. This thesis therefore aims to fill this literary gap while examining the empirical relationship between fashion entrepreneurs' personal characteristics, educational background, field of study, relevant industry experience, and previous entrepreneurial experience, and the impact of these competencies on the performance of their respective startups. The results of this study, carried out on a sample of 219 global fashion startups, founded by a single entrepreneur between 2014 and 2015 indicate a significant, positive relationship between previous entrepreneurial experience and startup performance. Aside its contribution to our extended understanding on fashion enterprises and the fashion entrepreneur, the current study thus sheds light on the importance of future research regarding entrepreneurial characteristics and competencies in the fashion industry and their relation to startup performance.

Keywords: entrepreneurship; fashion entrepreneurship; creative industries; founder characteristics; startup performance

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1. Introduction

1.1 General Introduction

As defined by the European Commission's *Entrepreneurship and Innovation Programme*, the notion of entrepreneurship is associated with innovative activity, which aims to pursuit value generation through the identification of new, alternative business solutions, the expansion of relevant market-processes, and the establishment and extension of relevant economic activity. "In this sense, entrepreneurship manifests itself throughout the economy and in many different forms with many different outcomes, not always related to the creation of financial wealth" (Ahmad & Hoffman, 2007, p. 4).

The creative industries are particularly relevant to the above statements, since their essence lies within the creation of new cultural and artistic forms and the elimination of the traditional constraints found in other sectors of the economy. Moreover, the economic importance of the creative industries in recent years has become undeniable. As noted by UNESCO, the commerce of creativity is "one of the most rapidly growing sectors of the world economy" (Isar, 2013, p. 10).

The increasing popularity and importance of the creative industries is reflected in the growing body of scholarly research aimed to understand the key drivers of entrepreneurial success as well as the cultural entrepreneur's persona. This is due to the increased belief that young firm performance is a function of industry structure, firm strategy, and the human capital of the founding entrepreneur. Various scholars have also argued that, in line with knowledge-intensive activities' amplified importance in most industries, human capital will receive increased attention in the future (Pennings et al., 1998; Honig, 2001; Bosma et al., 2004).

A key player of the creative industries is the fashion industry; a sector employing 26 million people globally, whilst accounted for the world trade value of 307 billion Euros (Euratex, 2015). It is perhaps due to such economical importance that the circuit of fashion is perceived as increasingly desirable – a tendency in line with the high number of fashion startups aiming to establish themselves in the industry. During the 2014 New York Fashion Week, the number of new fashion enterprises registered was 2808, where the 2014 Milan Fashion Week attracted 2823 fashion startups (Gola, 2014). Aside such high level of market entry, however, previous research claims the survival rate among fashion startups to be low, with up to 60% of newly founded ventures closing down in the first four years of their existence (Okonkwo, 2007; Negarandeh, 2008; Easey, 2009; Hauge, 2012).

1.2 Introduction to the Problem Definition and Research Question

In contrast to the ever-increasing scholarly focus on cultural entrepreneurs' personal characteristics and competencies and their impact on startup performance, findings specifically aimed at the association of these notions in the commerce of fashion are neglected. Nevertheless, it is an important field with different implications for investors, and policy makers; let alone fashion entrepreneurs.

The purpose of this paper is thus to empirically analyze the impact of fashion entrepreneurs' personal characteristics and competencies on startup performance. With such objective in mind, the current study analyzes how fashion entrepreneurs' age, gender, former education, field of study, relevant industry experience, and previous entrepreneurial experience affect the study's selected measure of business performance – startup survival.

The research question of the current paper is the following: '*To what extent do fashion entrepreneurs' personal characteristics and competencies impact the survival of their respective startups?'*

1.3 Research Objectives

This thesis aims to contribute to the expanding theoretical stream of creative industries-related research. Findings of this study guide fashion entrepreneurs in becoming more aware of their own competencies as well as the various challenges faced upon entering the industry. Moreover, given the similarities shared between the fashion industry and the creative industries, together with trending tendencies of an interconnected and globalized commerce of fashion, this research is meant to be relevant for every new fashion entrepreneur to an extent, regardless of their geographical location. Finally, the author expects to make a contribution to the creative industries overall, as similar challenges might be identified among alternative artistic markets.

1.4 Research Design

The current paper makes use of a filtered dataset collected through Crunchbase, consisting of globally selected fashion startups founded between 2014 and 2015 by a single entrepreneur. The geographical scope of the current research allows for the generalization of findings. The year of foundation is selected with regard to dependent variable, startup survival, keeping in mind the importance of eligible sample size and assuming that startup survival or mortality can be seen due to the sufficient time passed since the foundation of the startup. Lastly, those companies with a single founder are looked at to assure that the personal characteristics and competencies of each startup founder are affecting startup performance.

The current study measures the dependent variable, startup performance, via startup survival. Survival is selected as measure since it is considered a widely acceptable and non-biased measure of performance, as opposed to alternative, financial-, and non-financial means of performance previously considered in academia. The measures of the independent variable incorporate founders' age, gender, former education, field of study, relevant industry experience, and previous entrepreneurial experience. To examine the potential relationship between the dependent and independent variables, the current study utilizes a binomial logistic regression model, accompanied by several other empirical tests carries out with the help of the Statistical Package of Social Sciences (SPSS).

1.5 Outline of the Thesis

The remainder of this thesis is organized as follows. Chapter two – the Literature Review – details the theoretical and empirical studies of the fashion industry, the fashion entrepreneur, and the expected relationship between founder characteristics and startup performance introduced above. Followed by the Conceptual Model section (chapter three), summarizing those findings described in the literature review and introducing subsequently proposed hypotheses. Section four elaborates on the means of data collection and the methodological guidelines applied to the current study, while the Results chapter (chapter five) concerns key empirical results. Finally, chapter six elaborates on these findings, while giving some thought to the limitations of the thesis, as well as suggestions for potential future directions of research.

1.6 Conclusion to the Introduction

Even though a growing body of literature has indicated startup founders to be at the locus of startup performance, research has thus far neglected the exploration of fashion entrepreneurs' personal characteristics and their impact on the survival of their startups. The current thesis therefore attempts to find a link between fashion founders' age, gender, former education, field of study, relevant industry experience, and previous entrepreneurial experience and startup performance to gain new insights into what makes entrepreneurs of the emerging commerce of fashion able to sustain their businesses and to examine whether these characteristics are altered as opposed to those entrepreneurs operating in alternative sectors of the economy.

2. Literature Review

The following chapter aims to provide the literal background of concepts presented throughout the Introduction of the paper. Aside reviewing the specific conditions and challenges faced by the fashion entrepreneur, concepts of start-up performance, founder's age, gender, education, field of study, relevant industry experience, and entrepreneurial experience will be further elaborated on. Moreover, the current chapter aims to review the links that literature has previously established between these different concepts. The chapter starts with the examination of the fashion industry and its distinguishing tendencies as opposed to other members of the creative industries, followed by an elaboration on start-up performance, and those drivers of start-up performance frequently researched in the literature. The literature review then moves on to the analysis of founders' age, gender, former education, relevant industry experience, and entrepreneurial experience – and their relation to start-up performance to examine the potential relationship that was previously discovered between these concepts.

2.1 Entrepreneurship in the Creative Industries: An Introduction

The essence of entrepreneurship, according to Preece (2011), lies within new business creation, through which new opportunities are discovered and pursued. Entrepreneurial activity is therefore more than just profit maximization; it entails new idea generation from a constraint-free position. Likewise, creative and artistic processes are often about originality, and creatives seek to create conditions that help them in overcoming the restrictions posed by traditional industry structures.

In recent years, academia and public attention have been increasingly concerned with entrepreneurial activity and the arts – and the overlap of these notions. The motives behind such amplified attention are multiform. On one hand, it is related to the cultural sectors' dominant economic impact (Preece, 2011). On the other hand, it is due to the sector's tangible and intangible community-oriented benefits (Florida, 2002). Moreover, because studying entrepreneurial cultural organizations, thus far have contributed to our extended understanding on organizational theory and also have clear implications for other sectors of the economy (Preece, 2011).

Aside their relative importance within the general economy, however, organizations in the arts and culture sectors have to face an increasingly turbulent, mixed economical environment. Turbulent environment in the current case refers to

Peterson & Berger's (1971) description that perceives the surroundings of the economy as fast-paced and highly unpredictable. Moreover, as added by Burton (2003), today's economy is challenged by rapid technological and social change as well as increased market competition within and beyond the arts and culture sectors.

2.2 The Fashion Industry

By definition, the fashion industry is "an area of commercial activity that specializes on the design of fashion garments that are designed by fashion designers and manufactured in limited quantities" (Negarandeh, 2008, p. 19). While the fashion industry has gained undeniable importance and has been exponentially growing in recent years, the gap between creative entrepreneurial literature and literature specifically related to the fashion industry remains (Mills, 2012).

In terms of the segmentation of the industry, one can distinguish between the designer-, and commercial segments. Such segmentation is not a specific feature of the fashion industry, but the creative industries in general. Rooting from such segmentation, and among other diligences included in the creative sector, lies the conflict of creative-, and business efforts, defined by Mills (2012) as the "creativity-business tension" (Mills, 2012, p. 761). Such tension roots from fashion entrepreneurs' need to be able to transform individual creativity into a sustained business. In particular, the tension is intensified as entrepreneurs, who have previously been concerned with the pure creative process of creative good production, now hinder the creative side of their businesses for commercial gain (Malem, 2008; Mills, 2012). Moreover, Malem (2008) points out a common mistake fashion entrepreneurs fall into, namely the tendency to neglect the practical needs of their enterprise to focus on creative inputs, or the other way around – prioritizing business-, over creative needs. By doing so, however, one side of the creativity-business dynamics gets out of balance – a situation best eliminated (Mills, 2012).

Low entry barriers and a highly competitive, turbulent environment are also common traits shared between the creative industries and the fashion industry. The turbulent environment element in the fashion sector is recalled in a number of geographically independent studies. These include the 2008-paper by Malem reflecting on the London fashion circuit and related survival strategies of the industry, Mills' (2012) paper concerning the New Zealand fashion industry, a study by Shi et al. (2012) reviewing fashion startups in China and London, and a research regarding Belgian fashion management by Jacobs et al. (2016).

The easy accessibility of the fashion industry makes it possible for entrepreneurs to enter with a relatively diverse set of personal characteristics, competencies, and motivations. As explained by scholars Shane & Venkataraman (2000), these fundamental entrepreneurial differences lead fashion entrepreneurs to realize the harsh conditions of the industry upon entering it. Thus, fashion entrepreneurs face a *make it or break it* situation, where they have to compensate for their lack of necessary skills and industry-specific knowledge to eliminate chances of business failure.

On the other hand, the low entry barriers of the industry – including low financial-, and skill related requirements – are reflected in the high number of one-man fashion companies. An intuitive example is Negarandeh's 2008-study showing that out of approximately 4500 Danish small-, and medium-sized fashion enterprises, approximately 92% were operated by a single entrepreneur, with the average number of employees in the remaining 2% equal to 1.7 persons. Although less extreme, another example focused on the English fashion industry yield similar results, indicating the majority of UK-based micro-fashion businesses are operated by less than ten employees, with 20% of the overall market employing no staff at all (Malem, 2008).

Furthermore, the creative industries, and the commerce of fashion in particular, have been defined as industries where competitive advantage tends to get eliminated relatively fast (Malem, 2008). As argued by Malem, this is due to the difficulties associated with the ability to differentiate one's fashion products from the competition, especially in lack of a technological advantage. Such eliminated competitive advantage leads to two additional conditions found in the fashion industry in particular; namely short product life cycles, and seasonal intensity (Malem, 2008; Mills, 2012; Negarandeh, 2008). Seasonal intensity also entails the need for a constant evolution and change – a tendency that challenges the fashion entrepreneur to obtain the necessary skills and resources that help him/her in reacting to such conditions of the market efficiently (Marcella & Rowley, 2015).

In hand with the intense competition and fast-paced trends, lies the *winner takes all* mentality, characterized by tendencies of rapid startup growth and sudden exits of the market (Heslin, 2005). Such mentality has been intensified parallel to globalization, since it's increasingly eliminating the physical and mental gap between international and local fashion ventures (Shi et al., 2012).

Previous research has also highlighted fashion entrepreneurs' limited capability to network in their respective industry. The reason for fashion entrepreneurs' networking-related complications are twofold. One of these relates to the lack of network organizations providing institutional channels, which are often absent in the fashion industry. Moreover, it roots from the highly fragmented and individualistic perception of the fashion industry, where communication among parties is uncommon. Nonetheless, as highlighted by Riegels (2011), the fashion industry's networking barriers make it increasingly difficult for micro-fashion enterprises to gain necessary knowledge and advice, which leads them to become more vulnerable and potentially hinders performance.

2.3 The Fashion Entrepreneur

Aside the distinguished setup of fashion industry itself, specific characteristics of the fashion entrepreneur, as opposed to entrepreneurs operating in alternative sectors are to be highlighted. As mentioned above, it is common for fashion startups to be established by a single owner/manager. If that's the case, however, the founder must single-handedly allocate his/her focus in order to maximize both the commercial and creative sides of his business.

Another characteristic of fashion entrepreneurs are their specific orientation, categorized in Mills' 2011-study. These orientations vary between the "Creative Enterprise Orientation" (CEO), the "Creative Business Orientation" (CBO), and the "Fashion Industry Orientation" (FIO) (Mills, 2011, p. 257). What differentiates these orientations from one another is their focus on different elements of their business with the aim to establish themselves in the circuit of fashion. In particular, where CEO-oriented fashion entrepreneurs focus on the creative side of their business to become recognized, the CBO orientation emphasizes the need for self-employment and stresses the importance of the commercial side of a fashion business. Finally, those belonging to the FIO group aim to become and remain relevant while utilizing creativity. Thus, the different orientations each represent a different level of the creativity-business tension, and ways in which fashion entrepreneurs deal with such (Mills, 2012). In their interview-based study carried out in 2015, Marcella & Rowley find fashion entrepreneurs to prioritize the creative-, over the business-aspects of their company. It is therefore expected that those entrepreneurs with orientations focused on the creative side of their venture face difficulties when in need to handle a challenge related to the commercial side of their business.

With the high proportion of fashion enterprises operated by a single entrepreneur, and considering the high mortality among young fashion ventures, a high pressure is placed on the human capital of the fashion entrepreneur. Whereas most entrepreneurs realize the need to have a well-rounded set of skills, many believe creative skills to be at the locus of successfully establishing their fashion companies (Negarandeh, 2008; Marcella & Rowley, 2015). In particular, Negarandeh's (2008) research reviewing the business aspects of one's newly founded company was thought of by a relatively small number of fashion entrepreneurs only. Thus, it can be concluded that, based on the literature, fashion entrepreneurs' ability to acquire the right entrepreneurial skillset is a double-edged sword. On one hand, the right skills can help the fashion entrepreneur in sustaining his/her business; on the other, acquiring such skillset can be a great challenge.

2.4 Start-up Performance

As indicated above, the creative industries – and more precisely, the fashion industry – bleeds from several wounds. More specifically, the turbulent environment, highly segmented industry structure, low barriers of entry, eliminated competitive advantage, network barriers, and the conflict between creative-, and business efforts all pose challenges to fashion entrepreneurs to sustain their businesses in the industry. Aside the challenges present in the industry itself, specific entrepreneurial characteristics distinguish fashion entrepreneurs from the rest. Nonetheless, some of these characteristics seemingly pose a threat to fashion enterprises' performance.

Defining the performance of any company, let alone those companies in the early stages of their existence can range substantially, yet the following section aims to briefly present leading streams of existent research. Prior to examining if there is any potential relationship between the competency of entrepreneurs and start-up performance, our dependent variable – the performance of startups – has to be defined accurately.

2.4.1 Common Measures of start-up Performance

"Organizational performance is an important construct in strategic management research and a multi-dimensional issue" (Murphy, Trailer & Hill, 1996).

Whereas the measurement of startup performance has been done based on both financial and non-financial criteria, a stronger emphasis has thus far been placed on the former in literature. As coined by various scholars, the popularity of these ‘hard’ economic measures of performance root from their straightforward administration, conversion and application (Ibrahim and Goodwin, 1986; Gibb and Davies, 1992; Barkham et al., 1996).

Non-financial measures incorporate employee numbers (indicating firm growth) as well as means of financial performance; including revenue, profit, turnover, or return on investment (Walker & Brown, 2004). Generally speaking, these financial measures have to increase for businesses to be regarded as successful. As indicated by scholars Hall & Fulshaw (1993): “the most obvious measures of success are profitability and growth” (Hall & Fulshaw, 1993, p. 223).

The assumption that small businesses desire and are in need to ‘grow’ – financially or through an increased number of employees – is implicit to these measures (Jennings & Beaver, 1997; Walker & Brown, 2004). “Nonetheless, some businesses have no interest in growth, with some business owners deliberately refraining from taking on employees” (Neneh & Vanzyl, 2014, p. 172). The creative industries are a prime example, where small creative firm owners often neglect financial success to sustain the creativity of their enterprise (Chaston, 2008). The decision of whether one should generate output that meets market demand, or to produce in accordance to personal preferences is therefore considered a common dilemma faced by the creative entrepreneur (Caves, 2000; Chaston, 2008).

Given the assumption that maximizing financial performance is not their primary motivation, non-financial criterion can be just as important in establishing start-up success. When it comes to measuring startup success non-financially, one can think of the achieved autonomy, satisfaction gained from work-family balance, as well as the number of professional awards won, or the number of articles published (Green and Cohen, 1995; Parasuraman et al., 1996; Buttner and Moore, 1997; Kuratko et al., 1997). Nonetheless, these measures are mostly subjective and personally determined, wherefore they are more difficult to quantify.

“A prominent, non-subjective success measure is the survival of a start-up company, its persistence in the market” (Witt, 2004, p. 397). Furthermore, the data measuring startup success through survival is relatively easily obtainable, given startups' date of foundation. The collection of firm survival can also be done in multiple ways, including means of data mining, company calls, and well as personal visits. The determination of a suitable survival period, however, is crucial for such performance measure – and counts for one of the most important methodological problems faced by those utilizing this measure. Taking into account that survival in the short-term may be sustained due to initial levels of capital, it is key to select a long enough period after startups' foundation, otherwise the success measure is not demanding enough. On the other hand, too long reference periods shift the focus from startups to established companies. Thus, a careful balance has to be established in order for researchers to make use of the measure of survival efficiently.

2.4.2 Measures of start-up Performance Specific to the Fashion Industry

Aside the common measures of organizational performance described in the above section – which all are essential in evaluating entrepreneurial enactment – various additional metrics can be used to gain a better understanding of fashion ventures' business performance. These metrics, initially published as part of the Predetermined Time Measurement system in 1948, are summarized in the Appendix.

2.5 Founder Characteristics that Drive start-up Performance

The literature on start-up success has been focusing on whether there are systematic differences that distinguish successful start-ups from the rest, with specific focus on the nature of those differences. In general, entrepreneurs' main challenge upon establishing their enterprise is to break-even and to survive (Negarandeh, 2008). Nonetheless, after the identification of the main relevant challenges posed by the creative industries – let alone the fashion industry – it is clear that well-maintained startup performance takes an entrepreneur with a diverse set of skill and competencies. As coined by Jacobs et al. (2016), it is required of fashion entrepreneurs to be "ambidextrous" (Jacobs et al., 2016, p. 1408). What are key entrepreneurial characteristics driving startup performance and why do they matter? How do they impact startup performance? Are there any differences between general entrepreneurial characteristics and those of the fashion entrepreneur? The following sections aim to discuss it all.

Prior looking at the correlation between firm success and founder characteristics, it is important to understand the multiform importance of such link in the first place. According to Mullins (1996), the answer lies within the widely believed notion that founders – highly influencing the general moral and culture of their firms – are predominant influencers of their companies. Such claim is supported by Collins and Porras (1994) who recall the example of Walt Disney and the period after him passing away, when Disney executives would often ask *What would Walt do?* upon facing important firm-related decisions. Secondly many, including investors, assess new venture potential through the evaluation of its founders. For instance, crucial funding criteria established by venture capitalists regards their perception of founders (often referred to as entrepreneurs) or the founding team's ability to successfully launch their venture. The third importance roots from empirical and qualitative evidence regarding the difficulty of getting one's entrepreneurial idea off the ground. Related to these difficulties, it has been found that several individual difference variables, such as prior industry experience and/or the level of education are critical for the successful launch of new ventures. While looking at the most widely studied founder characteristics, the following section highlights key findings.

2.5.1 Age

"The relationship between an individual's age and the length of their work history and the probability of establishing a new business is complex" (Pickles & O'Farrell, 1987, p. 431). Looking at the fashion industry in particular, we are faced with a strong disconnect: "On the one hand, fashion pays endless aesthetic homage to youth; on the other, it remains firmly in the thrall, and power, of the mature" (Friedman, 2015, para. 20). Keeping the conditions of the fashion industry in mind, however, it can be argued that its low entry barriers, constant need for innovation and fashion entrepreneurs' limited understanding on the skill-, and competency-related requirements upon entering the industry lead to a high number of young entrepreneurs operating (or at least trying to operate) in the commerce of fashion.

Prior empirical evidence claims the effective capacity of an entrepreneur to establish a business to increase between the ages of twenty-five to thirty. As one grows older, however, effective capacity tends decrease on an increasing rate in line with risen obligations towards family as well as altered interests (Liles, 1981). Results of Gomolka's (1977) early study incorporating a survey design that compared 220 successful minority business owners with a previous study on well-performing nonminority entrepreneurs indicate differently. In particular, Gomolka's findings suggest the 40 to 44-age range to be the largest within the successful minority entrepreneur sample.

While studying 1992-data just after the turn of the century, Headd (2003) finds higher average success rates upon closing the business among owners below the age of 35. Nonetheless, as argued by the author itself, "high rates for those under 35 might be the result of keeping the venture small while learning or being enticed to close a business and work for an employer" (Headd, 2003, p. 56). Around the same time, Robb & Wolken (2002) indicate owners' age to be the only statistically significant owner characteristics. Moreover, the academic duo's study finds that firm-related loans are the most common for owners between the ages 36 to 45, and 46 to 55. Around the same time, and while examining Canadian micro-businesses' growth determinants, Papadaki & Chami (2002) find only 17% of micro-business owners to be below 40 years of age.

Finally, Gorgievski, Ascalon & Stephan's (2011) paper investigating small, Dutch business owners' personal characteristics and understanding of success showed that age matters. In fact, younger business owners revealed profitability as their highest-ranked understanding of success most frequently. Nonetheless, it is important to distinguish between desired monetary success and actual business performance, since the Gorgievski, Ascalon & Stephan study focuses on the former and thus, does not establish any significant relationship between founders' age and an actual, quantifiable measure indicating their start-up's performance.

2.5.2 Gender

"With the rising number of women-owned businesses have come a considerable amount of research, and even more speculation, on differences between male and female entrepreneurs and their businesses" (Fischer, Reuben & Dyke, 1993, p. 151). The differences in firm performance and their assumed connection to gender were previously reviewed with the help of a variety of metrics, and – generally speaking – have arrived to conclusions in favor of male-, over female entrepreneurs. The fashion industry is no exception to such rule, despite its perception as a feminized occupation.

While examining the New England business scene and controlling for employee numbers, Loscocco et al.'s (1991) study of 540 startups found male-owned businesses to have significantly higher income. According to a longitudinal study carried out on 1053 new, US-based ventures by Cooper et al. (1994), the likelihood of survival was equally expected for both male-, and female-led businesses, where results indicated male-owned ventures to be more likely to grow. Measuring business performance via capital assets, sales turnover, and their number of employees, Rosa et al. (1996) find male-led businesses to over-perform those led by women. Similarly, Honig (1998) – looking at 215 informal Jamaican microenterprises – arrives to the conclusion that men, overall, performed better than women.

At the turn of the century, Du Rietz & Henkerson (2000) ran multivariate tests on a sample consisting of 4200 Swedish entrepreneurs, out of which 405 were females. Their results indicate male over-performance for sales alone. Two years on, Robb & Wolken's (2002) multivariate results based on approximately 45,000 US firms commercing in 1992 and covering the period to 1996 suggested male-owned businesses to be less likely to close as compared to female-owned ones. According to Bosma et al. (2004), among the 1000 new businesses founded in the Netherlands between 1994 and 1997, female business owners performed worse on all performance measures. Moreover, Eastern European and central Asian male-owned enterprises reported higher profits, according to Sabarwal and Terrell's 2008-paper. Nonetheless, it is argued that such difference can be explained by differences in the scale of the businesses examined. In other words, male-owned businesses in this specific sample were known to be, in terms of sales, bigger than their female-owned counterparts. While utilizing the characteristics of business owners (COB) survey including 30,000 US businesses operating between 1992 and 1996, Fairlie & Robb (2009) conclude male-owners to have better average outcome than their female-led equivalents.

Finally, while using a dataset of one million Texan proprietorships, Kalnins & Williams (2014) look at data across various industries and geographical areas and how these might be affected by gender. Their findings suggest that in a number of industries, businesses owned by females continuously out-survived those ventures operated by men, including clothing, gift-giving, and alcohol sales and services. In terms of the geographical allocation of firms, the study finds female-owned businesses to have survived more consistently in larger cities, whereas males mostly operated sustained businesses outside big cities.

2.5.3 Former Education

Education's correlation to start-up success has been long considered in scholarly papers, frequently serving as a proxy depicting entrepreneurial skills and abilities. Initial scholarly efforts by Cooper et al. (1992) found that out of 17 previous studies concerned with the relationship between education and firm performance, 10 established a positive relationship, with no significantly negative results among the examined studies. In their 1997-article, for instance, scholars Sapienza & Grimm claim certain skills and abilities, such as search skills, foresight, imagination, and computational and communication skills, to be intensified through higher education. Additionally, it is found that particular knowledge-intensive forms of education related to engineering, information technology (IT) and Real Sciences (such as Mathematics, Physics, or Biochemistry) provide firm founders with an advantage in case their business is launched in a related area of expertise. In the same year, efforts by Gimeno et al. (1997) concluded that entrepreneurs that acquired a high school degree performed significantly worse than those with a higher educational degrees.

Similarly, Boure & Maidique's 1986 explanatory study - linking high-technology venture success and prefunding factors - found that those entrepreneurs previously undertaking higher education performed better in their new ventures. Around the same time, Gartner's (1985) research, focusing on four key entrepreneurial perspectives and their effect on new venture creation yield a number of significant results – with findings that suggest higher education to be a leading individual characteristic of successful entrepreneurs.

According to Negarandeh (2008), the fashion entrepreneur's understanding of the various aspects surrounding his/her business – including marketing and branding, sales, and accounting – are crucial to effectively operate in the market. As added by Hague (2012), brand and marketing management are at the heart of understanding the symbolic value of one's product, and allow for a better consideration of the highly segmented fashion industry as well as the segment to be targeted with one's fashion products. Furthermore, due to the endless choices in the fashion industry offered to customers, and the difficulty to gain substantial advantage over others, an accurately chosen brand image and/or marketing strategy, as well as the ability to understand budgeting and other economic concepts are important. Thus, it is argued that those fashion entrepreneurs with an acquired business education stand a higher chance in effectively sustaining their businesses (Marcella & Rowley, 2015).

In their 2004 paper, Simpson, Tuch & Bellamy (2004) consider the role of education and training on small business success. While transcribing semi-structured interviews within 14 service sectors in the Sheffield area (UK), the scholars' findings indicated that – despite each entrepreneur/owner-managers' individual perception on the meaning of success – the role of education, prior knowledge and experience all significantly contributed to monetary means of success. Another study by Colombo et al. (2004), looking at Italian high-tech start-ups showed that faster-growing enterprises were the ones led by those that took part in formal education. Using a randomly generated, cross-sectional sample of Dutch entrepreneurs, Parker and van Praag (2006) demonstrated that "extra years of schooling enhance entrepreneurial performance both directly and indirectly through the effect of capital constraints" (Parker and van Praag, 2006, p. 427). In particular, the academic duo estimated every additional year of formal education (referred to as "direct rate of return to schooling") to enhance the start-up's income by 13.7%.

Moving away from Europe, Philip's (2010) Bangladeshi study indicates a positive correlation between (higher) education and local SME success. In particular, Philip's results have shown that out of all respondents (N = 92), 84 have completed a Certificate/Diploma, Bachelor's-, or Master's Degree. Nonetheless, such correlation was proven not to be significant in latter stages of Philip's research. With the aim to contribute to the current understanding on factors influencing small to medium-sized enterprises (SMEs), Blackburn, Hart & Wainwright's 2013-paper shows increased educational levels to enhance business owners' capacities, and to have a positive association to business growth and performance. Nonetheless, "it is also suggested that the benefits of this knowledge is limited to the managerial, and not the operational roles of business-owners" (Blackburn, Hart & Wainwright, 2013, p. 9).

2.5.4 Relevant Industry Experience

Studies have been concerned with newly founded firm-success and founders' experience in the respective industry, where their business is launched. Considering the circuit of fashion in particular, Marcella & Rowley (2015) highlight the importance of effective communication and relationship management between the fashion enterprise and its various stakeholders. Thus, whereas the below-section mainly emphasizes relevant industry experience's direct impact on startup performance, it is important to keep in mind the indirect benefits of having operated in the sector – that is, of overcoming the specific challenges posed by relationship management due to one's expertise regarding the formal and informal stakeholder-relations as well as networks of the fashion industry.

In 1977, Cooper & Bruno's early attempt to consider patterns of success among 250 high technology firms around the San Francisco Peninsula found that relevant industry experience was significantly positive. In particular, after looking for similarities between newly founded firms and those organizations that start-up founders had left (in terms of the technology utilized), it was indicated that "80% of high-growth firms were similar to the "parent" organization in both technology utilized and markets served" (Cooper & Bruno, 1977, p. 21). Moreover, while arguing that the skills and knowledge of founders are predominantly important in gaining competitive advantage among small, high technology firms, the academic duo claims founders that start firms in a field they are personally and/or professionally familiar with to face lower probability of failure. Ten years on, MacMillan & Day's findings yield similar results. In particular, their 1987-research indicated that, aside their increased understanding of the requirements and know-hows of their respective industries, entrepreneurs with relevant past industry experience also enquire more extensive and matured industry networks – both of which affecting firm success positively. Looking at the influence of 1849 German entrepreneurs' general and specific human capital characteristics on start-up morality, Brüderl, Preisendörfer and Ziegler (1992) found that "among specific human capital variables, industry-specific experience is the most important effect - starting a business without experience in the industry sharply increases the mortality rate" (Brüderl, Preisendörfer and Ziegler, 1992, p. 237). With aim to define distinguishable characteristics of high-growth and low-growth companies, Siegel et al. (1993) compared two distinct samples, namely the Reynolds database to Price Waterhouse clients. The companies' discriminant analysis indicated that in both samples, the management's relevant industry experience single-handedly affected companies' rate of growth.

Looking at research proposed from the 2000s, Bosma, van Praag, Thurik, & de Wit's (2004) study measures the investment of social-, and human-capital and their effect on entrepreneurial performance. While measuring performance based on profits, survival and employment generated, the scholars' "empirical analysis of a rich Dutch longitudinal data set of firm founders conclude that specific investments indeed affect the three performance measures substantially and significantly" (Bosma, van Praag, Thurik, & de Wit, 2004, p. 3).

Using the Kauffman Film Survey to forecast the role of industry and start-up experience on new venture performance, Cassar's (2012) research shows that more accurate and less biased entrepreneurial expectations have a high, positive significant correlation to relevant industry experience. In particular, Cassar argues that due to their experience in similar settings, entrepreneurs have the ability to better evaluate the environment in which their ventures are to compete - including "substantial uncodified information" which cannot be learned from other sources – leading them to better evaluate opportunities of various kind within the industry, especially in highly uncertain environments, such as the high-technology industry (Cassar, 2012, p. 140).

More recently, Yaacob, Mahmood, Zin & Puteh's 2016-study, looking at factors shaping small, undergraduate student-founded businesses' performance found a significantly positive correlation between performance and founders' relevant industry experience. The scholars, who defined business experience as "the exposure associated with the business acquired by operators/owners before they start their own businesses" also prove that longer previous experience in a relevant industry is translated into higher rates of profitability, growth as well as employment opportunities (Rosman & Mohd, 2013, p. 447).

2.5.5 Entrepreneurial Experience

The next section of the paper focuses on the entrepreneur-specific components of human capital. Hence new venture induction is a compound process, entrepreneurs with past start-up experience have a distinct advantage. It is also found that those with no prior entrepreneurial experience are more likely to make pricey mistakes – a tendency that is highly relevant to start-up success. Moreover, as mentioned previously, fashion entrepreneurs are in need of a broad set of skills upon launching their companies. Such tendency, however, is only fully understood by those entrepreneurs that have previously worked in the fashion industry and is intensified among those who have been a part of/in charge of founding other entrepreneurial projects (Negarandeh, 2008).

Initial efforts to discover the relationship between start-up performance and entrepreneurial experience delivered mixed results. Whereas research by Stuart and

Abetti (1990) found such relationship to be significantly positive, Bates's (1990) research indicated that firms' survival was not significantly dependent on former entrepreneurial experience. Chandler and Jansen (1992) reach similar conclusions, showing that the growth of a newly established start-up is unrelated from the number of stat-ups previously founded by its owner.

According to a 1997-study by Gimeno et al., prior entrepreneurial experience positively influences start-ups` economic performance based on the sample, consisting of 1547 US start-ups. Utilizing a Dutch panel survey, consisting of a sample of over 1000 entrepreneurs collected between 1994 and 1997, Bosma et al. (2004) demonstrated a significant relationship between startup performance and the human capital of the entrepreneur.

2.5.6 Alternative Measures Enhancing start-up Performance

Aside the founder characteristics discussed in detail above, the profile of a successful creative entrepreneur features a number of additional peculiarities. The following section aims to briefly review these entrepreneurial competencies with the help of Frese & Gielnik's (2014) meta-analytic review, *The Psychology of Entrepreneurship*.

According to the scholarly duo, concepts of entrepreneurial alertness, business planning, financial capital, and entrepreneurial orientation all have a positive impact on startup performance. Entrepreneurial alertness refers to one's ability to notice business opportunities without looking out for them (Tang et al., 2012). Alternative streams of related research have placed stronger emphasis on general mental ability, basic cognitive capacities, and creativity – notions in strong correlation to entrepreneurial alertness (Baron & Ensley, 2006).

Aside entrepreneurial alertness, various academics argue for the positive relation between business planning and startup performance. Whereas formal business planning is lacking in the creative industries due to it being perceived as time-consuming and flexibility hindering, several empirical research supports the positive correlation between having an action-, and/or business plan and enhanced business performance.

As coined by Ho & Wong (2007), financial constrains are major factors hindering entrepreneurship. Whereas the pure economic and financial focus on business resources cannot explain entrepreneurial success, especially in the creative industries, overcoming financial constrains is at the heart of sustaining a startup over time. Entrepreneurial orientation is a collective term established by Lumpkin & Dess in 1996, consisting of notions autonomy, innovativeness, risk-taking, competitive aggressiveness, and proactivity. According to the scholars, these notions help firms seek and exploit new opportunities for business growth.

Aside entrepreneurial orientation, alternative streams of entrepreneurial research found certain cognitive and affective factors to be successful moderators of startup performance. In terms of cognitive factors, Frese & Gielnik (2014) mention practical intelligence, knowledge, and cognitive bias of overconfidence. Affective factors, on the other hand, contain growth-oriented goals and vision, personal initiative, as well as entrepreneurial passion. The complete framework developed by Frese (2009), depicting the action-characteristics model of entrepreneurship in shown in Figure 1.

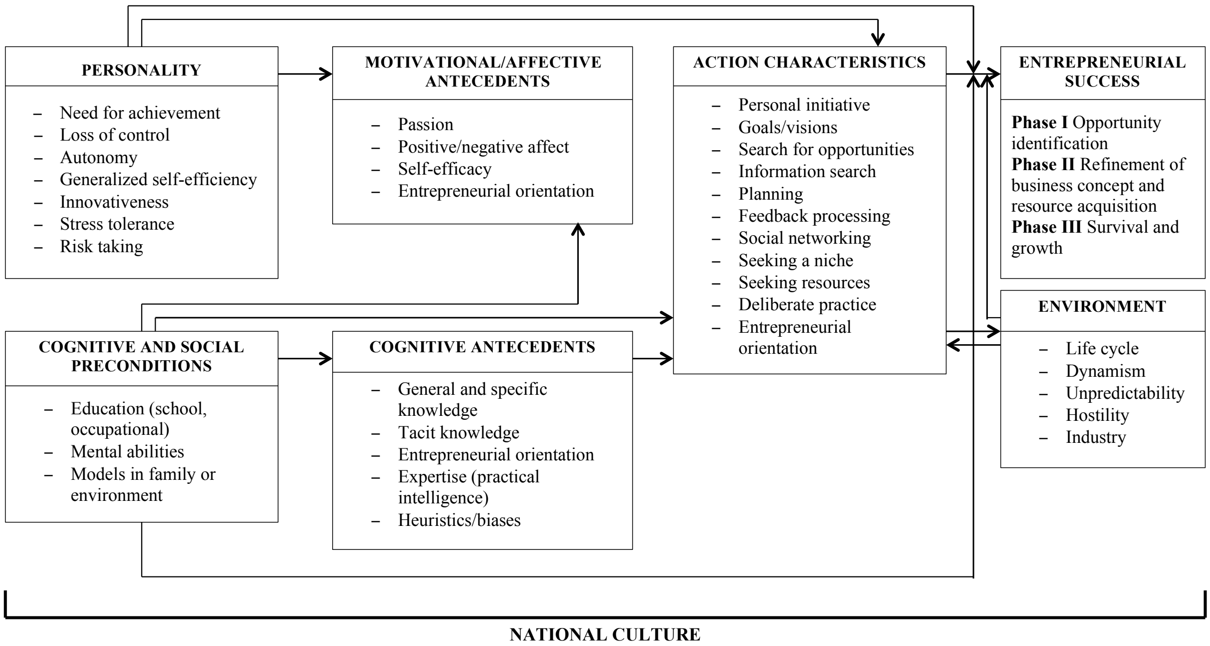


Figure 1: The action-characteristics model of entrepreneurship (Frese, 2009)

It is to be noted that, aside of the usefulness of these concepts in understanding the complexity of entrepreneurial performance; the founder characteristics included in the present section were not used to determine startup success in the current thesis.

3. Conceptual Model

As seen throughout the literature review, organizational outcomes are closely tied to their founders, especially since their decision-making, values, cognitive biases and beliefs are reflected in their company's culture. Furthermore, prior literature has identified various personal characteristics and competencies of the founder to be reliable approximations of their company's performance. The literature review thus shown that startup performance can be measured along the dimensions of *age*, *gender*, *former education*, *field of study, relevant industry experience*, and *previous entrepreneurial experience*. As discussed in the previous chapter, despite the availability of alternative founder characteristics found in previous literature, the current paper makes use of a selected group of variables only.

3.1 Age and start-up Performance

The anecdotes of young, successful entrepreneurs, such as 19-year old Mark Zuckerberg setting up Facebook from his dorm room, David Karp starting Tumblr at the age of 20, and the Apple Computer launched by 21-year old Steve Jobs have led us to believe that the key to newly-founded company success lies within founding one's business at 20-something. Moreover the conditions and recent trends of the fashion industry make us trust in young entrepreneurs' increasing dominance of the market.

The literature review, however, has revealed otherwise, indicating that – generally speaking – entrepreneurs aged between 35 and 45 are more likely to have better-performing businesses, as measured by founders' effective capacity to launch their businesses (Liles, 1981); average rates of success upon closing their business (Gomolka, 1977), rates of survival (Lussier, 1995); acquiring business loans successfully (Robb & Wolken, 2002); and indicated profitability (Gorgievski, Ascalon & Stephan, 2011). Following this logic, it is therefore proposed that age is a good determinant of startup performance and that startups are likely to perform the best with founders aged 35 to 45.

H_1: A founder's age is reversibly correlated with the performance of the firm.

3.2 Gender and start-up Performance

According to the Global Entrepreneurship Monitor's *Women's Entrepreneurship 2016/2017 Report*, "among 63 economies (out of 74) featured in this report and the previous one issued two years ago, overall female TEA rates have increased by 10% and the gender gap (ratio of women to men participating in entrepreneurship) has narrowed by 5%" (Kelley et al., Women's Entrepreneurship 2016/2017 Report, p. 8). In addition, the report reveals the differences in male-, and female business owners' opportunity perfection to be relative narrow, and capacity perceptions between genders showing that 67% of females believe they have the capabilities to start their own ventures at the factor-driven stage.

Nonetheless, scholars have predominantly placed the perceived business success of male-, above female entrepreneurs in the reviewed literature, even in the fashion industry, which is perceived to be highly dominated by women. In particular, the reviewed literature has revealed men to have significantly higher income in developed economies (Loscocco et al., 1991) and in developing ones (Honig, 1998); better chances of business growth (Cooper et al., 1994); significantly higher sales (Chaganti & Parasuraman, 1996); and better business performance via capital assets, sales turnover, as well as higher employee numbers (Rosa et al., 1996; Sabarwal & Terrell, 2008). Closing rates also favored male entrepreneurs over female ones (Robb & Wolken, 2002). Following this logic, it is hypothesized that gender is a fair determinant of startup performance, assuming that male entrepreneurs are more likely to own better-performing startups as opposed to female entrepreneurs.

H_2: A startup with a male founder will have greater performance than a startup with a female founder.

3.3 Education and start-up Performance

As discussed in the Literature Review, education has long been considered a key metrics in evaluating the performance of startups, with extensive positive relationship discovered between the two. In particular, college education is believed to intensify crucial abilities and skills needed for individuals to successfully take their businesses off the ground (Gartner, 1985; Boure & Maidique, 1986; Sapienza & Grimm, 1997; Simpson, Tuch & Bellamy, 2004; Colombo et al., 2004). This might be the reason why entrepreneurs acquiring a college degree are perceived to perform better as opposed to entrepreneurs with a high school education (Gimeno et al., 1997). The rate of business growth – another measure for startup performance – is also more common within those businesses owned by college-educated entrepreneurs (Parker & Van Praag, 2006; Blackburn, Hart & Wainwright, 2013). Such predicted positive correlation is also approved by studies examining developing economy-startups (Philip, 2010). Following this logic, former education is believed to be a fair determinant of startup performance, assuming that college-educated entrepreneurs are more likely to own better-performing startups as opposed to entrepreneurs with a lower level of education.

H_3: A founder's former education is positively correlated with the performance of the firm.

Aside the general interpretation that education has a positive impact on startup performance, several studies took an additional step to examine how specific subjects studied at a college level have an influence on business performance. Thus, the Literature Review has revealed business-related and knowledge-intensive fields of education to positively affect startup performance (Sapienza & Grimm, 1997). In addition, given the wide set of skills required to maintain their businesses, the literature review revealed the urging need for fashion entrepreneurs to acquire business skills. Following this logic, field-specific education is believed to be a reliable estimator of startup performance, assuming that business college graduates, and those businesses led by individuals holding an engineering, ITC or science-related degree outperform the rest.

H_4: A startup with a founder that completed business-related and/or a knowledge intensive field of education will have greater performance than a startup with a founder that completed an alternative field of education.

3.5 Relevant Industry Experience and start-up Performance

In recent year, the debate on industry-specific knowledge and its impact on companies' likelihood to succeed has been intensified (O'Conor, 2014). Generally speaking, relevant industry experience's correlation to startup success was found to be significantly positive throughout the reviewed literature. Focusing on the fashion industry, moreover, has indicated the direct and indirect positive correlation between relevant industry experience and startup performance.

In particular, relevant industry experience enhanced entrepreneurs' competitive advantage (Cooper & Bruno, 1977), provided founders with greater industry-relevant networks (MacMillan & Day, 1987), was associated with faster firm-growth (Siegel et al., 1993), and significantly diminished the likelihood of startup morality (Brüderl, Preisendörfer and Ziegler, 1992; Pennings, Lee & van Witteloostuijn, 1998). Relevant industry experience is also believed to help entrepreneurs evaluate opportunities better (Cassar, 2012). Following this logic, it is hypothesized that relevant industry experience is a good estimator of startup performance, assuming that founders with more extensive knowledge on the industry in which their startup operates in perform better as opposed to ventures led by entrepreneurs with no relevant industry experience.

H_5: A founder's relevant industry experience is positively correlated with the performance of the firm.

3.6 Previous Entrepreneurial Experience and start-up Performance

There is no formula to success. Nonetheless, whereas every scale-up entails a unique story, entrepreneurial-rich backgrounds, both in a professional and a personal sense are commonly seen to materially increase the scale of success (van Dijk et al., 2015. p. 5). As seem throughout the literature review, entrepreneurial experience positively impacted startups' recital, let it be in terms of general performance (Stuart and Abetti, 1990; Gimeno et al., 2000; Brüderl and Preisendörfer, 2000); startup growth (Chandler and Jansen, 1992); or the survival of newly founded ventures (Bates, 1990). It was also revealed that, due to the complexity and high turbulence of the commerce of fashion, industry-specific experience pays off, especially at the early stages of startup foundation. Following this logic, it is theorized that the relationship between previous entrepreneurial experience and startup performance is significant and positive, with the assumption that better-performing startups are the ones founded by individuals with extensive entrepreneurial experience.

H_6: A founder's previous entrepreneurial experience is positively correlated with the performance of the firm.

3.7 Conclusion to the Conceptual Model

Based on the Literature Review, the Conceptual Model of the current thesis predicts startup performance to be enhanced with a founder: (a) who is between the ages of 35 to 45 and male; (b) who was previously engaged in former education; (c) whose field of education relates to business and/or a knowledge intensive subject; (d) with relevant industry experience; and (e) with previous entrepreneurial experience. Based on the sample provided, the following chapter looks at how these variables are expected to influence startup performance in details. The framework presented in the conceptual model will be used as an outline for the subsequent chapters on data & methods. The visualization of the conceptual model is shown in Figure 2.

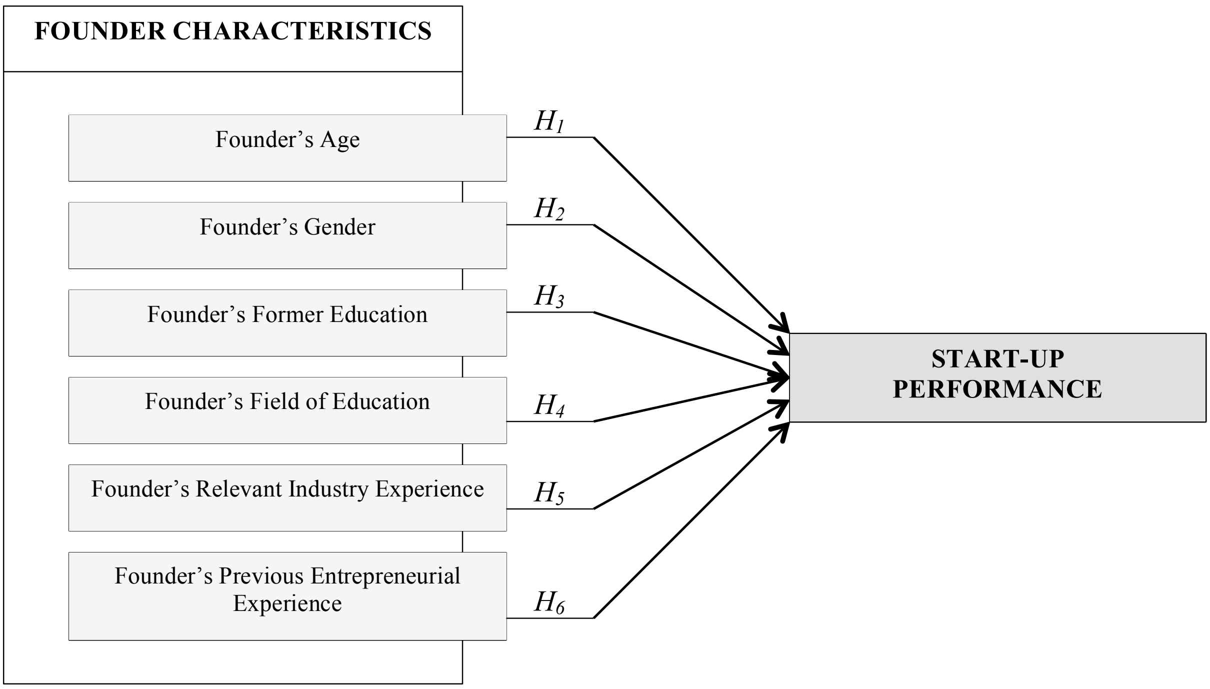


Figure 2: Visualization of the Conceptual Model

4. Data & Methodology

The following chapter describes the collected data sample, while elaborating on the measurement of the dependent variable start-up survival, and independent variables age, gender, education, field of education, relevant industry experience, and previous entrepreneurial experience. The chapter then moves on to the data transformation process of the dataset, and concludes with the methods of data analysis.

4.1 Sample and Data Sources

4.1.1 Crunchbase Dataset

The current study utilizes data collected through Crunchbase – leading commercial online platform that accumulates available company information. Since its establishment is 2007, Crunchbase has become increasingly popular among scholars and researchers. Inter alia, Dalle, den Besten, & Menon (2017) document over 90 publicly available, scientific contributions based on Crunchbase data. Moreover, it is claimed that Crunchbase has become the primary information source on start-up activity. As reported by the Kauffman Foundation, venture capitalists increasingly make use of the database, treating it as "the premier data asset on the tech/start-up world" (Eckhardt, Hallen, Krishnan, & Nanda, 2016, para. 4).

Given Crunchbase's newly earned position as key investor-focused data source, it is reasonable to assume that entrepreneurs have a strong incentive to register their enterprise on the website and to keep their information frequently updated. Aside the comprehensiveness of the database, Crunchbase is ideal to use together with empirical analyses, as it does not require huge amounts of data handling. Moreover, as opposed to alternative databases covering similar information, which are also frequently used for economic research, Crunchbase is conditionally free to access for researchers (conditional on applying for a license and on complying with the terms of use). On the contrary, Crunchbase's open source characteristics imply that – unless closely supervised on an ongoing basis – it is difficult to keep track and evaluate the quality of company-related data provided. However, considering the scope of this thesis and the lack of available startup-related information, the Crunchbase dataset was selected as the baseline source of the current study due to its accessibility, transparency, relatively easy data handling, and increasingly extensive startup-related information available. Nonetheless, all accessible startup-related information on Crunchbase was further evaluated to make sure that only unbiased, valid and reliable information was included in the sample.

More specifically, the initially selected Crunchbase dataset was further filtered in order for the sample to be of a suitable size and to have increased focus on a specific sector of the creative industries. The criteria for selected companies included their year of foundation. In particular, the Crunchbase data was filtered for those ventures founded between 2014 and 2015. This allowed for a more accurate comparison regarding ventures' chances of survival, measured over the same time frame.

Aside of their year of foundation, the filtered dataset was concerned with the fashion industry alone. Besides the current study's aim to add to the neglected body of research concerning the fashion industry, the study selected fashion startups specifically for two main reasons. One of the reasons relates to the current study's original focus, which aimed to collect information on Dutch, Belgian, and German high-technology wearable startups from the WEAR Sustain online ecosystem network. During the data collection phase, however, it became clear that the information available on the WEAR Sustain database and additional efforts of data mining did not provide enough information on the variables the current paper was concerned with. In particular, very limited information was made available on startup performance. The WEAR database was therefore replaced by the Crunchbase dataset. At the same time, it was intended to keep a strong focus on a similar industry.

The second reason was more of a practicality. The Crunchbase dataset allows for filtering based on categories and category groups. A number of cultural and/or creative industries were included among these categories; namely gaming, design, music, visual arts, and fashion. On the contrary, a closer look into each of these categories highlighted certain issues for some. For instance, a number of the creative industry-related categories did not yield a significant amount of startups after all filters were applied to the original database. Other cultural industry-related categories had ideal amounts of filtered matches, yet Crunchbase considered their cultural industry categories in a very broad sense. For instance, filtering for category 'Design' yield a sufficient amount of data points, yet a closer look into these startups revealed that within the sample, a broad understanding of design was present that meant the inclusion of those design categories within the filtered sample that did not overlap with the current study's understanding of design. Nonetheless, the exclusion of unrelated design firms only led to an insufficient number of sample size that, again, was unsuited for the current research purposes.

Finally, start-ups founded by a single entrepreneur were the only ones selected for the research to assure that start-up performance, measured through start-up survival, was influenced by the age, gender, level of education, field of study, relevant industry experience, and previous entrepreneurial experience of one person and one person only. Thus, considering the above specifications, 219 globally selected fashion start-ups, founded between 2014 and 2015 by a single entrepreneur, made it through the initial selection of the study. The demographic orientation of these countries, in addition to other descriptive characteristics is further elaborated on in the results chapter of this paper.

4.2 Dependent variable: Start-up Performance

After the initial study sample was established through Crunchbase, additional information related to the examined variables was collected from multiform sources. Data regarding the dependent variable, start-up performance - measured by startup survival, is evaluated through a number of systematic steps. First, the companies' official websites were visited to see whether they were active. In various cases, this led to a certain suspicion since some websites were inactive and/or had their domains put up for sale. Nonetheless, further examination was needed to see whether these companies were inactive or have simply changed their domain names since their foundation.

Aside looking at official websites, new ventures' survival was put to test via the examination of their various social media pages. In particular, the pages' recent content posted and engagement rates were paid close attention to. Naturally, some startups engage their followers more frequently than others; therefore the main focus of such social media-related examination was on the date of their last post.

Startup survival-related information was also collected via founder-based data. These included the examination of founder's LinkedIn profiles as well as online interviews and – in various cases – founder biographies. The examination of individual-level data was proven to be exceptionally useful in cases where ventures have 'passed' the first two rounds of examination to qualify as survived, yet they were in fact inactive.

4.3 Independent variables

4.3.1 Age

Out of all examined independent variables, the collection of founders' age was proven to be the most difficult, mainly due to the absence of concrete numerical data available for a large number of selected startup founders. Thus, founders' age had to be calculated in an indirect way – based on their year of graduation in particular. According to OEDC's *Education at a Glance 2017* report, across OECD countries, the average age of first-time[1], bachelor's or equivalent level graduates was 21 years (OECD, 2017, p. 68). The founders' age was thus indirectly calculated based on such estimation. In particular, founders' year of graduation was collected through multiple sources, such as various social media channels, LinkedIn profiles, and university alumni databases. Upon the collection of these results, their age was approximated, assuming that they all graduated at the age of 21.

It can be argued that such estimation is vague and therefore does not provide accurate empirical data points for the analysis. Nonetheless, the above-described indirect method to collect data on variable age was proven to be most ideal even among several alternative solutions, which were each considered individually. For instance, age-related data was grouped into 5-year ranges. Alternatively, it was attempted to estimate age with the help of other, indirect measures, such as founders' age at high school graduation, assumed to be 18. Nonetheless, it was decided to incorporate the age option based on the aggregate, approximated age of college graduation because measuring founders' age on a ratio-level, given the possibility of it not being the most accurate estimate, provides more information for the binomial logistic regression analysis than other, previously described ways of estimating age.

4.3.2 Gender

The collection of gender-related data was gathered through subjects' personal Crunchbase profiles. In cases where personal Crunchbase profiles did not reveal founders' gender, additional sources were used for such indication. In extreme cases, where neither ones name, nor their personally indicated information had revealed gender, various interviews were examined, which – in each case – acted as strong indicators for gender's evaluation.

[1] A "first-time graduate is a student who has graduated for the first time at a given level of education during the reference period. Therefore, if a student has graduated multiple times over the years, he or she is counted as a graduate each time, but as a first-time graduate only once" (OECD, 2017, p. 68).

4.3.3 Education

Prior to collecting actual, education-related information, the criteria for completed former education had to be established throughout the sample. For the current study purposes, founders had to have acquired a bachelor's or equivalent level degree in order to belong to the group with those who have completed former education. As defined by OEDC's *Education at a Glance 2017* report, bachelor's level of education is "designed to provide participants with intermediate academic and/or professional knowledge, skills and competencies, leading to a first degree or equivalent education" (OECD, 2017, p. 69). It is also revealed that the typical duration of completing a bachelor's or equivalent-level degree full-time takes approximately three to four academic years.

Once these criteria got established, founders' educational background was reviewed via a number of relevant, online sources. Generally speaking, founders' LinkedIn profiles revealed a fair amount of information regarding their former education. Nonetheless, given LinkedIn's employment-oriented setup, any indicated information – including one's educational background – had to be evaluated with caution. Thus, additional sources were looked at to verify whether the information noted on founders' personal profiles were correct.

4.3.4 Field of education

As discussed in the literature review chapter, certain fields of study have a stronger positive impact on startup performance than others. During the data collection, founders' specific field of education was documented aside of the presence/absence of any completed former education. One complication that arose during the collection of such data was with those founders that have completed a study program with overlapping fields of study. For instance, certain subjects in the data sample completed degrees consisting of a major and a minor, where others had completed more than one bachelor-level degrees, each with a different field of study.

Thus, the current data was collected systematically to guarantee consistency of the sample. In particular, the major/minor degree issue was settled by indicating someone's major field of study as this is considered to be most influential. This limitation took some relevant information away from the sample, yet the collection of codifiable data was prioritized, keeping in mind the scope of the study.

4.3.5 Relevant Industry Experience

Since the current study concerns fashion startup founders and their enterprises, relevant industry experience was present for those subjects with industry experience in the fashion industry in particular. The relevant industry experience of startup founders in the sample was multiform, including work experience in fashion retail, sports retail, fashion consultancies, and modeling agencies. To make sure that data on variables relevant industry experience and previous entrepreneurial experience are not overlapping, those subjects with previous entrepreneurial experience in the fashion sector were accounted for the variable measuring the presence of past entrepreneurial experience and not for their experience in the examined industry.

Sources of data collection for this particular variable were mainly concerned with founders' LinkedIn profiles. In a number of cases, limited amount of information was provided on LinkedIn. In those cases, and to review information objectively, additional founder-centered sources (such as interviews with founders and/or founder biographies) were searched for.

4.3.6 Previous Entrepreneurial Experience

As indicated throughout the literature review, previous entrepreneurial experience is hypothesized to enhance fashion startup performance positively. The data for previous entrepreneurial experience was collected through LinkedIn, as well as additional founder-related sources like founder biographies and interviews. All collected variables, different data sources and measurements utilized in the current study are summarized in Table 1.

Table 1: Collected variables, data sources, and data measurements

Variable	Data Source and Measurement
Age	Variable measured indirectly using founder's average age at first-time, bachelor's or equivalent level graduation. Graduation-related data acquired through LinkedIn and university alumni databases.
Gender	Variable measured directly and acquired through Crunchbase and LinkedIn.
Education	Variable measured directly using LinkedIn and university alumni databases.
Field of education	Variable measured directly and acquired via LinkedIn and university alumni databases.
Relevant industry experience	Variable measured directly using LinkedIn, interviews and founder biographies.
Previous entrepreneurial experience	Variable measured directly using LinkedIn, interviews and founder biographies.
Startup performance	Variable measured directly via official company website, company's social media channels, founder-related data (LinkedIn, interviews, biography).

4.4 Data Cleaning & Transformation

A number of factors affect the types of errors and anomalies that are likely to occur in the provided dataset. Thus, both the codification of the raw data values and the creation of new (dummy) variables were required ahead of the data analysis. The process of data transformation entails the conversion of data from one format or structure to another. Within the current sample, raw, categorical data was transformed into a number of respective numerical categories prior to its transition to SPSS. This process concerned categorical variable *education_subject* – reflecting on considered founders' field of study – in particular.

Ahead of the transformation of raw-, into coded, numerical data, the different fields of study were established by grouping founders' indicated study programs into bigger categories. The current data sample had a wide selection of indicated subjects to start with, which meant that each individual's field of study had to be evaluated accordingly to decide on which group categories to create. After reviewing all data points and using the *Classification of Instructional Programs* (CIP 2000) as the main reference point, five individual categories were created, namely Business, Sciences, Mathematics & Computer Science, Arts & Humanities, and Other. The specific subjects included in each of these categories are presented in Table 2.

Table 2: Subject Classifications

Subject classification	Subjects acquired through Data Mining
Business	Economics, Applied Economics, Business Economics, Econometrics, Business Administration, Business Management, Business Studies, Business Communication, General Management, Management Science, Marketing, International Business, Finance, Accounting,
Sciences	Psychology, Gemology, Physics
Mathematics & Computer Science	Applied Mathematics, Mathematics, Technology, Information Technology, Computer Science, Computer-aided drafting
Arts & Humanities	Studio Art, English, Art History, Design, History, Visual & Dramatic Arts, Music, Fashion/Apparel Design, Textiles, Fine Arts, Convergent Media, Film, Film Studies, Modern Languages, English, Anthropology, History, Graphic Design
Other	Architecture, Engineering, Mechanical Engineering, Geological Engineering, Electrical Engineering, Chemical Engineering, Medical Engineering, Computer Engineering, Electronics, Manufacturing, Communication, Telecommunication, Global Media Studies, Human Development, Entrepreneurship, Personal Shopping, Image Consulting, Law, International Relations, Clinical Social Work, Cosmetology, Political Science

Once the above-mentioned categories were established, they were translated into numerical values to make them more suited for SPSS. More specifically, category Business was assigned number one, Sciences to number two, Mathematics & Computer Sciences to number three, Arts & Humanities to number four, and those with a degree of an alternative subject to number five.

Since variables *gender*, *education*, *industry_experience*, and *entrepreneurial_experience* are dichotomous, the creation of dummy variables was also a required step of the data transformation process. In particular, male entrepreneurs were assigned the number one, where female entrepreneurs got assigned a zero. All founders with former education were labeled with the number one, and those with no former education – a zero. Those individuals with relevant industry experience received the number one, whereas those with no relevant industry experience, a zero. Finally, the presence of previous entrepreneurial experience was labeled one, whereas no previous entrepreneurial experience received the number zero. The summary of all data cleaning and transformation processes can be found in the Appendix.

4.5 Data Analysis

The empirical data has been analyzed by means of the statistical application of SPSS, which is commonly utilized within the field of social sciences. The analysis was sub-classified into five phases, namely (1) assessing criteria to test whether the current sample is suited for the selected regression purposes; (2) the analysis of descriptive statistics and frequencies of the dataset; (3) Pearson's correlation coefficients; (4) Crosstabs; and (5) the binomial logistic regression to test related explanatory questions.

4.5.1 Assessing Criteria

Prior to testing the hypotheses with a binomial logistics regression, certain criteria had to be assessed in order for the regression model to show appropriate results. In total, the current sample was tested against seven criteria, of which four concerns the design and data measurements of the study, where the latter three evaluates how well the selected data fits the utilized regression model.

The first and second criteria relate to variables' level of measurement. In particular, in order to be eligible for a binomial logistic regression analysis, the dependent variable is to be measured on a dichotomous-, and the independent variables on a continuous-, or categorical-scale. According to criterion three, observations should be independent, which implies that the categories of the dependent variable are mutually exclusive and exhaustive. In other words, the observations should not come from repeated measurements or matched data and the outcome of the dependent variable cannot occur simultaneously. The forth condition refers to the size of the sample. Since the binomial logistic regression method relies on maximum likelihood estimation (MLE), it is suggested to account for approximately 15 cases per independent variable in order for the reliability of estimates to remain high.

In terms of criteria reflecting on the regression model itself, the fifth principle highlights the need for a linear relationship between the continuous independent variables and the logit transformation of the dependent variable. This assumption is assessed using the Box-Tidwell (1962) procedure, which requires two separate procedures in SPSS Statistics. The first part of the Box-Tidwell (1962) procedure assures that all continuous independent variables are transformed into their natural logs. The second part of the procedure requires the creation of interaction terms for each of these continuous independent variables and their respective natural log transformed variables. The only continuous independent variable included in the sample was *age*. Thus, it was the only independent variable that was transformed in accordance to the previously described Box-Tidwell criteria.

Aside single continuous variable *age*, categorical independent variables *gender*, *ethnicity*, *education*, *education_subject*, *industry_experience*, and *entrepreneurial_experience* were defined based on their level of measurement. As a final step that allowed for the execution of the second half of the Box-Tidwell method, an interaction term was created for variable age. Upon the creation of such interaction term, it was examined whether it is statistically significant, meaning that the original continuous independent variable and the logit of the dependent variable are not linearly related.

One way to assess such linearity assumption is to apply a Bonferroni correction based on all terms of the model, including the intercept (Tabachnick & Fidell, 2014). Because of the increased risk of a type I error in multiple statistical testing, probability (*p*) values are adjusted upon the application of the Bonferroni correction. “The routine use of this test has been criticized as deleterious to sound statistical judgment, testing the wrong hypothesis, and reducing the chance of a type I error but at the expense of a type II error; yet it remains popular in recent academic research” Armstrong, 2014, p. 502). Furthermore, as stated by Streiner and Norman (2011), the use of the Bonferroni correction depends on the circumstances of a study. In particular, no correction is advised when (1) the sample is small and a number of planned comparisons are expected (Schulz & Grimes, 2005; Streiner & Norman, 2011); (2) we are faced with an explanatory study with post-hoc testing looking at unplanned comparisons; (3) the results of each individual test carried out in the data analysis is of high importance; and (4) when type II errors are to be eliminated in the study. Given the relatively small sample size of the study and the importance of individual test results, the Bonferroni procedure was regarded as too conservative for the current study purposes, wherefore it was excluded from the procedure of assessing criteria.

The sixth assumption requires the data to be multicollinearity free. According to Alin (2010), “multicollinearity refers to the linear relationship among two or more variables, which also means lack of orthogonality among them” (Alin, 2010, p. 370).

To test whether the issue of multicollinearity has affected the data, the sample was tested through Multicollinearity Diagnostics.

According to condition seven, the utilized data should be free of significant outliers, high leverage points or highly influential points. The outliers were tested using a simple boxplot – a graphical plot for understanding the distribution of the data and for detecting outliers.

4.5.2 Pearson correlation coefficients

"In the philosophy of science, it has long been debated whether explaining and predicting are one or distinct" (Shmueli, 2010, p. 292). Why should there be a difference between explaining and predicting? The answer lies within the assumption that the data we measure does not always represent related constructs accurately. While utilizing statistical models to be able to operationalize theories, one must keep in mind the difference between explaining a phenomenon on a conceptual level and the way predictions can be concluded on a measurable level.

In a regression analysis, one or more dependent variables are explained in the model, whereas the Pearson product-moment correlation is used to indicate whether there is any linear association between two variables as well as the strength of such association. Whereas the purpose of these statistical tests are different, they are sensible to use together in the current study. In particular, measuring the Pearson correlation coefficients show the presence or absence of any potential correlation between observed variables – a sensible and effective step to take prior to explaining the relationship of such variables with the help of a binomial logistic regression model.

The correlation coefficient can take any value on the scale of positive one (+1; indicating a perfect positive association) and negative one (-1; indicating a perfect positive association). No association is signified by a correlation coefficient of zero. Whilst the rules for pairing the strength of the association with a certain correlation value are not set in stone, the current study utilizes the rules of thumb delivered by Cohen (1988). Cohen argues a correlation coefficient close to zero depicts a weaker association, whereas getting closer to the two ends of the scale (e.g. +1 and -1) indicate a stronger positive or negative link.

Aside of the strength of the Pearson's correlation coefficient value, its statistical significance needs to be determined in order to see whether to reject or accept the null hypothesis. If the set alpha equals 0.05 ($\alpha = 0.05$; i.e., $p < .05$), a significant Pearson correlation coefficient denotes that the strength of the relationship found through the examined correlation coefficients – if the null hypothesis were true – has less than a 5% chance.

4.5.3 Chi-square Test of Independence

As discussed in detail in the previous subsection, the prediction of any potential association between two variables can be done through Pearson correlation coefficients. Aside testing the existence of such correlations in the first place, one can choose to examine whether differences can be found between the different categories these variables.

Aside Pearson correlation coefficients, alternative correlation coefficients exist to measure the relationship between two nominal (categorical) variables. Thus, a Chi-square test for homogeneity was executed ahead of the logistic regression analysis to determine whether there is an association between two, nominal level independent variables.

4.5.4 Binomial Logistic Regression Analysis

A binomial logistic regression is used to predict the probability of an observation falling into one of two categories of a dichotomous dependent variable, based on one or more continuous or categorical independent variables. More specifically, the current study utilizes a binomial logistic regression to understand whether start-up performance can be predicted based on start-up founders' age, gender, formed education, field of study, relevant industry experience, and previous entrepreneurial experience.

4.5.5 Receiver Operating Characteristic and the ROC curve

The binomial logistic regression of the current study was accompanied with the Receiver Operating Characteristic method to assess the regression's ability to correctly classify cases. Receiver Operating Characteristics were tested with the help of the ROC curve, which "plays a central role in evaluating diagnostic ability of tests to discriminate the true state of subjects, finding the optimal cut off values, and comparing two alternative diagnostic tasks when each task is performed on the same subject" (Hajian-Tilaki, 2013, p. 627).

In a binomial logistic regression, a cut-off point of 0.5 (50%) is present, with calculated measures based on such point. For instance, having an event (e.g. a survived firm) is accepted for all cases (e.g. startups) where the predicted probability of that event is greater or equal to 0.5. Similarly, the absence of an event (e.g. a inactive firm) is classified for all those cases with a predicted probability below 0.5. What the ROC curve does is taking all possible cut-off points of the data into account, instead of focusing on a single cut-off point. With a wide variety of cut-off points considered, one can also assess how the sensitivity and specificity of the test is altered with each cut-off point. A higher cut-off point will increase specificity, but lower sensitivity as it makes it more difficult for startups to be classified as survived, but lowers the barrier for them to be inactive. The ROC curve, thus, provides the reader with the visual representation of such dynamics, where sensitivity versus 1 minus specificity is displayed (Hilbe, 2009).

5. Results

The following chapter presents the results of the analyses described in detail in the Methodology chapter. The results are reported as follows: Figures 3a and 3b display the associations found between various independent variables. Tables 3 and 4 report on the descriptive statistics, and frequencies examined between the dependent variable and multiple independent variables. Subsequently, Table 5 indicates the Pearson correlation coefficients. Followed by Table 6, displaying the results of the Binomial Logistic Regression. Finally, Table 7 provides an overview of the ROC curve results.

5.1 Assumption Testing

Prior to reporting on main statistical results, certain important assumptions were elaborated on in order for the final binomial logistic regression to show appropriate results. Overall, the current sample has met all but one assumption.

In particular, Assumption 5 was tested via the Box-Tidwell (1962) procedure to see assess the linearity of the continuous variables with respect to the logit of the dependent variable. The Bonferroni correction was not applied to the model. The detailed reasoning such exclusion is included in the Methodology chapter. Based on this assessment, *age* – the single continuous dependent variable incorporated in the model – was found to be linearly related to the logit of the dependent variable. Assumption 6 was tested through Collienarity Diagnostics, where Variance Inflation Factor (VIF) scores indicated that the model does not suffer from multicollinearity issues. Potential outliers were tested using a simple boxplot. The first boxplot indicated data point BUS004 as an extreme outlier (Figure 3a). After examining the case, it was excluded from latter stages of the analysis. Upon the extreme outlier's exclusion, the simple boxplot command was repeated, which led to no further extreme outliers within the sample (Figure 3b).

Figure 3a: Boxplot prior the exclusion of extreme outlier
(Mean = 34.65; Std. Deviation = 7.229)

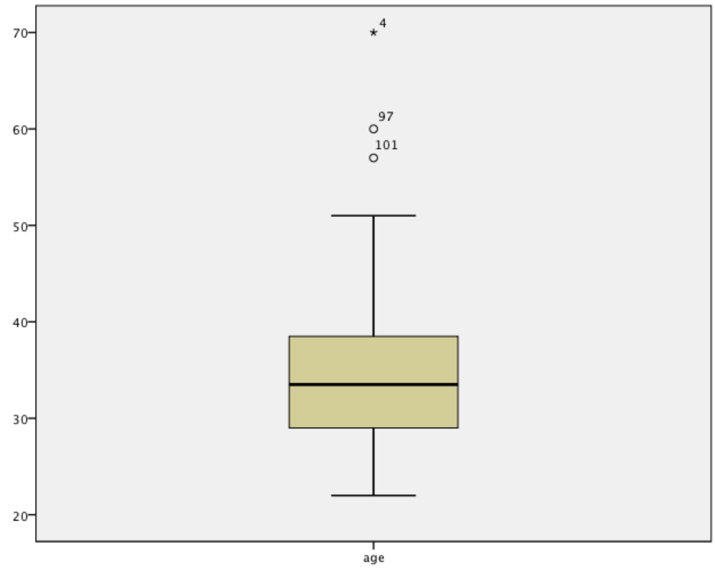
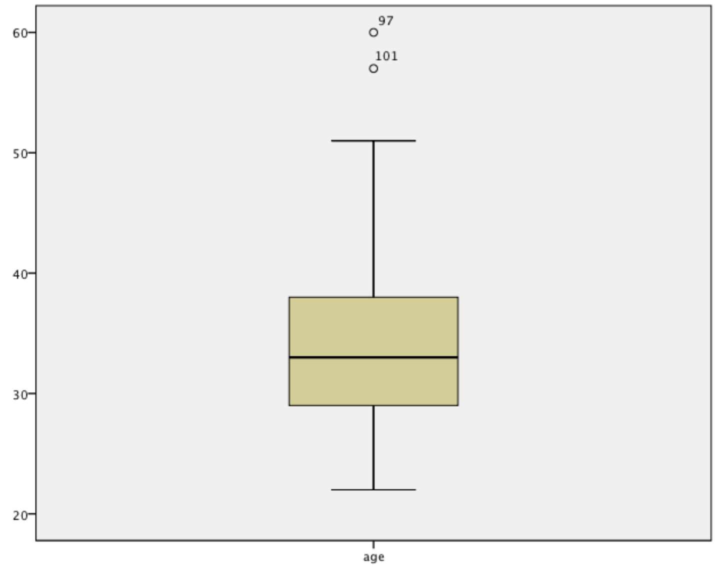


Figure 3b: Boxplot after the exclusion of extreme outlier
(Mean = 34.45; Std. Deviation = 6.681)



5.2 Descriptive Statistics

The descriptive statistical results of this study are summarized in Tables 3 and 4. Of the sample, 59% were male (Table 4). Age varied between 22 and 60 as the single extreme outlier for age (70 years) was previously excluded from further analyses, with the mean value of 34.45 years (Table 3). Furthermore, 90.1% of the respondents completed former education, with a significant diversity of respondents' chosen field of study (Table 4).

Considering relevant industry experience, 64.6% of subjects had no relevant industry experience in the fashion industry (Table 4). For the presence of previous entrepreneurial experience, this proportion was slightly lower, at 60.9% (Table 4). Finally, the ratio of survived and non-survived firms was 67.7% to 32.3% (Table 4).

Table 3: Descriptive Statistics

Variable	Valid N	Minimum	Maximum	Mean	Standard Deviation
age	159	22	60	34.45	6.681
gender	161	0	1	.59	.493
education	159	0	1	.91	.284
education_field	161	0	5	2.28	1.805
industry_experience	161	0	1	.35	.480
entrepreneurial_experience	161	0	1	.39	.490
firm_status	161	0	1	.68	.469

Table 4: Frequencies

Variable		Frequency	Percent (%)	Valid N	Missing
gender	Female (0)	66	41.0	161	–
	Male (1)	95	59.0		
education	No former education (0)	14	8.7	159	2
	Former Education (1)	145	90.1		
education_field	Not indicated (0)	20	14.1	161	–
	Business (1)	65	39.6		
	Natural Sciences (2)	4	2.4		
	Mathematics & Computer Science (3)	17	10.4		
	Arts & Humanities (4)	25	15.2		
	Other (5)	30	18.3		
industry_experience	No relevant industry experience (0)	104	64.6	161	–
	Relevant industry experience (1)	57	35.4		
entrepreneurial_experience	No previous entrepreneurial experience (0)	98	60.9	161	–
	Previous entrepreneurial experience (1)	63	39.1		
firm_status	Non-survived firm (0)	52	32.3	161	–
	Survived firm (1)	109	67.7		

5.3 Pearson Correlation Coefficients

As described in the previous chapter, the linear association between variables of the sample was tested ahead of the binomial logistic regression. The variables of the model, together with their corresponding Pearson correlation coefficients are displayed in Table 6.

Table 5: Pearson Correlation Coefficients

Variables	1	2	3	4	5	6	7
1. *age*	–						
2. *gender*	.020	–					
3. *education*	-.032	.100	–				
4. *education_field*	-.101	-.013	.256**	–			
5. *industry_experience*	.074	-.246**	-.001	-.007	–		
6. *entrepreneurial_experience*	.144	.156*	.068	.008	.029	–	
7. *firm_status*	.041	-.113	.120	-.031	.155*	.150	–

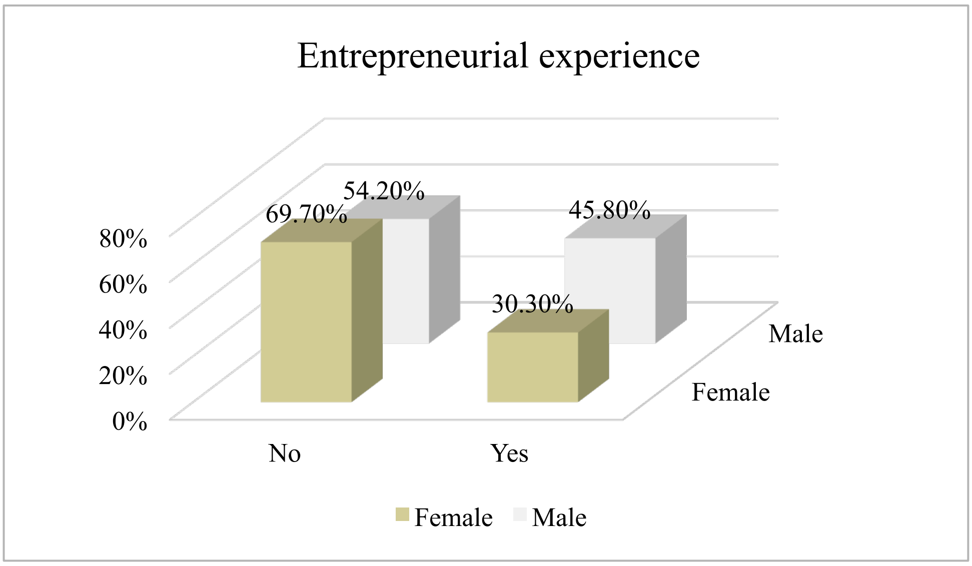
Correlation is significant at the 0.01 level (2-tailed) **
Correlation is significant at the 0.05 level (2-tailed) *

As indicated in the correlation matrix, there is a positive, significant correlation between startup performance and relevant industry experience, ($r = 0.049$, $p < 0.05$). In other words, the increase in relevant industry experience is associated with an increase in firm survival. Moreover, relevant industry experience is significantly, negatively correlated to gender ($r = -0.246$, $p < 0.01$). This refers to the association between relevant industry experience and females in the sample. On the contrary, entrepreneurial experience has a positive, significant correlation to gender ($r = 0.156$, $p < 0.05$). In other words, previous entrepreneurial experience is associated with males within the sample.

5.4 Chi-square Test of Independence

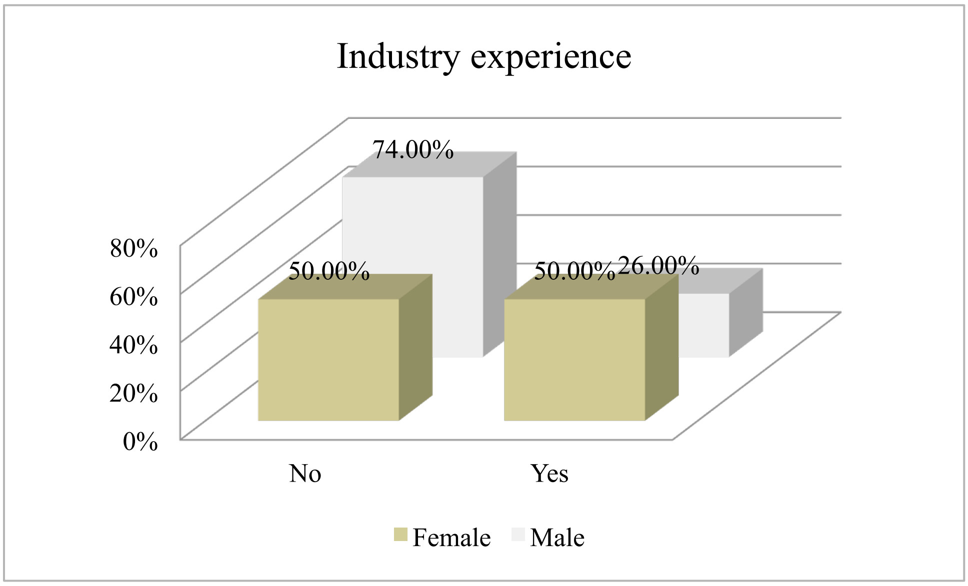
First, a chi-square test of independence was conducted between gender and relevant entrepreneurial experience (Figure 4a). There was a statistically significant association between gender and relevant industry experience, $\chi^2(1) = 3.947$, $p = .047$. The strength of the association was weak (Cohen, 1988), with Cramer's V = .156.

Figure 4a: Crosstabulation gender * entrepreneurial_experience



The second chi-square test of independence was conducted between gender and previous industry experience (Figure 4b). The association between gender and relevant industry experience was significant, $\chi^2(1) = 9.767$, $p = .002$. The association was moderately strong (Cohen, 1988), Cramer's V = .246.

Figure 4b: Crosstabulation gender * industry_experience



5.5 Logistic Regression Analysis

In accordance to the methodology of the current paper, a binomial logistic regression was performed to determine the impact of start-up founder's age, gender, ethnicity, former education, field of study, relevant industry experience, and entrepreneurial experience on the likelihood that their start-up survives. Table 6 summarizes key findings derived from the binomial logistic regression.

Table 6: Variables in the Equation

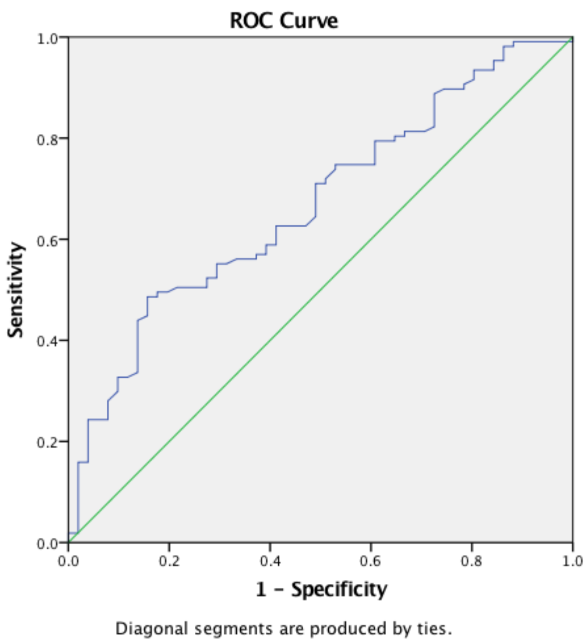
		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	*age*	.001	.027	.001	1	.975	1.001
	gender	-.576	.387	2.209	1	.137	.562
	education	.962	.633	2.304	1	.129	2.616
	education_field	-.328	.380	.746	1	.388	.720
	industry_experience	.506	.400	1.597	1	.206	1.659
	entrepreneurial_experience	.817	.386	4.472	1	.034	2.263
	Constant	.054	1.153	.002	1	.963	1.056

a. Variable(s) entered on step 1: age, gender, education, education_field, industry_experience, entrepreneurial_experience.

The logistic regression model was statistically significant, $\chi^2(4) = 14.628$, $p < .0005$. The model explained 12.4% (Nagelkerke R^2) of the variance in start-up survival and correctly classified 68.2% of cases. As opposed to optimal cases with higher R^2, the current sample indicates that 12.4% of the variation of startup survival is explained by the independent variables age, gender, ethnicity, formal education, field of study, relevant industry experience, and entrepreneurial experience. It is, however, to be noted that in most empirical models – especially those in social or behavioural sciences – fail to include all relevant predictors that have an impact on the outcome variable. Thus, it is understandable that for a complex concept like start-up survival, and with the inclusion of only seven independent variables, the overall explanatory power of the current model is limited.

As explained in detail throughout the current paper's methodology, the probability of an event occurring (in this case, startup survival) can be estimated through a binomial logistic regression. SPSS Statistics classifies an event as occurring when its estimated probability is greater than or equal to 0.5, and classifies an event as not occurring upon an estimated probability below 0.5. To accurately predict whether cases included in the model can be correctly classified, a method that assessed the effectiveness of the predicted-, against actual classification was included. In the current model, sensitivity was 89.6%, specificity was 23.5%, positive predictive value was 70.9% and negative predictive value was 47.8%. Aside the measures displayed in the previous paragraph, assessing the current binomial logistic regression model's ability to correctly classify cases was presented in a Receiver Operating Characteristic (ROC) curve. The ROC curve is presented in Table 7.

Table 7: ROC Curve



The area under the ROC curve is .668. According to Hosmer et al. (2013) a value of .668 puts the discrimination of this model at the lower border of accepted discrimination. Furthermore, the 95% confidence interval (CI) ranges is from .581 to .755.

Of the seven independent variables, only one – namely previous entrepreneurial experience – was found to be statistically significant (Table 6). In other words, the odds of survival for a startup whose founder has previous entrepreneurial experience is .451 times higher, compared to those startup founders with no previous entrepreneurial experience.

6. Discussion and Conclusions

With the revision and integration of various literary sources, the current study predicted likelihood between startup founders' personal characteristics, educational resources and opportunities, former professional and entrepreneurial experiences and the likelihood that their businesses are sustained over time. This field of study is barely new in the empirical literature, yet prior research had very limited focus on startups founded in the fashion industry.

Subsequently, information on essential variables was collected through means of data mining. Regarding founder characteristics, data was collected along six dimensions: age, gender, former education, field of study, relevant industry experience, and previous entrepreneurial experience. The dependent variable, startup survival was tested following a multi-step process described in the methodology chapter of this thesis. Formed hypotheses of the current study were then tested empirically, with data collected on 219 fashion startups founded between 2014 and 2015. The results of the paper suggest previous entrepreneurial experience to have a significant impact on startup survival.

The below section provides an extensive interpretation of results introduced in the previous chapter, followed by the theoretical and managerial implications of the current study. Furthermore, limitations of the current paper, as well as suggestions for future research will be postulated. The remainder of this section will offer concise concluding remarks.

6.1 Interpretation of Findings

All in all, the empirical results of this study support the literature. In particular, it is proven that the knowledge and skills of the entrepreneur are mirrored in his/her human capital and that these capabilities are key determinants of start-up performance. The paper collects evidence that the nature of fashion entrepreneurs' work experience has a significantly positive impact on performance. Contrary to assumptions based on the reviewed literature, neither age nor gender affected startup performance significantly. Even though the years of education and field of education did not yield significant results either, the years of business and knowledge-intensive education came close to have a significant positive impact on performance. Relevant industry experience of the entrepreneur was assumed to have a significantly positive relationship with performance but according to the results there was no significant difference identifiable.

6.2 Theoretical Implications

The current thesis contributed to various streams of scholarly investigation. First of all, it adds to the rapidly growing stream of research on entrepreneurship and adds to our understanding on its connection to newly founded businesses' performance. More specifically, this thesis adds to the existing literature on creative entrepreneurship by widening our understanding on how creative entrepreneurs operate in their respective industries and how they can utilize human capital to cope with the challenging conditions of their respective industries. Moreover, how founders' previous entrepreneurial experience influence the perception and interpretation of situations and subsequent strategic choices, helping them towards a sustained business.

The current thesis also contributes to the lacking literature on fashion entrepreneurship in particular. While utilizing a great number of relevant and relatively recent academic sources, the paper does not stop at the collection and systematic revision of these fashion-related sources, but aims to highlight the complexity and challenges of operating in the fashion industry – a tendency that, to the author's best knowledge, has not been commonly practiced in previous literature.

While the difficulties of objectively measuring startup performance are well presented in the literature (Quine & Lancaster, 1989), the chosen measure – startup survival – used in the current study helps to overcome some of the ambiguities associated with research on startup performance. Furthermore, by demonstrating that a founder's previous entrepreneurial experience is visible in his/her company's performance, this thesis helps fashion entrepreneurs to understand how their experience can influence decision-making and alter organizational outcomes.

This thesis was one of the first of its kind to connect the streams of research in entrepreneurial characteristics, competencies, and the stream of research focused on entrepreneurship in the fashion industry. By demonstrating the influence of entrepreneurial competencies on the performance of global fashion startups, the study answers Ioannou & Serafeim's (2010) call for a more comprehensive theoretical-, and empirical investigation into the particularities of entrepreneurial success.

The results of this thesis have provided new insights for personal characteristics' impact on cultural enterprises in sustaining their businesses over time, a field that is becoming increasingly important for cultural entrepreneurs. The next section will therefore elaborate on the implications and practical relevance of this thesis for startups and their founders in the creative industries and beyond.

6.3 Practical Implications

Besides contributing to various streams of literature, the results of this thesis also entail practical implications. The literature review has shown the reasons why relevant educational, industry-related, and entrepreneurial competencies are becoming such an increasingly relevant topic, and how startups are in need of gradually devoting more resources towards people with the right competencies to ensure and sustain promising organizational outcomes and strategic advantages.

Moreover, the results presented in this thesis have important strategic implications on an individual entrepreneurial level. In particular, the author hopes that the current paper can enhance individual understanding on the differences between personal characteristics and – more importantly – educational-, industry-specific-, and entrepreneurial development, and their impact on newly founded ventures' faith. A young firm's decision to appoint or take on board someone with more extensive previous entrepreneurial portfolio can improve its chances of survival. The implication for future entrepreneurs is therefore to assemble individuals with capabilities necessary to start a company. Furthermore, the paper may be a useful tool for investors, as it highlights key entrepreneurial competencies that may discriminate between well-performing and troubled startups. Policy makers could concentrate on ways to improve the flow of external competencies and other resources into the start-ups, if these competencies are not available in the entrepreneurial team.

Alternatively, the current paper paints a realistic picture on the difficulties of sustaining a young enterprise, especially in lack of previous industry-relevant and entrepreneurial efforts taken for the better understanding the sector the startup operates in. The presented results therefore provide guidance for first-time fashion entrepreneurs as well as those who might have had an unsuccessful business in the past and would like to gain insight into possible explanations of what they can do differently and how can they better prepare on a personal level next time.

6.4 Limitations and Suggestions for Future Research

As with most empirical research, the limitations of the study are to be reflected upon, especially to encourage future research in refining and extending current findings.

The first and foremost limitation of this thesis roots from its scope of research. In particular, a relatively small sample of 219 was initially collected, which then was further reduced to the final sample to fit established criteria, accounting for 161 fashion startup founders and relevant founder characteristics. Aside its small sample size, the current study consists of a global sample, which allows for the reflection on a wide range of social, institutional, and geographical settings. On the other hand, it can be argued that – taking the current paper's relatively small sample size into account – better implications could have been drawn from a sample with a specific geographical focus. Given the lack of sufficient information on fashion startups and their founders in a smaller geographical scope, future research could focus on individual countries in order to improve the reliability and specificity of results presented in the current thesis.

It is also revealed that – besides strong assumptions regarding the relations between various variables predicted based on previous literary sources – the current study did not yield but one significant result. Although suitable for the scope of this thesis, it is believed that increasing the size of the data sample could be exceptionally useful, especially due to the regression model used.

The scope of research can also be interpreted as the industry-focus of the thesis. Whereas the current paper had valid reasons to focus on the creative industries and more specifically, the fashion sector, it would be interesting to research and potentially compare different creative and cultural industries.

Aside its scope, an additional limitation roots from the fact that the paper utilizes data collected on firms founded between 2014 and 2015 instead of having its focus on startups founded in a specific year, or even during a specific month of that year. Again, the reason for such limitation was the difficulty in finding a sufficient number of data points for such narrow range of founding time. Future research could therefore attempt to overcome such limitation. Furthermore, the current study drawn conclusions based on data collected at a specific point in time. Future research could potentially look at time-series data on founder characteristics and startup survival to see whether the impact of personal characteristics on the likelihood of startup survival is altered over time. It would also be interesting to consider key economical, social, and political events when looking at such time-series data, which would likely to allow for a deeper understanding on the ever-changing trends of entrepreneurship and current events as well as the interconnected dynamics of the two.

The data collected on the explanatory variables had a strict focus on founders' characteristics alone. Nonetheless, it is clear that for a complex construct like startup performance, the founder and his/her competencies are only one of the various factors that can have an effect on such construct. To gain a more complete picture, future research could thus include characteristics of the firm as well as business practices and human resource management practices and networks. Since acquiring the founder-level data was done through secondary sources, the risk remains that sources may lack authenticity and objectivity in addition to a lack of control over data quality (Saunders, 2009). This general disadvantage of secondary data is especially limiting for the measurement of former education, relevant industry experience and previous entrepreneurial experience, since some startup founders may indicate untrue competencies to appeal to potential investors and collaborators. The binomial logistic regression used in this thesis yield significant results, yet future research could focus on acquiring primary data through interviews and/or surveys directly from the founders to ensure the quality of data collected.

Besides its reputation as widely accepted-, and unbiased measure of startup performance, it can be argued the current study could have utilized a broader spectrum of dependent variables to measure startup performance. Thus, it is suggested for future research attempts to have multiple binomial logistics regressions included, each focusing on an alternative measure of startup performance. These measures could include company revenue, total amount of funding received in the first two years of foundation, and alternative measures of financial-, and non-financial profitability. Moreover total employee numbers and employee growth could be looked at to measure startup performance via growth.

Upon reflecting on performance, it is crucial to keep in mind the differences the creative industries entail both in terms of market structures and the mindset of creatives. As discussed throughout the previous chapters, success in the creative industries and by standards of the creative crowd may be unrelated from financial performance or growth (Walker & Brown, 2004). In particular, previous research concerned with the interpretation of business success in the creative industries found that being autonomous, founders ability to freely create and to ‘just’ sustain their businesses without the desire to grown financially or size-wise were seen as key measures of success, with traditional measures of business performance considered as irrelevant and, in certain cases, unimportant. The current research prioritized empirical testing over qualitative and mixed methods to explore the impact of founder characteristics and startup performance, mainly due to the scope expected at this stage of research. It is therefore crucial to consider the expansion of the paper in terms of its means of analysis. In particular, future research could utilize a mixed method analysis, where qualitative empirical testing collected through means of data mining is accompanied by interviews with various startup founders. This way, the quantitative testing would indicate the ‘how it is supposed to be’ scenario, using success measures determined by literature, whereas the qualitative addition would gain personal insights on the relationship between founder characteristics and competencies and their individual measures of business success – in other words: ‘how it really is’.

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Appendix

Summary of measures of start-up performance specific to the fashion industry

Metrics	Metric Description
Standard Allowed Minute (SAM)	Used to estimate the total length of making a garment.
Operator Efficiency	Measures the expertise and skills of a particular employee.
Production Batch/Line Efficiency	Measures the daily efficiency of the production line.
Labor Productivity	Measures the number of garments produced in a specific time period. Measured as a ration of inputs & outputs.
Perfect Order Fulfilment	Measures the percentage of products delivered to customers with full documentation and no defects on time.
Repeated Order	Measures the percentage of orders by existent customers as opposed to all incoming orders.
Upside Supply Chain Flexibility	The amount of time a supply chain takes to respond to a service-, and cost-penalty free increase of demand by 20%.
Accuracy of Production Queuing	Measured the time elapsed before work is performed on a particular garment.
Accuracy of Production Planning	Measures the average total time spent on making a garment.
Accuracy of Material Planning	Measures the accuracy of the purchased materials ordered and looks at whether it is aligned with what was needed to create a garment.
Sourcing Time	Measures the average time spent sourcing raw materials.
Inventory Turnover	Measures the number of times a company's entire inventory was sold. Measure based on a specified accounting period.
Approved Sample Product	Measures the percentage of customer-approved product samples.
Rework Production Ratio	Measures the percentage of product alterations required.
Amount of Dead Stock	Measures the amount of fabric left upon an order shipment.
Cut to Ship Ratio	Measures the ration of shipped-, and cut garments.
Return of Defective Product	Measures the percentage of faulty products, returned by customers.

Data Cleaning Summary

Variable		Description of cleaning process		Count (N)
age	⟶ *age*	Recoded into the same variable	Variable ranges from 22 to 60; Extreme outlier (= 70) was excluded from the analysis.	159
gender	⟶ *gender*	Dummy variable created	= 1 if male	161
education	⟶ *education*	Dummy variable created	= 1 if former education present	159
education_field	⟶ *education_business* ⟶ *education_sciences* ⟶ *education_mathematics* ⟶ *education_arts* ⟶ *education_other*	Five independent dummy variables created	= 1 if field of study is related to Business = 1 if field of study is related to Sciences = 1 if field of study is related to Mathematics = 1 if field of study is related to Arts = 1 if field of study is related something else	161
industry_experience	⟶ *industry_experience*	Dummy variable created	= 1 if relevant industry experience present	161
entrepreneurial_experience	⟶ *entrepreneurial_experience*	Dummy variable created	= 1 if previous entrepreneurial experience present	161