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Modeling the Determinants of Entrepreneurial Success and Failure in Newly Created Moroccan SMEs: A Machine Learning Approach

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Abstract

In Morocco, SMEs play an undeniable role in economic development and job creation to combat unemployment. However, studies of newly created businesses, mainly SMEs, reveal a very high mortality rate. This article aims, firstly, to identify the endogenous and exogenous factors that explain the success and/or failure of entrepreneurship in newly created SMEs; secondly, to develop a predictive model based on Machine Learning techniques. Thus, statistical tools such as the chi-2 test, contingency coefficient, correlation matrix, and principal component analysis (PCA) were used to analyze the data and test the hypotheses. Next, binary logistic regression enabled us to model the relationship between the independent variables and the dependent variable, while measuring the impact of each explanatory variable. Finally, Machine Learning techniques were applied to identify the most significant variables in our conceptual model. These variables will be integrated into our predictive model based on the Random Forest technique. The results show that out of the 27 variables comprising our conceptual model, only 12 variables have a significant influence in explaining the entrepreneurial situation of entrepreneurs in newly created SMEs, with a dominance of factors aligned with the resource-based and skills-based approach.

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1. Introduction

Over the past twenty years, entrepreneurship has attracted increasing interest in both political and academic circles. One of the main reasons for this is the belief that entrepreneurship is a vital force in national economies, stimulating and fostering growth (Acs, Audretsch, Braunerhjelm, & Carlsson, 2012). The new trend is also due to the fact that entrepreneurship is increasingly viewed as a credible alternative to supporting wage employment in the fight against unemployment (O'Leary, 2022). With this in mind, successive Moroccan governments have implemented policies primarily aimed at supporting self-initiated employment, assisting entrepreneurs, and fostering creativity and innovation. These policies have led to the adoption of several programs to promote entrepreneurship (Imtiaz, Moussanada, Moukawalati, Intilaka, Forsa) and the establishment of various support structures, including regional investment centers (RIC), the National Agency for the Promotion of SMEs (NAPSME), the Moroccan Confederation of VSE-SMEs, and others.

Furthermore, a number of studies have shown that, despite the efforts made by the Moroccan government to promote entrepreneurship, very few of the companies created survive (Inforisk, 2021, 2022). Thus, one of the main aspects of entrepreneurship research is to examine the reasons why some entrepreneurs succeed and others do not. This question has been widely debated by academics and practitioners alike. However, the failure or success of new businesses, particularly SMEs, remains a relatively underexplored topic in the entrepreneurship literature (Khelil, Smida, & Zouaoui, 2018).

In the Moroccan context, an important characteristic of SMEs is their high failure rate. In 2022, the number of failing businesses was approximately 15,000. By category, 99.9% of failing businesses in Morocco are SMEs (Inforisk, 2022). This disconcerting fact is not recent. Indeed, a study carried out by the Casa-Settat regional investment center, in partnership with the World Bank, on a representative sample of 1,230 companies, highlights that 32% of small and medium-sized businesses created manage to survive five years, and only 6% of companies are still active ten years after their creation (CRI Banque Mondiale & Capital Consulting, 2018). This high mortality calls on researchers to gain a better understanding of the factors that explain both the failure and success of this type of business, with a view to developing predictive models capable of detecting the warning signs of imminent failure.

In the Moroccan context, research dealing with a topic similar to ours is most often part of a qualitative approach (Abriane & Aazzab, 2016; El Manzani, Asli, & El Manzani, 2018; Ghiffi, Mounir, & Nekka, 2017) and the limited amount of research taking a quantitative approach uses conventional statistical tools or attempts to explain the failure or success of SMEs based exclusively on financial ratios (Kherrazi & Ahsina, 2016).

Beyond the Moroccan context, in order to identify the factors that explain the success or failure of SMEs, a great deal of research has focused on the use of statistical modeling methods, mainly binary logistic regression. The latter is considered an essential tool for developing predictive models (Boubakary, 2021; Ben Boubakary, Boukar, & Tsapi, 2017; Dié, 2016; Kherrazi & Ahsina, 2016; Mmbengwa, Qin, & Nkobi, 2021; Molou, Fotso, & Tchankam, 2020; Rahman & Besra, 2020; Wamba & Hikkerova, 2014). However, using only binary logistic regression can restrict the scope and accuracy of predictive models (Ranganathan, Pramesh, & Aggarwal, 2017). So, in our research, we decided to combine binary logistic regression with other machine learning techniques, mainly the decision tree method and the random forest method, to improve the accuracy of our predictive model and consequently identify factors with greater explanatory power for entrepreneurial failure or success.

With this in mind, we based our research on a positivist paradigm. We have mobilized a conceptual framework structured around three main theoretical foundations: population ecology theory (Hannan & Freeman, 1977) the resource-based approach (Wernerfelt, 1984) and approaches based on commitment and motivation (McClelland, 1987). These theoretical foundations led us to formulate three main hypotheses. These were subsequently broken down into sub-hypotheses. Each sub-hypothesis corresponds to an independent variable in our conceptual model. In total, our conceptual model included 27 variables that could potentially explain entrepreneurial failure or success in newly created SMEs.

To test the formulated hypotheses, we adopted a quantitative approach. Statistical tools such as the chi-squared test, contingency coefficient, correlation matrix, VIF, and principal component analysis (PCA) were used. Subsequently, machine learning techniques such as binary logistic regression, decision tree, random forest, and top-down selection were employed to model the relationship between the independent variables and the dependent variable (entrepreneurial situation) and, consequently, to identify the most significant variables for inclusion in our predictive model.

By combining the binary logistic regression method with other machine learning techniques, this research contributes to a better understanding of the explanatory factors of entrepreneurial success and failure in newly created SMEs, while developing a robust predictive model. The results obtained enabled us, firstly, to identify 12 variables with significant explanatory power among the 27 variables initially comprising our conceptual model and, secondly, to build a predictive model with a high performance of 95%.

This article is structured into five sections: the first section briefly presents the literature review on which we based our conceptual model. The second section presents the theoretical framework used and the research hypotheses derived from it, while describing the methodological approach adopted. The third and fourth sections present and discuss the results of our empirical study. Finally, the last section outlines the conclusions and limitations of our research, while highlighting its practical and scientific implications, and proposing future research perspectives.

2. Literature Review

2.1. Entrepreneurial Success Factors in SMEs

2.1.1. Entrepreneurial Success: A Polysemic Concept in Need of Clarification

The success of small businesses, including micro-businesses, is a subject of considerable discussion. It is generally defined as the ability to ensure the growth or survival of the business. It is also viewed as the company's capacity to achieve its objectives and generate a profit (Gerba & Viswanadham, 2016). The concepts of small business performance, success, and growth are interchangeable (Gerba & Viswanadham, 2016). However, other researchers challenge this financial view of performance, considering that small business success can also be assessed in terms of the achievement of entrepreneurs' personal goals (Jarvis, Curran, Kitching, & Lightfoot, 2000). This definition of performance aligns with that suggested by St-Pierre and Cadieux (2011) who measures it by the ability to achieve the objectives set by entrepreneurs.

2.1.2. Endogenous Determinants of Entrepreneurial Success in SMEs

Many scientists have attempted to propose that success in entrepreneurship depends on possessing certain personal traits that may favor an entrepreneur's success (Hayward, Forster, Sarasvathy, & Fredrickson, 2010).

In an exploratory study on the factors influencing business survival in the first three years, Littunen, Storhammar, and Nenonen (1998) postulate that people who are highly motivated to succeed in their projects perform better than others. Consequently, those motivated by necessity are less successful than those motivated by opportunity. Also, Frederic Delmar and Wiklund (2008) emphasize that the entrepreneur's willingness and desire to grow are precursors and even predictors of business performance..

In contrast to the personality traits and motivation approach, entrepreneurial success is not significantly related to the psychological characteristics or personality factors of the entrepreneur. For example, according to research conducted by Lorrain, Belley, and Dussault (1998) and Omrane, Fayolle, and Ben-Slimane (2011) entrepreneurial skills play a key role in entrepreneurial performance, compared with personality traits.

Human capital is often illustrated by four variables: age, level of education, type of training, and gender. According to several authors, human capital influences entrepreneurs' chances of success or failure. According to Cooper, Gimeno-Gascon, and Woo (1991) a substantial body of research supports the existence of a link between an entrepreneur's level of education and business performance. Unger, Rauch, Frese, and Rosenbusch (2011), for their part, observe that profits are higher among entrepreneurs with university degrees than those without. Similarly, Bosma, van Praag, Thurik, and de Wit (2004) find that Dutch entrepreneurs with higher education qualifications achieve higher profits than their counterparts.

Regarding age and entrepreneurial success, Azoulay, Jones, Kim, and Miranda (2020) put forward the idea that the entrepreneurial age, combined with significant experience in the company's field of activity, has a positive effect on entrepreneurial success. It is middle-aged entrepreneurs (around 45) who are the most successful, and not young people (Azoulay et al., 2020).

Brush (1992) and Welsh, Kaciak, Fadairo, Doshi, and Lanchimba (2023) have studied the impact of gender on entrepreneurial success and have found that businesses created by women are less exposed to the risk of failure than those created by men, but they tend to perform less well than men.

With regard to social capital, some authors, such as Stam, Arzlanian, and Elfring (2014) emphasize that a business's success depends on its social capital and the business relationships that stem from it. In this sense, Davidsson and Honig (2003) observe that the quality of social capital enables the entrepreneur to obtain strategic information quickly, which constitutes a competitive advantage. In the same vein, Burt (1995) highlights the network's potential in terms of information gathering, while bringing into play the synergy effect of the network.

With regard to digital transformation, He, Huang, Choi, and Bilgihan (2023) point out that digital investment within SMEs provides them with immediate and easily accessible tools and resources to strengthen organizational resilience, which in turn ultimately increases their chances of success. Similarly, Corvello, Verteramo, Nocella, and Ammirato (2023) explain how the integration of new technologies in SMEs has helped companies to cope with the recent Covid-19 crisis and adapt to new constraints. The same observation was made by Amghar, Mrhari, and Ait Lahcen (2023) in a qualitative study on the effect of digital transformation on Moroccan SMEs during times of crisis. Fabre and Kerjosse (2006) compare the characteristics of companies created and still operating after 5 years of existence with those of companies created in the same year but having failed to make it past the five-year mark. The latter concluded that capital invested at the outset considerably increases the chances of survival by up to twofold. In very simplified words, businesses with high initial capital are more likely to survive. In the same vein, Hichri, Yami, Givry, and M'chirgui (2017) point out that the level of initial capital ensures the longevity and performance of SMEs newly established. While endogenous factors are partly responsible for entrepreneurial success, there are also exogenous factors that can explain the success of SMEs.

2.1.3. Exogenous Factors of Entrepreneurial Success in SMEs

On one hand, Carpenter and Petersen (2002) based on a sample of 1,600 SMEs, the importance of access to finance in ensuring the growth of small businesses is highlighted. In the same vein, Bakhtiari, Breunig, Magnani, and Zhang (2020) focus on the need to reduce constraints on access to finance for SMEs in order to ensure their expansion. On the other hand, a study conducted by Chrisman and McMullan (2004) shows that entrepreneurial support is a decisive factor in business success. In this sense, companies that benefit from support seem to outperform those without. In a large-scale study of 64,622 American companies, Liao and Gartner (2006) concluded that entrepreneurs who had drawn up a business plan were 2.6 times more likely to keep their business going than those who had not.

2.2. Business Failure Factors in SMEs

2.2.1. Different Approaches to Entrepreneurial Failure

Known as "business failure" in Anglo-Saxon literature, entrepreneurial failure was originally employed in the field of corporate finance by Walsh and Cunningham (2016). The most widespread definition of entrepreneurial failure is that of Shepherd (2003). According to Shepherd, entrepreneurial failure is seen as the consequence of a decline in revenues and/or an increase in expenses that are of such magnitude that the business becomes insolvent and is unable to incur new debt or raise new equity; consequently, it cannot continue to operate under the ownership of the founder and/or current manager" (Shepherd, 2003).

According to the economic approach, entrepreneurial failure occurs when the return on the funds invested in the created business is lower than that of another project requiring the same funds (McKenzie, 2008). Apart from these two dimensions, these same authors introduced the notion of the minimum threshold of economic viability. Based on the "Threshold theory", Gimeno, Folta, Cooper, and Woo (1997) suggest that the minimum threshold of economic viability increases as the entrepreneur's human capital increases.

To conceptualize business failure, researchers such as Thornhill and Amit (2003) distinguish between two types of failure. The first type concerns start-ups that fail due to a lack of resources and managerial skills. The second type concerns companies that have failed due to a lack of valid and reliable strategic alignment (Crutzen & Van Caillie, 2009).

2.2.2. Endogenous Factors of Entrepreneurial Failure in SMEs

According to Cultrera (2016), the entrepreneur's management difficulties translate into a lack of anticipation, planning, and excessive optimism about the profitability of invested funds, which can ultimately result in a situation of entrepreneurial failure. On another note, the "goal achievement gap theory" emphasizes the importance of entrepreneurial motivation (Cooper & Artz, 1995). Entrepreneurs have an affective and emotional relationship with their business, which is simply the result of their commitment. This theory views failure as a personal disappointment following the failure to achieve expected goals.

According to the results of various research studies conducted in this field, young SMEs are more vulnerable to the risk of failure than older, more experienced companies. Indeed, young SMEs rely heavily on debt, which can lead them into troubled situations (Abdullah, Ahmad, Zainudin, & Rus, 2016). Their lack of experience and low social capital are partly to blame. Some authors have pointed to a lack of managerial skills as a reason for the failure of young entrepreneurs. Nevertheless, in practice, the entrepreneur is faced with the dilemma of managing a limited amount of resources to achieve maximum immediate and short-term benefits (Jennings & Beaver, 1995). Faced with this dilemma, the managerial efforts of SMEs are directed more towards operational management at the expense of strategic management. Given this situation, if entrepreneurs lack sufficient managerial expertise, the risks of failure for SMEs would be very high (Jennings & Beaver, 1995).

As far as human resources are concerned, many researchers emphasize that they play a vital role in the development and sustainability of SMEs (Singh & Vohra, 2009; Williams & Jones, 2010). While endogenous factors are partly responsible for entrepreneurial failure, exogenous factors also have significant consequences.

2.2.3. Exogenous Factors of Entrepreneurial Failure in SMEs

A number of studies have highlighted the fact that the context in which entrepreneurs operate has a considerable influence on the sustainability of their businesses. In this respect, Temtime and Pansiri (2004) and El Manzani et al. (2018) consider that the reasons why small and medium-sized businesses fail are linked to the characteristics of the economic context in which they operate. Temtime and Pansiri (2004) have also developed the idea that the probability of failure of SMEs increases if they are unable to effectively meet the demands imposed by the competitive environment of their sector of activity.

Krauss (2009) explores in depth the idea that even if the entrepreneur possesses the skills essential for success, he or she may be unable to sustain the business in an unfavorable context. One of the challenges facing SMEs, particularly the more recent ones, is access to external funds (Fielden, Davidson, & Makin, 2000). Indeed, most SMEs face obstacles and constraints in accessing external funding. In this respect, Liao, Welsch, and Moutray (2008) assert that entrepreneurs are often forced to mobilize their personal savings during the operating cycle or to call on "love money" type financing. Similarly, Beck and Demirguc-Kunt (2006) have called for the development of specific financing tools for SMEs in order to alleviate the constraints on access to finance that hinder their future.

SMEs often face problems related to the absence, insufficiency, or inadequacy of support from authorities in several countries, particularly those in the developing world (Gagoitseope & Pansiri, 2012). In this context, Everett and Watson (1998) point out that the failure of SMEs is most often associated with the duration of procedures for obtaining state funding, the insufficiency and inadequacy of financial support, poor distribution of public aid, and the lack of specific training, advice, and support programs for the benefit of SMEs.

This immersive exploration of the literature review led us to design a conceptual model that integrates the various endogenous and exogenous factors mentioned above, which can influence the fate of newly created SMEs in terms of entrepreneurial failure or success (Figure 1).

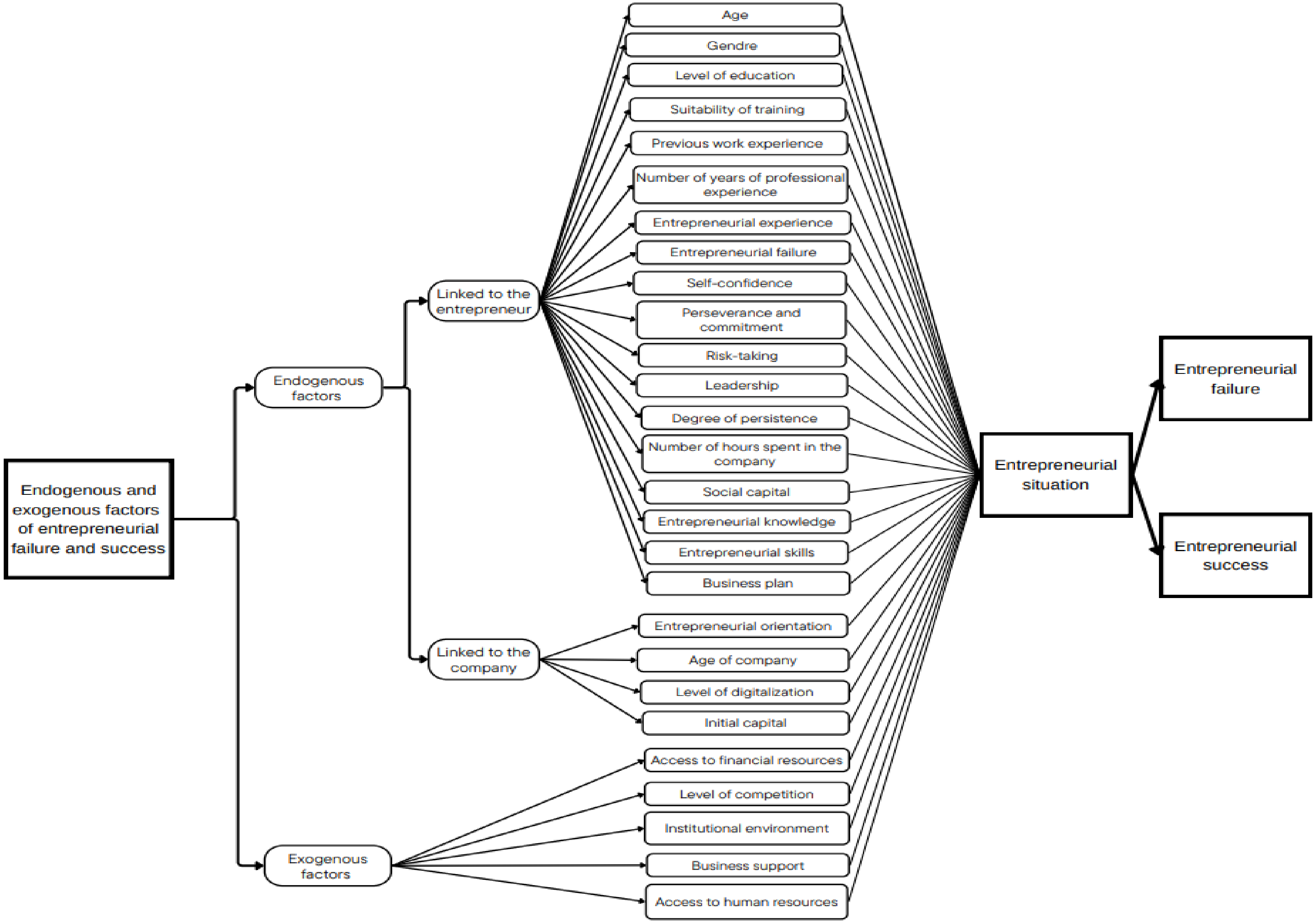

Figure 1. Conceptual model of entrepreneurial success and failure factors in SMEs newly created.

3. Research Hypotheses and Methodological Approach

3.1. Research Hypothesis

The empirical study of this research work is fundamentally based on the respective contributions of three theoretical foundations, namely population ecology theory, the resource-based approach, and motivational approaches. We will attempt to identify the most significant factors likely to explain the success or failure of entrepreneurship in newly created SMEs in the Moroccan context by using these theoretical foundations.

Population ecology theory focuses more on contextual factors to explain the causes of failure and/or success of new ventures, while considering the entrepreneur as a passive actor (Hannan & Freeman, 1977).

In contrast, the resource-based approach is based on the idea that performance is strongly influenced by the resources available to the entrepreneur, which have certain specific characteristics. To delve deeper, some authors argue that the resources mobilized during the company's creation condition its performance (Cooper, Gimeno-Gascon, & Woo, 1994). Thus, it is possible to consider the initial resources at the time of creation as predictors of the success of newly established SMEs (Cooper et al., 1991). Finally, approaches based on commitment and motivation consider that some entrepreneurs fail despite their talent and the opportunities offered by the environment in which they operate. This dimension emphasizes the importance of entrepreneurial motivation and commitment. Therefore, business success is linked to entrepreneurial motivation, as Wiklund and Shepherd (2003) emphasize. Shane, Locke, and Collins (2003) have also considered that success depends on the motivation and commitment of entrepreneurs.

In line with the theoretical foundations mentioned above, the hypotheses we have attempted to confirm or refute in this research work are as follows.

Hypothesis 1: The success or failure of entrepreneurship in newly created SMEs depends considerably on the resources available to the entrepreneur.

Hypothesis 2: The success or failure of entrepreneurial action in newly created SMEs depends on the motivation and commitment of the entrepreneur.

Hypothesis 3: Environmental factors determine the success or failure of entrepreneurship in newly created Moroccan SMEs.

These three hypotheses were in turn, broken down into sub-hypotheses, as shown in Table 1.

Table 1. Research hypotheses and sub-hypotheses.

Hypotheses	Sub-hypotheses
H1: The success or failure of entrepreneurshi pdepends largely on the resources available to and under the controlof the entrepreneur.	H11: The age of entrepreneurs significantly impacts their chances of success or failure in newly created SMEs.
	H12: The gender of entrepreneurs significantly impacts their chances of success or failure in newly established SMEs.
	H13: The level of education significantly impacts their chances of success or failure in newly created SMEs.
	H14: The suitability of training in relation to the business activity impacts the chances of success or failure in newly established SMEs.
	H15: Professional experience significantly influences their chances of success or failure in newly established SMEs.
	H16: The number of years of professional experience of entrepreneurs significantly impacts their chances of success or failure in newly created SMEs.
	H17: The social capital available to entrepreneurs significantly impacts their chances of success or failure in newly created SMEs.
	H118: Entrepreneurial knowledge has a significant impact on the chances of success or failure for newly created SMEs.
	H119: Entrepreneurial skills significantly impact the chances of success or failure for newly created SMEs.
	H110: Entrepreneurial experience has a significant impact on the chances of success or failure for newly created SMEs.
	H111: The establishment of a solid business by entrepreneurs significantly impacts their

	chances of success or failure in newly created SMEs.
	The degree of digitalization in SMEs significantly impacts the likelihood of success or failure for newly established SMEs.
	H113: The age of a company significantly impacts the likelihood of success or failure for newly established SMEs.
	H114: The level of initial capital significantly impacts the chances of success or failure for newly created SMEs.
H2: The success or failure of entrepreneurial action depends on the will, motivation and commitment of entrepreneurs.	H21: The number of hours spent by entrepreneurs in their businesses significantly impacts the chances of failure or success of their newly created companies.
	H22: The nature of entrepreneurial orientation has a significant impact on the chances of success or failure for newly created SMEs.
	H23: The degree of persistence among entrepreneurs significantly impacts their chances of success or failure in newly established SMEs.
	H24: Entrepreneurs' level of commitment has a significant impact on their chances of success or failure in newly created SMEs.
	H25: Entrepreneurs' level of risk-taking has a significant impact on their chances of success or failure in newly created SMEs.
	H26: Entrepreneurs' level of leadership has a significant impact on their chances of success or failure in newly created SMEs.
	H27: Entrepreneurs' level of self-confidence has a significant impact on their chances of success or failure in newly created SMEs.
	H28: Entrepreneurs' previous failures have a significant impact on their chances of failure or success within newly created TMPEs.
H3: Environmental factors determine the success or failure of Moroccan SME entrepreneurship.	H31: Access to financial resources significantly impacts the chances of success or failure for newly created SMEs.
	H32: Access to human resources significantly impacts the chances of success or failure for newly created SMEs.
	H33: Competitive intensity has a significant impact on the chances of success or failure for newly created SMEs.
	The institutional environment significantly influences the likelihood of success or failure for newly established SMEs.
	H35: Support structures have a significant impact on the chances of success or failure for newly created SMEs.

3.2. Methodological Approach

3.2.1. Epistemological Positioning and Research Methodology

This research is part of a positivist approach. We have adopted a hypothetico-deductive approach to our research. In line with our mode of reasoning, and given the nature of our subject, we opted for a quantitative approach. The latter relied on the questionnaire technique as a primary data collection tool. We based our questionnaire on the above-mentioned hypotheses, broken down into clear sub-hypotheses, and translated into specific questions.

We have structured our questionnaire into 9 sections, as shown in Table 2. All these sections group together questions (with 56 questions) referring to the different factors from our literature review.

Table 2. The sections structuring our questionnaire.

Sections	Titles
1	Contractor profile and professional experiences
2	Company characteristics
3	Entrepreneurial experiences
4	Creation process and institutional environment
5	Access to resources
6	Information on business financing
7	Digitalization and its degree of maturity within the company
8	Entrepreneurial success factors (Success situation)
9	Entrepreneurial failure factors (Failure situation)

For the construction of our questionnaire, the questions are sometimes “closed,” with answers fitting into a grid with pre-coded response modalities, and sometimes “semi-open.”

Based on measurement scales in articles published in indexed management journals on similar subjects (articles in indexed databases such as Scopus and Elsevier), we chose the five-level Likert scale (ranging from “too low” to “too high”) for variables measured by items.

In order to guarantee a better return rate, we took care to ensure that the questions were clear without being lengthy. Similarly, we ensured that the estimated average time taken to complete the questionnaire was no more than 10 seconds per question as recommended by Kato and Miura (2021) which means a total of 10 minutes for the entire questionnaire.

The validity of the questionnaire was first tested with four researchers from our laboratory, who are experts in survey techniques and possess relevant knowledge related to our research topic. We then administered the questionnaire face-to-face to six members of our sample.

3.2.2. Description of the Population and Data Collection Technique

We have combined the legal and managerial approaches in our selection of failing entrepreneurs. The legal concept refers to the notion of a company in difficulty, encompassing not only bankrupt companies but also those facing problems likely to jeopardize the continuity of their activities in the long term. In addition to economic difficulties, the managerial conception also includes companies whose entrepreneurs are experiencing feelings of disappointment, dissatisfaction, and despair as a result of failing to achieve expected objectives.

To select successful entrepreneurs, we used a mixed approach, combining objective criteria (profit, financial performance) and subjective criteria (a level of satisfaction in relation to expected objectives). Specifically, we defined the following criteria: the company is still in business, has been in existence for at least 3 years, and has achieved a satisfactory level of performance relative to expected objectives. Finally, the SME must be newly created and between 3 and 5 years old.

To build our empirical study base, we opted for the snowball technique, given the nature of the population studied, which is difficult to access, and the subject, which is personal and delicate, especially for entrepreneurs in a situation of failure. With the help of our "contact persons," we were able to establish a chain of successive contacts to build our sample. In concrete terms, these "contact persons" (source persons) are both entrepreneurs and professionals who are in contact with the public concerned by the study.

At the start of our field survey, we chose a post-COVID-19 sampling period to minimize the direct impact of the pandemic on the results. Thus, in October 2023, we used the snowball sampling method by distributing our questionnaire via the Internet. We implemented the “integrated web system” technique as outlined by Ganassali and Moscarola (2004). This approach enabled us to create and share our questionnaire using Google Forms. Participants were contacted by e-mail with a link to the URL of the online form, enabling us to monitor the progress of the study via dashboards. However, despite the many measures taken and the reminders sent out at regular intervals, we recorded a relatively low response rate of 10%. This finding led us to conclude that, in the Moroccan context, addressing this issue would be more effective if we had human contact to assure respondents about the use of the data collected. Therefore, to compensate for the low response rate, we began a face-to-face approach in December 2023 and observed an improved response rate.

We received 80 complete responses out of the 96 contractors identified using the "contact persons". Thus, the profile of our sample (80 entrepreneurs) and the characteristics of their respective companies are as follows:

Table 3. Profile of contractors.

Features	Success	Failure	Features	Success	Failure
Gender			**Education level**		
▪ Men	25	36	▪ Primary school	1	3
▪ Woman	15	4	▪ College	1	2
Age			▪ BAC	2	2
▪ 18-24 years old	2	0	▪ BAC+2	8	20
▪ 25-34 years	18	3	▪ Bac+3	8	6
▪ 35-44 years	11	31	▪ Bac+5	16	4
▪ 45-54 years	8	4	▪ PhD	4	3
▪ 53+ 55 years	1	2	**Type of training**		
Civil status			▪ Professional training	13	18
▪ Married	28	27	▪ Management sciences	7	9
▪ Single	12	13	▪ Engineering sciences	12	3
▪ Divorced	0	0	▪ Humanities	1	0
Previous professional situation			▪ Computer science	6	9
▪ Contractor	7	9	▪ Legal sciences	1	**1**
▪ Employee	20	18			
▪ Unemployed	9	10			
▪ Student	4	3			

Table 4. Company description.

Features	Success	Failure	Features	Success	Failure
Company status			**Age of the company**		
▪ SARL	35	27	▪ From 3 to 5 years	21	20
▪ SA	4	0	▪ Over 5 years	10	8
▪ Cooperatives	1	0	**Initial capital**		
▪ Sole proprietorship	0	13	▪ Between 10,000 MAD and 50,000 MAD	2	9
Number of associates			▪ Between 50,000 MAD and 100,000 MAD	15	11
▪ No partners	25	26	▪ More than 100,000 MAD	23	20
▪ 1 partner	8	12			
▪ 2 associates	5	0			
▪ 3 or more associates	2	2			
Field of activity					
▪ Service	22	23			
▪ Service, industry	2	0			
▪ Service, trade	1	0			
▪ Service, trade, agriculture	1	0			
▪ Trade, industry	1	0			
▪ Trade	3	6			
▪ Industry	10	4			
▪ Agriculture	0	7			

3.2.3. Data Preparation

Regarding the operationalization of the variables constituting our conceptual model, we have considered the entrepreneurial situation as a dependent variable (explained) and the endogenous and exogenous factors in relation to the entrepreneur as independent variables (explanatory). Variable encoding is a crucial step in the data preparation process, enabling us to explore and process non-numerical data. This operation was made possible by executing several Python code scripts on Google Colab (Appendix 1).

The explanatory variable is a dichotomous binary variable. Thus, the coding (0, 1) is set up to indicate whether the entrepreneur is in a successful or unsuccessful situation (code 0 is assigned to the entrepreneurial success situation and 1 to the entrepreneurial failure situation). The explanatory variables are categorical variables, oscillating between categorical nominal variables and categorical ordinal variables.

4. Results

4.1. Exploratory Data Analysis

Like the conceptual model, the explanatory variables are grouped along three dimensions: endogenous factors (linked to the entrepreneur or the company) and exogenous factors. Given the mixed nature of our variables, the vast majority of which are categorical, we employed the following statistical tools: Chi-squared test of independence, contingency coefficient, correlation matrix, VIF, and principal component analysis (PCA).

In order to test the independence between the independent explanatory variables and the dependent variable being explained, we used the chi-squared (χ^2) test of independence with a threshold of 0.05. Two hypotheses are formulated:

Null hypothesis (H_0): There is no significant relationship between the independent variable and the dependent variable.

Alternative hypothesis (H_1): There is a significant relationship between the independent variable and the dependent variable.

To achieve this, we ran a series of codes on Python (Appendix 2). Looking at the results of the chi- square (χ^2) test of independence (Table 5), the null hypothesis (H0) is rejected in favor of the alternative hypothesis (H1) for the independent variables: *Age, Gender, Suitability of training, Self-confidence, Perseverance and commitment, Risk-taking, Leadership, Number of hours spent in the business, Social capital, Entrepreneurial orientation, Entrepreneurial skills, Degree of persistence, Business plan, Initial capital, Institutional environment, and Access to financial resources.* These variables have a p-value of less than 0.05. As a result, these variables demonstrate a statistically significant relationship with the dependent variable (Entrepreneurial situation). Consequently, they are considered determinants and are likely to explain entrepreneurial success or failure. However, the remaining 11 variables have a p-value above the 0.05 threshold. Therefore, we cannot reject the null hypothesis (H0), indicating that these variables do not have a significant impact on the outcome of the entrepreneurial venture in newly created SMEs.

Table 5. Results of chi-square independence test (χ^2) and contingency coefficient test.

Dimensions	Independent variable	Chi-2 test	p-value	Contingency coefficient	Comment
Endogenous factors linkedto the entrepreneur	Age	13.259	0.0257*	0.4296	SA
	Gender	5.845	0.0156**	0.3674	SA
	Education level	10.3815	0.1094	0.4159	NSA
	Training suitability	8.6441	0.0132**	0.4199	SA
	Work history	1.2117	0.7501*	0.1342	NSA
	Number of years of professionalexperience	16.5871	0.2789	0.5257	NSA
	Entrepreneurial experience	0.0089	0.9245	0.0122	NSA
	Entrepreneurial failure	3.4114	0.0674	0.1066	NSA
	Self-confidence	23.4248	0.0001***	0.6427	SA
	Perseverance and commitment	23.4248	0.0001***	0.6248	SA
	Risk-Taking	27.2587	1.7622×10^{-5}***	0.6740	SA
	Leadership	31.2426	2.7315×10^{-6}***	0.7216	SA
	Degree of persistence	28.0018	1.2462×10^{-5}***	0.6831	SA
	Number of hours spent into the company	24.1939	0.0021**	0.6350	SA
	Social capital	8.8263	0.0029**	0.3198	SA
	Entrepreneurial knowledge	1.875	0.17090	0.1767	NSA
	Entrepreneurial skills	14.1125	0.0027***	0.5216	SA
	Entrepreneurial orientation	6.2198	0.01263**	0.4282	SA
	Business plan	28.4790	9.4719×10^{-9}***	0.7729	SA
Endogenous company factors	Level of digitization	8.9657	0.0619	0.2611	NSA
	Initial capital	6.624	0.0100**	0.3181	SA
	Age of company	0.4589	0.7949	0.0874	NSA
Exogenous factors	Business support	2.93	0.087	0.1767	NSA
	Institutional environment	25.5902	1.1619×10^{-5}***	0.7043	SA
	Level of competition	6.1708	0.1035	0.3206	NSA
	Access to financial resources	21.4477	0.0002***	0.6088	SA
	Access to human resources	7.1799	0.0663	0.2253	NSA

Note: *** significant at 1% level, ** significant at 5% level and * significant at 10% level.
SA: Significant association/ NSA: No significant association.

According to the results of the chi-square test of independence (χ^2), our binary logistic regression model will retain only 16 variables.

To complement the chi-square test of independence (χ^2) and measure the strength of association between the explanatory variables and the variable being explained, we calculated the contingency coefficient (Table 3).

The closer the coefficient is to 1, the stronger the relationship between the variables. Conversely, a coefficient close to 0 indicates an absence of relationship. To analyze this, we used Python (Appendix 3).

Reading Table 4 above reveals different levels of association between the explanatory variables and the dependent variable. Indeed, the conclusions drawn from the results of the contingency coefficients for all the variables are in line with the findings of the chi-square test of independence (χ^2). Thus, variables describing entrepreneurial traits show a strong association with the dependent variable. Their contingency coefficients are, respectively, 0.7216, 0.6740, 0.6248, 0.6427, 0.6831 for the variables leadership, risk-taking, perseverance and commitment, self-confidence, and degree of persistence.

Still in relation to the variables endogenous to the entrepreneur, we highlighted a medium level of association between the variables age, gender, suitability of training with the business line, entrepreneurial orientation, level of digitization, entrepreneurial skills, and whether or not initial capital was insufficient. However, unexpectedly, contrary to what the literature review suggests, we noted a low level of association of the variables entrepreneurial failure and professional background with the dependent variable. In fact, these variables had contingency coefficients of around 0.1066 and 0.1342, respectively. Additionally, the contingency coefficients show a strong association between the variables business plan development, number of hours spent in the company, and the variable explained. The latter have contingency coefficients of the order of 0.7729 and 0.6350, respectively.

As for the variables exogenous to the entrepreneur, we found a strong association between the institutional environment variable (0.7043) and access to financial resources (0.6088) with the dependent variable. However, this association is relatively weaker for the variables access to human resources and social capital.

Following up on our exploratory analysis, we have focused on potential relationships between the independent variables. The aim of this analysis is to detect any risk of multicollinearity. To this end, we began with an overview by calculating the correlation between the residuals:

Table 6. Correlation between residuals.

Residual correlation	P-value
0.7385	0.006

Based on the results obtained from the correlation between the residuals and at the 0.05 threshold (Table 6), we can conclude that there is a significantcorrelation (P-value<0.05) Between certain explanatory variables, thus, in attempting to model the dependent variable, entrepreneurial situation, as a function of several independent variables, we are likely to encounter the problem of collinearity or even multicollinearity. To this end, we first established a correlation matrix to assess the relationships between the variables and identify possible associations. The correlation matrix (Table 7) shows that some variables are highly correlated with each other, while others are moderately correlated. In particular, there is a strong positive correlation of around 0.7 between five variables in our conceptual model. These variables are those that characterize entrepreneurialtraits: *"Self-confidence"*, *"Degree of persistence"*, *"Perseverance and commitment"*, *"Risk-taking" and "Leadership"* (Table 7). The Appendix 4 presents the code that was executed on Python to establish the Spearman correlation matrix

In order to thoroughly assess the problem of multicollinearity between highly correlated explanatory variables, we calculated the VIF (Variance Inflation Factor). The VIF is part of the classical approach to measuring multicollinearity (Larmarange et al., 2022). Generally, a VIF greater than 10 indicates strong multicollinearity between variables. Therefore, based on the VIF results, we observe strong multicollinearity among the variables (Table 8). Faced with this problem, several solutions are available to us, ranging from the simple deletion of highly correlated variables to the factor analysis technique, via the total score technique and principal component analysis (PCA). We chose the latter because it allows us to reduce the dimensionality of the data by finding a set of principal components that incorporate the maximum variance in the data, while retaining as much information as possible. Although suitable for quantitative variables, PCA can also be used, where appropriate, for ordinal categorical variables after the encoding process.

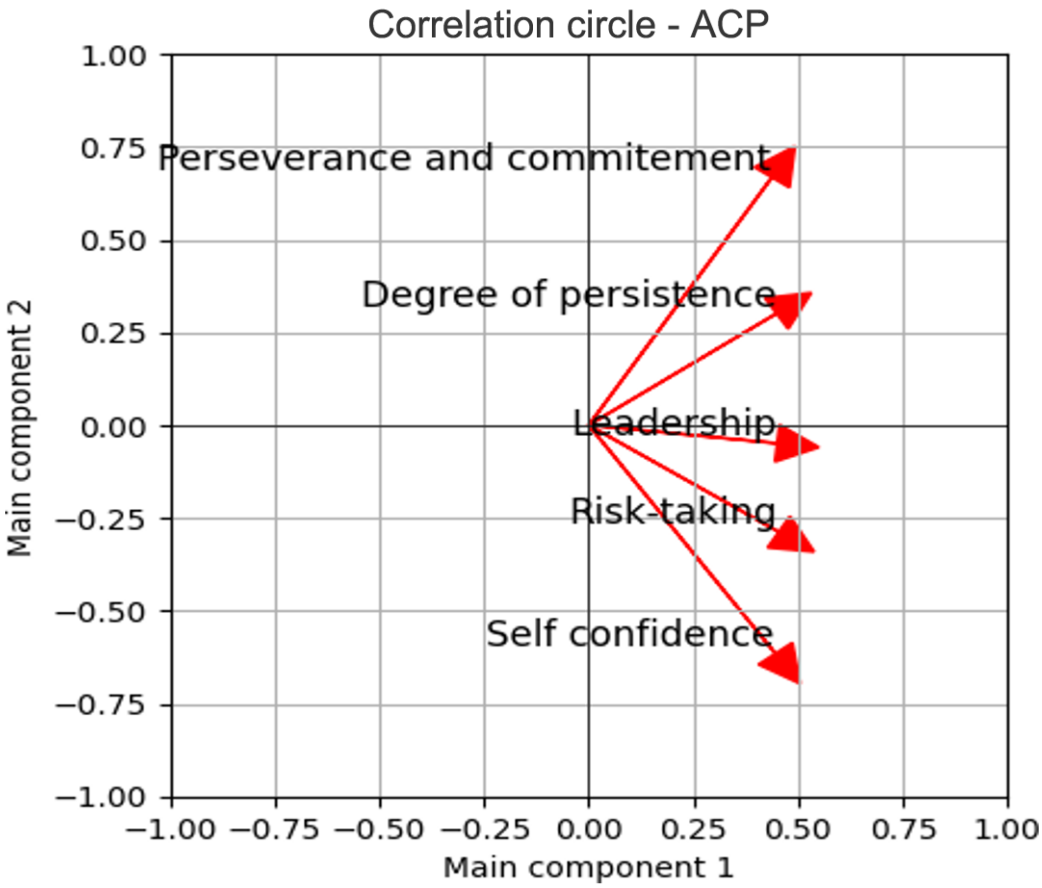

Figure 2. Correlation circle – PCA.

Table 7. Spearman correlation matrix.

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Age (1)	1.000	0.233	0.090	-0.241	-0.094	0.055	-0.118	-0.268	-0.467	-0.442	0.249	0.250	-0.223	-0.235	-0.141	-0.149
Gender (2)	0.233	1.000	-0.012	-0.184	-0.058	-0.112	-0.189	-0.236	-0.505	-0.342	0.042	0.115	-0.241	-0.211	-0.029	-0.263
Suitability of training (3)	0.090	-0.012	1.000	0.193	0.106	0.077	0.036	0.137	0.062	0.192	-0.007	0.071	0.175	0.137	0.192	0.104
Number of hours spent in the company (4)	-0.241	-0.184	0.193	1.000	0.225	0.209	0.303	0.465	0.396	0.401	-0.153	0.046	0.440	0.435	0.477	0.436
Social capital (5)	-0.094	-0.058	0.106	0.225	1.000	0.326	0.586	0.388	0.358	0.563	-0.378	0.235	0.400	0.411	0.532	0.377
Entrepreneurial orientation (6)	0.055	-0.112	0.077	0.209	0.326	1.000	0.418	0.318	0.273	0.370	-0.201	0.314	0.493	0.336	0.402	0.446
Entrepreneurial skills (7)	-0.118	-0.189	0.036	0.303	0.586	0.418	1.000	0.596	0.529	0.547	-0.389	0.389	0.532	0.488	0.531	0.482
Degree of persistence (8)	-0.268	-0.236	0.137	0.465	0.388	0.318	0.596	1.000	0.626	0.649	-0.375	0.276	0.621	0.656	0.692	0.655
Business plan (9)	-0.467	-0.505	0.062	0.396	0.358	0.273	0.529	0.626	1.000	0.638	-0.307	0.135	0.548	0.631	0.532	0.600
Institutional environment (10)	-0.442	-0.342	0.192	0.401	0.563	0.370	0.547	0.649	0.638	1.000	-0.472	0.321	0.516	0.620	0.531	0.602
Access to financial resources (11)	0.249	0.042	-0.007	-0.153	-0.378	-0.201	-0.389	-0.375	-0.307	-0.472	1.000	-0.363	-0.393	-0.426	-0.516	-0.453
Initial capital (12)	0.250	0.115	0.071	0.046	0.235	0.314	0.389	0.276	0.135	0.321	-0.363	1.000	0.257	0.269	0.343	0.337
Self-confidence (13)	-0.223	-0.241	0.175	0.440	0.400	0.493	0.532	0.621	0.548	0.516	-0.393	0.257	1.000	0.609	0.687	0.680
Perseverance and commitment (14)	-0.235	-0.211	0.137	0.435	0.411	0.336	0.488	0.656	0.631	0.620	-0.426	0.269	0.609	1.000	0.648	0.643
Risk-taking (15)	-0.141	-0.029	0.192	0.477	0.532	0.402	0.531	0.692	0.532	0.531	-0.516	0.343	0.687	0.648	1.000	0.656
Leadership (16)	-0.149	-0.263	0.104	0.436	0.377	0.446	0.482	0.655	0.600	0.602	-0.453	0.337	0.680	0.643	0.656	1.000

Based on the results of the correlation circle-PCA (Figure 2), we found that there are two groups of correlated variables. The first group consists of the variables: Perseverance and degree of persistence, and the second group includes the variables: Leadership, Risk-taking, and Self-confidence. We therefore decided to group the first set of variables into a single variable, which we named "Commitment and Persistence," and the second set into a single variable, which we named "Self-confidence and Risk-taking." This grouping of variables was again based on the PCA technique.

Table 8. Multicollinearity test between the most correlated variables.

Before grouping highly correlated variables		
Variables	**VIF**	**1/VIF**
Self-confidence	47.14	0.02
Perseverance and commitment	37.96	0.03
Risk-taking	32.02	0.03
Leadership	36.52	0.03
Degree of persistence	35.72	0.03
After grouping highly correlated variables		
Variables	**VIF**	**1/VIF**
Self-confidence and risk-taking	3.081	0.3245
Commitment and persistence	3.081	0.3245

4.2. Explanatory Analysis and Development of a Predictive Model

In order to complete and deepen the results of our exploratory analysis, and above all to assess the impact of each explanatory variable on the target variable, it was necessary to carry out binary logistic regression tests. The latter is a probabilistic model, advocated by several authors such as Li, Sun, and Wu (2010), as it allows the inclusion of categorical variables necessary to improve predictions of entrepreneurial success or failure.

Before setting up the binary logistic regression model, we had to verify the conditions for its application. The first condition pertains to the nature of the dependent variable, which must be binary (0 or 1). This condition is satisfied in our case, where the dependent variable, entrepreneurial situation, can indicate either entrepreneurial success (0) or entrepreneurial failure (1).

The second condition concerns sample size. It must be large. However, there are no formal, objective indicators for determining the number of observations required to validate and generalize the results. A rule of thumb suggests a minimum of 5 observations per dependent variable (Hosmer Jr, Lemeshow, & Sturdivant, 2013; Vittinghoff & McCulloch, 2007). In our case, after exploratory analysis and resolution of the multicollinearity problem, we retained 13 variables, which is the required minimum of 65 observations. We conducted 80 observations. Therefore, we have reached the total number of observations necessary for our model.

The third condition concerns the absence of multicollinearity between variables (Sohil, Sohali, & Shabbir, 2022). This problem was also addressed during the exploratory analysis of the explanatory variables in our sample by calculating the VIF. A VIF<5 for all variables, there is no indication of strong multicollinearity between explanatory variables.

The final condition concerns the independence of observations from one another. This means that there must be no relationships between the observations (Hosmer Jr et al., 2013). Our study focused on two populations of entrepreneurs with no relationship between them.

The general form of the logistic model for a binary variable Y as a function of n independent variables X1, X2, X3, ..., Xn is expressed in the following probability form:

$$P(Y) = 1/(1 + exp[-(\beta 0 + \beta 1X1 + \beta 2X2 + \ldots + \beta nXn)])$$

In this expression, P(Y) represents the conditional probability that the event Y = 1 occurs given the independent variables X1, X2, X3,...,Xn. β0, β1, β2, β3, ..., βn are the coefficients associated with the independent variables X1, X2, X3,...Xn.

The first stage of our analysis involved integrating all the variables remaining after the exploratory analysis stage (13 variables). As a result, Table 9 summarizes the results of estimating the logistic regression model after implementing and running a series of Python code scripts (Appendix 5, Appendix 6), taking into account the three dimensions mentioned above.

Table 9. Estimation results for logistic regression coefficients and marginal effects.

Dependent variable: Entrepreneurial status		Regression coefficient	Effects marginal
Explanatory variables			
Dimensions	Determinants		
Endogenous factors linked to the entrepreneur	Age:		
	Age_18-24	-0.2285	-0.0563
	Age_25-34	-0.4992	-0.1231
	Age_35-44	0.7367	0.1817
	Age_45-54	-0.3329	-0.0821
	Age_55 and over	0.0288	0.0071
	Gender:		
	Woman	-0.3900	-0.0962
	Men	0.3900	0.0962
	Training suitability:		
	Partially adequate	0.4042	0.0997
	Not at all adequate	0.2469	0.0609
	Fully adequate	-0.6583	-0.1623
	Social capital:		
	No	0.4354	0.1074
	Yes	-0.4354	-0.1074
	Entrepreneurial orientation:		
	Necessity	0.1585	0.0391
	Opportunity	-0.1585	-0.0391
	Drawing up a business plan:		
	No	0.9364	0.2309
	Yes	-0.9364	-0.2309
	Number of hours spent with the company	-0.3435	-0.0847
	Entrepreneurial skills	-0.2133	-0.0526
	Commitment and persistence	-0.4047	-0.0998
	Self-confidence and risk-taking	-0.6119	-0.1509
Endogenous company factors	Initial capital:		
	No	0.5982	0.1475
	Yes	-0.5982	-0.1475
Exogenous factors	Institutional environment	-0.6083	-0.1500
	Access to financial resources	-0.2986	-0.0736
	Intercept	-0.0382	
Nickname R-squared			0.772
Log-Likelihood			-10.111
LL-Null			-44.252
LLR p-value			9.0272×10^{-9}
BIC			87.2573

With regard to the overall significance of the model, the likelihood ratio (Table 9) shows that the model is satisfactory. Indeed, with a Pseudo R-squared value of 0.77, the model explains 77% of the variance in entrepreneurial situation. A high Pseudo R-squared value suggests that the independent variables included in the model significantly aid in predicting the entrepreneurial situation, whether in terms of entrepreneurial failure or success. Additionally, low values of AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) indicate a preferable model over the null model. Furthermore, the probability associated with the likelihood ratio test is low, indicating that the adjusted model is statistically more significant than the null model.

Like the likelihood ratio, the classification report (Table 10) shows that the model performs statistically well. Thus, an accuracy of 75% means that the model correctly predicted 75% of entrepreneurial cases compared to observed values. To establish the classification report and confusion matrix, we executed the code displayed in Appendix 7 on Python.

Table 10. Classification report.

Precision		Recall	f1-score	Support
Entrepreneurial success	0.71	0.71	0.71	7
Entrepreneurial failure	0.78	0.78	0.78	9
Accuracy	0.75	0.75	0.75	16

To further assess the model's performance and predictive power, we used Python (Appendix 8) to plot the ROC curve (the Receiver Operating Characteristic) (Figure 3). With an AUC of 0.86, the model performs very well. In other words, the model has an excellent ability to distinguish between entrepreneurs who will succeed and those who will fail. In terms of prediction, the model has significant predictive power for entrepreneurial success and failure, based on the characteristics provided by the explanatory variables.

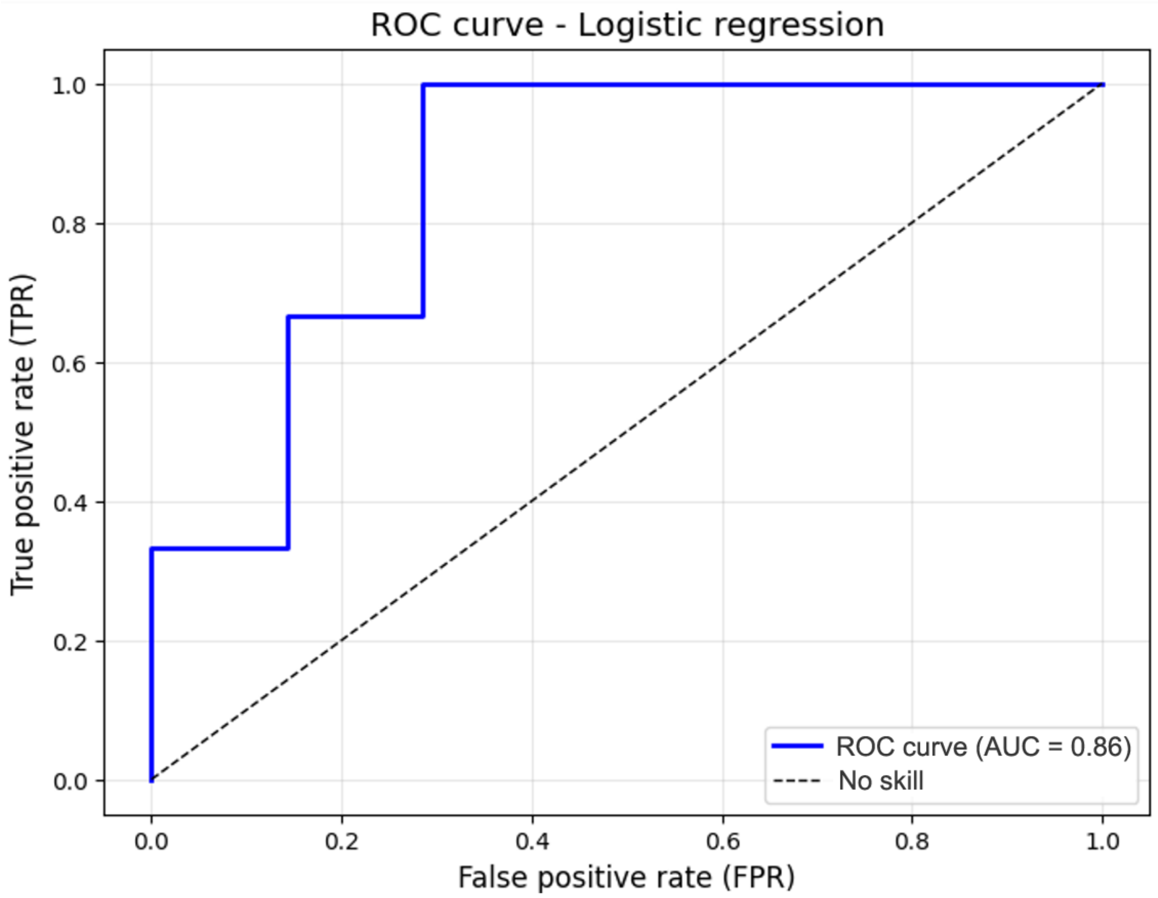

Figure 3. The ROC curve.

To further assess the predictive power of our model, we also used the confusion matrix (Table 11). This was carried out on a sample of 16 subjects. The prediction yielded a success rate of 75% (Table 11). In fact, out of 16 companies, the model made only 4 errors, classifying 2 entrepreneurs as successful when they were actually in a situation of failure, and vice versa (False positives) (Table 11).

Table 11. Confusion matrix.

Predicted values	Actual values	
	Entrepreneurial success	Entrepreneurial failure
Entrepreneurial success	5	2
Entrepreneurial failure	2	7

Having assessed the performance of our model, we now turn to our explanatory analysis, based on the regression coefficients and marginal effects of our model.

For the age variable, Table 9 reveals that the probability of failure for young entrepreneurs aged 18 to 24 years drops slightly by 5.6%. The same is true for entrepreneurs aged between 25 and 34, who are more likely to succeed, with their probability of failure decreasing by around 12%. However, entrepreneurs aged 55 and over and those aged between 35 and 44 are more likely to fail than to succeed, with their probability of failure increasing by 18%. This indicates that, in our sample, young entrepreneurs in newly created SMEs are more likely to succeed than older entrepreneurs.

The logistic regression model also indicates that the gender of the entrepreneur influences the probability of success. Specifically, women entrepreneurs are more likely to succeed than men. Being a woman entrepreneur increases the probability of success by approximately 10%.

With regard to the suitability of training for the company's business, the study reveals that, on one hand, the level of suitability of training with the company's activity increases entrepreneurs' chances of success by 16.23%. On the other hand, partial or total mismatch of training increases the risk of entrepreneurial failure by 10% and 6%, respectively.

With regard to social capital, we found that entrepreneurs who benefited from the support of social capital in its family and professional dimensions were more likely to succeed than those who lacked social capital, and their probability of success increased by 10.74%.

According to the results of our logistic regression model, entrepreneurs who embarked on entrepreneurship with the aim of seizing an opportunity have a greater chance of success than those following an orientation of necessity. Thus, entrepreneurs who are driven by an opportunity to be seized see their chance of success increase slightly by around 4%.

With regard to the "Business plan" variable, the results of the logistic regression model reveal that drawing up a business plan considerably increases entrepreneurs' chances of success by approximately 23.09%.

From Table 9, we can also say that spending several hours within the company significantly improves entrepreneurs' probability of success by around 9%, and vice versa. In fact, we can say that being present for a long time within the company is a sign of commitment and involvement on the part of entrepreneurs.

With regard to "Entrepreneurial skills," the results of the study led to the unusual finding that possessing entrepreneurial skills only slightly increases the probability of entrepreneurial success by approximately 5.26%.

With regard to the entrepreneurial traits measured by the two variables "Commitment and Persistence" and "Self-Confidence and Risk-Taking," the results of the model show that a high level of these two traits increases the chances of success by 9.99% and 15.09%, respectively.

The regression model also shows that insufficient capital impacts the entrepreneur's chances of success. Indeed, according to the results obtained, sufficient initial capital significantly increases the chances of entrepreneurial success by 14.75%.

For the variable "Access to financial resources," the results reveal that the easier an entrepreneur has access to financing, the more likely he is to succeed. Thus, easy access to financing increases entrepreneurs' chances of success by 7.36%.

Finally, for the "Institutional environment" variable, the results from our regression model indicate that it has a considerable effect on entrepreneurs' chances of success. Indeed, a favorable institutional environment increases entrepreneurs' chances of success by approximately 15%.

In addition to the value of the regression coefficient and marginal effects used to identify variables with a statistically significant impact on the dependent variable, tests such as the Wald test and the T-test are commonly referenced in the literature. However, both tests are sensitive to sample size and the number of variables. Furthermore, these tests cannot capture the sometimes complex non-linear relationships. Therefore, given our sample size and the number of variables in our model, we opted to use supervised machine learning methods (for which the independent variables have a known binary output, entrepreneurial failure or success). For this purpose, we selected three methods: the decision tree method, the random forest method, and the backward stepwise regression method. Using Python (Appendix 9), the results of these methods are summarized in Table 12:

Table 12. Result of the selection of the most significant variables.

The decision tree method		**Logistic regression with Lasso penalty (Stepwise top-down selection)**		**The random forest method**	
Variables	**Scores**	**Variables**	**Scores**	**Variables**	**Scores**
Self-confidence and risk-taking	0.4770	Business plan	-0.8554	Business plan	0.2038
Business plan	0.4559	Initial capital	-0.6055	Self-confidence and risk-taking	0.1567
Number of hours spent with the company	0.1112	Age	-0.546	Age	0.0956
Access to financial resources	0.0932	Entrepreneurial skills	-0.4922	Commitment and persistence	0.0929
Training suitability	0.0914	Social capital	-0.4884	Institutional environment	0.0796
Social capital	0.0857	Gender	-0.381	Number of hours spent with the company	0.0698
Entrepreneurial orientation	0.0444	Number of hours spent in the company	-0.3776	Initial capital	0.0631
Commitment and persistence	0.0355	Training suitability	-0.3181	Social capital	0.0534
		Self-confidence and risk-taking	-0.3050	Entrepreneurial orientation	0.0506
		Entrepreneurial orientation	-0.2201	Training suitability	0.0491
		Access to financial resources	-0.0202	Entrepreneurial skills	0.0413
				Access to financial resources	0.0252

From the results in Table 12, we can see that the decision tree method selected only 8 of the 13 variables in our logistic regression model as being of significant importance. For its part, the Random Forest method identified 12 variables with a significant impact in explaining entrepreneurial failure or success in SMEs. The backward stepwise regression method applied to logistic regression with lasso penalization identified 11 variables with a significant impact. In order to choose the most appropriate and efficient method for selecting explanatory variables, we used the cross-validation method. In concrete terms, based on the average of the cross-validation scores, we can compare the performance of one model against the other to select the best-performing model (Appendix 10).

According to the cross-validation results (Table 13), the most effective method for selecting the most significant variables is the random forest method. As a result, we can conclude that in our logistic regression model, the most determining variables that can explain the entrepreneurial situation, in decreasing order of importance, are: *Development of a business plan, self-confidence and risk-taking, age, commitment and persistence, institutional environment, number of hours spent in the company, initial capital, social capital, entrepreneurial orientation, suitability of training, entrepreneurial skills, and access to financial resources.*

Table 13. Cross-validation results.

Method for selecting significant variables	**Average cross-validation scores**	**Std accuracy**
Binary logistic regression with Lasso penalization (Stepwise top-down selection)	0.86	0.1
Decision tree method	0.77	0.145
Random forest method	0.91	0.093

To sum up in the light of the results obtained, we can validate the explanatory model below (Figure 4) concerning the most decisive factors that can explain the fate of the entrepreneurial venture within newly created SMEs. To predict entrepreneurial success or failure in these companies, we integrated a probabilistic predictive model based on Machine Learning techniques, specifically *Random Forest*, which we developed using Python on Google Colab (Appendix 11).

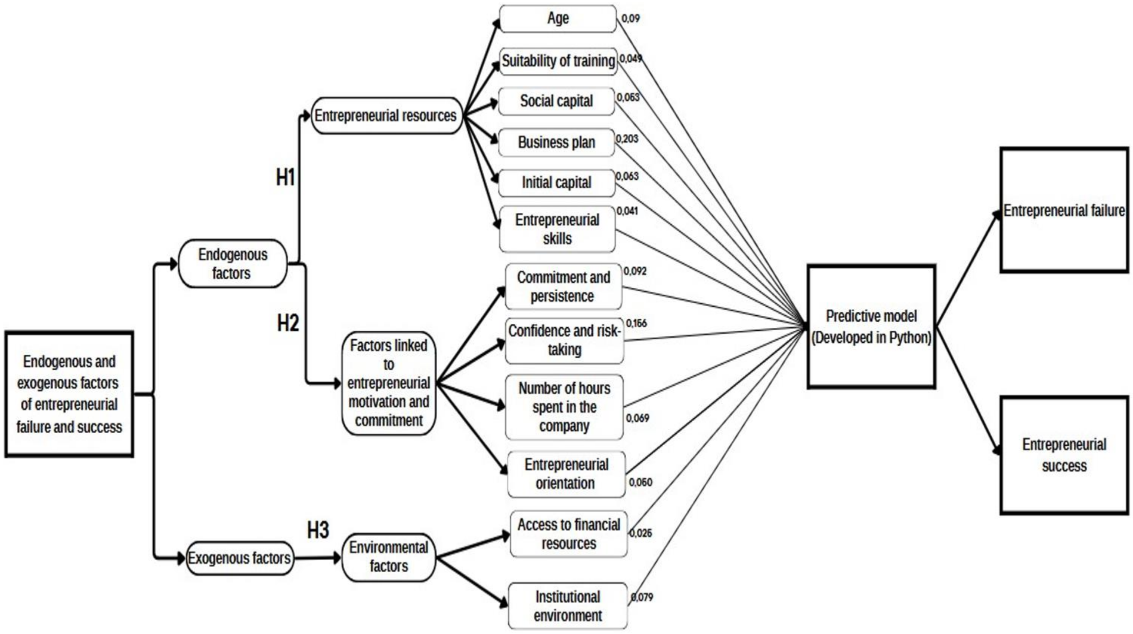

Figure 4. Explanatory model for entrepreneurial success and failure factors in newly created SMEs.

To assess the robustness of our predictive model (based on the Random Forest method), we used four evaluation techniques in Python (Appendix 12): the 10-iteration cross-validation method, the ROC curve, the confusion matrix and Accuracy.

With the cross-validation method, we obtained an average score of 90.66%. This indicates that our predictive model is capable of accurately predicting the target classes on average over the 10 iterations of cross-validation.

Also, with an AUC of 0.93, the predictive model performs very well. In terms of prediction, the model has significant predictive power for entrepreneurial success and failure based on the characteristics provided by the explanatory variables (Figure 5).

Like the AUC, an accuracy of 80% indicates that the model has correctly predicted 80% of the entrepreneurial situations compared to the observed values (Table 14).

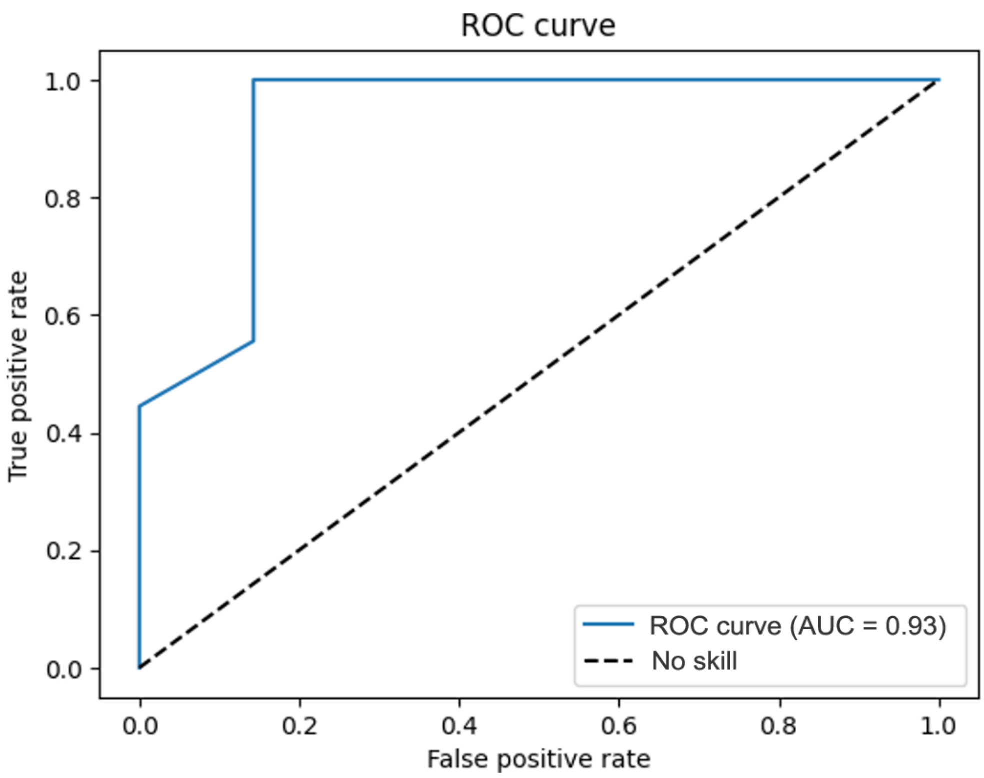

Figure 5. The ROC curve to assess the robustness of the predictive model.

Table 14. The Confusion Matrix and Accuracy to assess predictive model performance.

Predicted values	Actual values		
	Entrepreneurial success	Entrepreneurial failure	Accuracy:0.80
Entrepreneurial success	6	1	
Entrepreneurial failure	1	8	

5. Analysis and Discussion of Results

In this section, it is appropriate to discuss the findings of our empirical study in relation to the existing literature, in order to highlight their significance for practitioners and researchers. Thus, in relation to the age of the entrepreneur, the results of our empirical study showed that young entrepreneurs, aged between 18 and 34, are more likely to succeed than other age groups. Conversely, entrepreneurs aged 35 and over have a higher or lower probability of failure. This result runs counter to the idea defended by some authors, such Azoulay et al. (2020) that the advanced age of the entrepreneur has a positive impact on the success of entrepreneurs.

With regard to the gender of entrepreneurs, our study shows that women are more likely to succeed than men. This conclusion is in line with ideas put forward by authors such as Brush (1992) and Gicheva and Link (2013).

With regard to the variables level of education and type of training, our results diverge from those of some authors who suggest that the level of education and the nature of training are often determining criteria for entrepreneurial success (Abriane & Aazzab, 2016; Davidsson & Honig, 2003; Unger et al., 2011).

With regard to the variable matching of training to the company's business, our findings are consistent with the results of several authors. The latter have pointed out that the probability of business survival increases in cases where the fields of study align with the company's business (Marvel, Davis, & Sproul, 2016; Unger et al., 2011).

Contrary to what is described in the literature, the results of our research reveal that the professional background and number of years of experience have no impact on the professional situation of the entrepreneurs in our sample. Contrary to this finding, several authors, such as Fabre and Kerjosse (2006) and Frédéric Delmar and Shane (2006) emphasize that the absence or lack of entrepreneurial experience has a negative impact on the survival of start-ups..

Against all expectations, the results of our research have shown that the entrepreneurial situation in which the entrepreneur finds himself does not depend on his entrepreneurial experience and/or previous entrepreneurial failure. In contrast, Politis (2005) and Rauch and Rijsdijk (2013) emphasize the importance of past entrepreneurial experience in improving the future performance of entrepreneurs.

With regard to entrepreneurial personality traits, the results of our research are largely in line with the conclusions of several authors who highlight the important role played by personality traits in explaining entrepreneurial failure or success. These authors conclude that the success of a company depends largely on the personality traits, past life characteristics, and motivations of its managers. Similarly, authors such as Hayward et al. (2010) and Khelil, Smida, and Zouaoui (2012) have pointed out that these personality traits revolve around self-confidence, risk-taking, and commitment.

In line with the existing literature, our results also confirm that the number of hours spent within the company increases entrepreneurs' chances of success. This result corroborates the findings of the study conducted by Nikolić, Jovanović, Nikolić, Mihajlović, and Schulte (2019). Indeed, according to these authors, the number of hours spent in the company indicates a certain commitment on the part of the entrepreneur, which ultimately increases his chances of success (Nikolić et al., 2019).

With regard to the social capital formed, our results are consistent with the extensive literature on the subject, which states that an entrepreneur's success depends on their ability to establish a solid network of relationships and to exploit available business opportunities. This connectivity facilitates access to necessary resources, particularly information, providing the entrepreneur with a competitive advantage over others (Davidsson & Honig, 2003; Stam et al., 2014).

With regard to entrepreneurial orientation, the results of our study show once again that entrepreneurial orientation has a significant impact on entrepreneurial status. Indeed, entrepreneurs who embark on entrepreneurship with the aim of seizing an opportunity have a greater chance of success than those who follow an entrepreneurial orientation out of necessity. Several authors, such as Frédéric Delmar and Shane (2006) and Giacomin, Janssen, and Guyot (2016) have defended this finding.

In the case of "Entrepreneurial knowledge," the results of our research show that it has no impact on the outcome of the entrepreneurial venture in terms of entrepreneurial failure or success. This result contradicts the findings of the qualitative study by Lahcen, Oukassi, and Amghar (2021), who highlight the preponderant role of entrepreneurial knowledge in the success of entrepreneurs, particularly in the context of nascent SMEs.

As far as "entrepreneurial skills" are concerned, our results align with the findings of the literature review. In this respect, Chandler and Jansen (1992) explained that entrepreneurial skills play a vital role in entrepreneurial success. Chandler and Jansen (1992) and Wiklund and Shepherd (2003) also demonstrated that the experience accumulated by the entrepreneur can increase the probability of business success.

With regard to the "Business plan" variable, the results obtained from our study reveal that drawing up a business plan has a significant impact on the chances of entrepreneurial success. Liao and Gartner (2006) concluded that entrepreneurs who had drawn up a business plan were 2.6 times more likely to succeed than those who had not.

With regard to the initial capital variable, our research results show that sufficient initial capital significantly increases the chances of success for start-up SMEs. This finding confirms the idea put forward by Hichri et al. (2017) that the level of initial capital is a determining factor in the growth and performance of newly created businesses.

In contrast to the literature that advocates the vital role that support can play in helping entrepreneurs acquire the knowledge, skills, and managerial qualities they need to succeed in their entrepreneurial projects (Amezcua, Grimes, Bradley, & Wiklund, 2013; Chrisman & McMullan, 2004) our study has highlighted the absence of any significant impact of support on the entrepreneurial situation.

On the subject of the institutional environment, our results demonstrate the influence exerted by this variable on the fate of entrepreneurs. A favorable institutional environment increases the chances of success for SMEs, and vice versa. This supports the findings of Krauss (2009), who concluded that even if an entrepreneur possesses the skills essential to success, he or she will struggle to make the business survive in an unfavorable environment. Entrepreneurs who fail are those who are unable to keep their newly created business running in the face of these constraints (Gagoitseope & Pansiri, 2012).

According to our results, and in line with the literature, access to financing has a significant influence on entrepreneurial status. SMEs with easy access to various means of financing have a greater chance of success. In a large-scale study carried out in several developed and developing countries, Beck and Demirguc-Kunt (2006) demonstrated that facilitating access to finance for SMEs contributes significantly to their survival and development.

6. Conclusion

In a cumulative logic of knowledge, our research aims to enrich but also deepen knowledge and understanding of the factors that significantly influence entrepreneurial success or failure in nascent SMEs, particularly within the Moroccan context. The empirical study of our research was primarily based on the respective contributions of three theoretical foundations: population ecology theory, the resource-based approach, and motivational approaches. In line with these theoretical foundations, we have formulated three main hypotheses, each subdivided into sub-hypotheses referring to the independent variables comprising our conceptual model.

The use of machine learning techniques such as logistic regression, decision trees, and random forest was crucial because these techniques allow us to analyze complex relationships between variables and overcome the constraints imposed by our sample, which is modest in size and coupled with a considerable number of variables. Compared with existing literature, the results of our empirical research confirm the significant importance of several factors, with a dominance of factors related to the resources and skills-based approach (Hypothesis 1), followed by factors related to motivational approaches (Hypothesis 2). However, the influence of factors related to population ecology theory (Hypothesis 3) remains marginal. Thus, the results of our research revealed that out of the 27 explanatory variables in our initial conceptual model, only 12 have a significant impact on the entrepreneurial situation. Consequently, we proposed an improved predictive model that incorporates these 12 most influential factors. This model provides a broader perspective on entrepreneurial dynamics in small and medium-sized enterprises (SMEs).

The results of this research provide valuable information that entrepreneurs can use to increase their chances of success.

Furthermore, the results of our study suggest a number of recommendations for public decision-makers. In terms of access to financing, public authorities need to double their efforts and focus on facilitating access to financing for SMEs.

In terms of targeting support and assistance, our predictive model can help public authorities identify entrepreneurs with high potential for success. In the same vein, public authorities, through appropriate public policies, must ensure a favorable institutional environment for the development of entrepreneurship within SMEs.

Given the importance of social capital, which stems from our results, public authorities should play a catalytic and facilitating role by organizing professional meetings, sector events, and incubators for start-ups.

From another perspective, our predictive model can be of significant use to the banking sector in targeting entrepreneurs with high potential for entrepreneurial success, thereby reducing the banking risk associated with potentially failing entrepreneurs. Incubators can also incorporate our predictive model into their assessment processes to identify at-risk SMEs in their early stages.

Like all research work, ours has certain limitations affecting specific aspects of our empirical study. Although statistically sound, our sample size may limit the generalizability of our results. A larger sample could enhance the internal and external validity of the study.

On another note, we cannot claim to include all factors in our model. Indeed, other factors not taken into account in our model may influence the fate of entrepreneurs, notably with the recent emergence of a new field of research, namely "Neuroentrepreneurship," but also with the possibility of the existence of other factors not mentioned in the literature. Furthermore, despite the machine learning tools deployed to analyze relationships between independent variables, there may be complex non-linear interactions between variables that have not been fully captured by our model. Similarly, some factors, especially exogenous ones, may change rapidly over time. This longitudinal dynamic has not been taken into account, which may undermine the relevance of our conclusions in different contexts.

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Appendix

```python
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
from sklearn.metrics import classification_report, confusion_matrix
from tabulate import tabulate
import matplotlib.pyplot as plt
from sklearn.pipeline import Pipeline

# Loading the dataset
dataset = pd.read_excel('Dtaset_R.xlsx')

# Searching for missing data
missing_values = dataset.isnull()

# Counting the number of missing values per column
missing_count_by_column = missing_values.sum()

# Replacing missing values with the mode of each variable
dataset_filled = dataset.apply(lambda x: x.fillna(x.mode().iloc[0]))

# Separating independent variables (X) and the dependent variable (y)
X = dataset.iloc[:, :-1]
y = dataset.iloc[:, -1].values

# Using LabelEncoder to encode the dependent variable
le = LabelEncoder()
y = le.fit_transform(y)

# Using OneHotEncoder to handle categorical variables
ct = ColumnTransformer(
    transformers=[('encoder', OneHotEncoder(), [0, 1, 2, 3, 4, 5, 6, 8, 9, 10, 11, 13, 14, 15, 18, 19, 25])],
    remainder='passthrough'
)
X_transformed = ct.fit_transform(X)
```

Appendix 1. Scrypt Python code for data preparation and encoding of independent variables and dependent.

```python
import pandas as pd
from scipy.stats import chi2_contingency

# Definition of variables to analyze
independent_variable = "Age"
dependent_variable = "Entrepreneurial situation"

# Creating the contingency table
cross_tab = pd.crosstab(dataset[independent_variable], dataset[dependent_variable])

# Displaying the contingency table in tabular form
table_results = tabulate(cross_tab, headers='keys', tablefmt='fancy_grid')
print("Contingency Table:\n", table_results)

# Performing the chi-square test
chi2, p, _, _ = chi2_contingency(cross_tab)
```

Appendix 2. Scrypt Python code for chi-square (χ^2) test of independence.

```
# Definition of the function to calculate the contingency coefficient
def calculate_contingency_coefficient(dataframe, variable1, variable2):
    contingency_table = pd.crosstab(dataframe[variable1], dataframe[variable2])
    chi2, _, _, _ = chi2_contingency(contingency_table)
    num_obs = dataframe.shape[0]
    min_dim = min(contingency_table.shape)
    contingency_coefficient = np.sqrt(chi2 / (num_obs * (min_dim - 1)))
    return contingency_coefficient

# Replacing 'variable1' and 'variable2' with the actual names of categorical variables
variable1 = "Age"
variable2 = "Entrepreneurial situation"

# Calculation of the contingency coefficient between the two variables
contingency_coefficient = calculate_contingency_coefficient(dataset, variable1, variable2)
```

Appendix 3. Scrypt Python code for calculating contingency coefficients between independent variables and the dependent variable.

```
import seaborn as sns
import matplotlib.pyplot as plt
from tabulate import tabulate

# Calculation of the correlation matrix from your DataFrame
correlation_matrix = encoded_data.corr()

# Displaying the correlation matrix in table format
table_results = tabulate(correlation_matrix, headers='keys', tablefmt='fancy_grid')
print("Correlation Matrix:\n", table_results)
```

Appendix 4. Scrypt Python code for constructing the Spearman correlation matrix.

```
import pandas as pd
from tabulate import tabulate
from sklearn.metrics import confusion_matrix

# Displaying regression coefficients for logistic regression
coefficients = logistic_model.coef_[0]
intercept = logistic_model.intercept_[0]

# Retrieving explanatory variable names from the dataset
feature_names = X.columns

# Creating a DataFrame for the coefficients
coefficients_df = pd.DataFrame({'Variable': feature_names, 'Coefficient': coefficients})
intercept_df = pd.DataFrame({'Variable': ['Intercept'], 'Coefficient': [intercept]})

# Merging coefficients and intercept
coeff_table = pd.concat([coefficients_df, intercept_df], ignore_index=True)

# Formatted display using tabulate
print("\n--- Logistic Regression Coefficients ---")
print(tabulate(coeff_table, headers='keys', tablefmt='fancy_grid'))
```

Appendix 5. Scrypt Python code for calculating regression coefficients.

```
# Displaying regression coefficients for logistic regression
coefficients = logistic_model.coef_[0]
intercept = logistic_model.intercept_[0]

# Retrieving explanatory variable names from the dataset
feature_names = X.columns

# Creating a DataFrame for the coefficients
coefficients_df = pd.DataFrame({'Variable': feature_names, 'Coefficient': coefficients})

# Calculating average probabilities
mean_pred = logistic_model.predict_proba(X_test_scaled)[:, 1].mean()

# Calculating marginal effects
coefficients_df['Marginal_Effect'] = coefficients * mean_pred * (1 - mean_pred)
```

Appendix 6. Scrypt Python code for calculating marginal effects.

```
# Splitting the dataset into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X_transformed, y, test_size=0.2, random_state=1)

# Standardization of independent variables
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Creating and training the logistic regression model
model = LogisticRegression(random_state=0)
model.fit(X_train_scaled, y_train)

# Making predictions on the test set
y_pred = model.predict(X_test_scaled)

# Evaluation model
print("Confusion matrix:\n", confusion_matrix(y_test, y_pred))
print("\nClassification report:\n", classification_report(y_test, y_pred))
```

Appendix 7. Scrypt Python code for establishing the classification report and the confusion matrix.

```
from sklearn.metrics import roc_auc_score, roc_curve
import matplotlib.pyplot as plt

# Compute probabilities for the positive class
y_prob = logistic_model.predict_proba(X_test_scaled)[:, 1]

# Compute the AUC score
auc_score = roc_auc_score(y_test, y_prob)
print(f"AUC-ROC Score: {auc_score:.2f}")

# ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_prob)
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, label=f"ROC Curve (AUC = {auc_score:.2f})", color='blue', linewidth=2)
plt.plot([0, 1], [0, 1], 'k--', label='No Skill', linewidth=1)
plt.xlabel('False Positive Rate (FPR)', fontsize=12)
plt.ylabel('True Positive Rate (TPR)', fontsize=12)
plt.title('ROC Curve - Logistic Regression', fontsize=14)
plt.legend(loc="lower right", fontsize=10)
plt.grid(alpha=0.3)
plt.show()
```

Appendix 8. Scrypt Python code for constructing the ROC curve (Logistic regression).

```
# Standardization of explanatory variables
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Logistic regression with Lasso penalty
lasso_model = LogisticRegression(penalty='l1', solver='liblinear', random_state=0, C=1.0)
# Adjust the C parameter to control regularization strength
lasso_model.fit(X_scaled, y)

# Retrieve the coefficients
lasso_coefficients = lasso_model.coef_[0]

# Create a DataFrame for the coefficients
lasso_results = pd.DataFrame({
    "Variable": X.columns,
    "Coefficient": lasso_coefficients
})
# Filter variables with significant coefficients
significant_variables_lasso = lasso_results[lasso_results["Coefficient"] != 0]
```

```
from sklearn.ensemble import RandomForestClassifier
import pandas as pd

# Create and train the Random Forest model
rf_model = RandomForestClassifier(n_estimators=100, random_state=0)
rf_model.fit(X, y)

# Feature importance
feature_importances_rf = rf_model.feature_importances_

# Create a DataFrame for feature importances
rf_results = pd.DataFrame({
    "Variable": X.columns,
    "Importance": feature_importances_rf
})

# Filter important variables (e.g., threshold > 0.01)
significant_variables_rf = rf_results[rf_results["Importance"] > 0.01]

print("\nVariables selected with Random Forest:")
print(significant_variables_rf)
```

```
from sklearn.tree import DecisionTreeClassifier
import pandas as pd

# Create and train the Decision Tree model
tree_model = DecisionTreeClassifier(random_state=0)
tree_model.fit(X, y)

# Feature importance
feature_importances_tree = tree_model.feature_importances_

# Create a DataFrame for feature importances
tree_results = pd.DataFrame({
    "Variable": X.columns,
    "Importance": feature_importances_tree
})

# Filter important variables (e.g., threshold > 0.01)
significant_variables_tree = tree_results[tree_results["Importance"] > 0.01]
```

Appendix 9. Scrypt Python code to identify significant variables by using Machine Learning methods.

```
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import StandardScaler

# Standardization of explanatory variables for logistic regression
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Model 1: Logistic regression with Lasso regularization
lasso_model = LogisticRegression(penalty='l1', solver='liblinear', random_state=0, C=1.0)

# Model 2: Random Forest
random_forest_model = RandomForestClassifier(n_estimators=100, random_state=0)

# Model 3: Decision Tree
decision_tree_model = DecisionTreeClassifier(random_state=0)

# Cross-validation (5 folds) for each model
lasso_cv_scores = cross_val_score(lasso_model, X_scaled, y, cv=5, scoring='accuracy')
random_forest_cv_scores = cross_val_score(random_forest_model, X, y, cv=5, scoring='accuracy')
decision_tree_cv_scores = cross_val_score(decision_tree_model, X, y, cv=5, scoring='accuracy')

# Mean and standard deviation of cross-validation scores
lasso_mean_score = lasso_cv_scores.mean()
lasso_std_score = lasso_cv_scores.std()

random_forest_mean_score = random_forest_cv_scores.mean()
random_forest_std_score = random_forest_cv_scores.std()

decision_tree_mean_score = decision_tree_cv_scores.mean()
decision_tree_std_score = decision_tree_cv_scores.std()
```

Appendix 10. Scrypt Python code for applying cross-validation to Machine Learning methods.

```
# 1. Data Preparation
def prepare_data(file_path):
    dataset = pd.read_excel(file_path)
    X = dataset.iloc[:, :-1]
    y = dataset.iloc[:, -1]
    le = LabelEncoder()
    y_encoded = le.fit_transform(y)
    categorical_columns = [0, 1, 2, 3, 4, 5]
    ct = ColumnTransformer(
        transformers=[('encoder', OneHotEncoder(), categorical_columns)],
        remainder='passthrough'
    )
    X_transformed = ct.fit_transform(X)
    return X_transformed, y_encoded, le, ct

# 2. Modeling
def train_model(X, y):
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)
    scaler = StandardScaler()
    X_train_scaled = scaler.fit_transform(X_train)
    X_test_scaled = scaler.transform(X_test)
    model = RandomForestClassifier(n_estimators=100, random_state=0)
    model.fit(X_train_scaled, y_train)
    return model, X_train_scaled, X_test_scaled, y_train, y_test, scaler

# 3. Prediction for a New Observation
def predict_new_data(model, ct, scaler, le, new_data):
    new_data_transformed = ct.transform(new_data)
    new_data_scaled = scaler.transform(new_data_transformed)
    new_prediction = model.predict(new_data_scaled)
    new_prediction_proba = model.predict_proba(new_data_scaled)
    predicted_class = le.inverse_transform(new_prediction)
    print("Predicted Class:", predicted_class[0])
    possible_classes = le.classes_
    probabilities = new_prediction_proba[0]
```

Appendix 11. Scrypt Python code for building the predictive model of entrepreneurial situation based on explanatory variables (Based on random forest technique).

```
# 4. Evaluation
def evaluate_model(model, X_test, y_test):
    y_pred = model.predict(X_test)
    conf_matrix = confusion_matrix(y_test, y_pred)
    print("\nConfusion Matrix:\n", conf_matrix)
    print("\nClassification Report:\n", classification_report(y_test, y_pred))

    disp = ConfusionMatrixDisplay(confusion_matrix=conf_matrix)
    disp.plot(cmap='viridis')
    plt.title("Confusion Matrix")
    plt.show()
from sklearn.metrics import roc_auc_score, roc_curve
import matplotlib.pyplot as plt

# Compute probabilities for the positive class
y_prob = logistic_model.predict_proba(X_test_scaled)[:, 1]

# Compute the AUC score
auc_score = roc_auc_score(y_test, y_prob)
print(f"AUC-ROC Score: {auc_score:.2f}")

# ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_prob)
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, label=f"ROC Curve (AUC = {auc_score:.2f})", color='blue', linewidth=2)
plt.plot([0, 1], [0, 1], 'k--', label='No Skill', linewidth=1)
plt.xlabel('False Positive Rate (FPR)', fontsize=12)
plt.ylabel('True Positive Rate (TPR)', fontsize=12)
plt.title('ROC Curve - Logistic Regression', fontsize=14)
plt.legend(loc="lower right", fontsize=10)
plt.grid(alpha=0.3)
plt.show()
from sklearn.model_selection import cross_val_score

# Cross-validation with 10 iterations
cv_scores = cross_val_score(model, X_train_scaled, y_train, cv=10, scoring='accuracy')

print("Cross-validation scores for each fold:", cv_scores)
print("Mean score:", cv_scores.mean())
print("Standard deviation:", cv_scores.std())
```

Appendix 12. Scrypt Python code for evaluating predictive model performance.