Journal of Ecohumanism
2024
Volume: 3, No: 6, pp. 878 – 897
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v3i6.4058

Anticipating Success or Failure: A Comprehensive Analysis of Entrepreneurship Factors Using Machine Learning Predictive Models

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Abstract

The research, a pioneering effort in Morocco, explores the intricate elements driving new startups' viability using AI models. It employs a range of advanced techniques such as decision trees, random forests, logistic regression, support vector machine (SMV), ensemble techniques, and neural networks. The study uncovers unique perspectives on the complex interplay between internal variables like human capital, strategic planning, and internal bureaucracy and external factors like government support, mentorship, and competition that shape entrepreneurship performance. The findings, which reveal a dual and unexpected influence of internal bureaucracy and a multifaceted contribution of human capital, are particularly relevant in the dynamic startup landscape. Mentorship and financial resources emerge as critical contributors to startups' success. This review, the first of its kind in Morocco, offers special insights into the factors influencing entrepreneurial success. The discoveries have the potential to revolutionize our understanding of how organizations operate in Morocco and their significant implications for enterprising undertakings, providing a practical guide for startups in the region.

Keywords: *Entrepreneurship, Machine Learning, Predictive models, Startups, Decision Trees, Neural Networks, Ensemble Models.*

Introduction

In the discipline of machine learning (ML), the expectation of business achievement or failure has advanced and presently includes a few modern applications and approaches. The latest review has upgraded bankruptcy forecasts using information mining strategies and clustering algorithms (Xia and Taos, 2017). Jin and Song (2018) use media exploration and AI (ML) to estimate competitiveness, while Rahman et al. (2018) underscore the utilization of ML in assessing an organization's performance. Various models and approaches might be utilized to estimate the likelihood of coming out on top or failure in enterprising exercises. As per Piskunova et al. (2022), models in light of properties might be made by applying AI strategies. Among the considerations are the duration between the beginning of the organization and its underlying raising support round, the sort and measure of financing, the company, the business methodology, and the important procedures. Studies like Chan et al. (2016)'s ML bankruptcy model for predicting and Wang et al. (2017)'s improved model, which uses feature selection and ensemble learning, further improve prediction skills.

Aidis and colleagues (2012) highlight the importance of quality governance, while Klapper, Amit, and Guillén (2010) emphasize the role of having access to capital. Kibler et al. (2014) explore networks and cultural values as factors. Additionally, Khan et al. (2020), Beck, Klapper, and Maksimovic (2018), and Cuevas et al. (2019) offer insights into the dynamics, resource accessibility, and cultural contexts that influence endeavors. Shifting attention to entrepreneurship research in Morocco, the failure issue is multifaceted. El Alami et al. (2019) comprehensive study underscores the significance of accessibility to financial resources. El Kacemi et al. (2017) confirmed and highlighted challenges related to accessing funding, leading to government programs such as those discussed by Haddoud and Bouazza (2020). Societal perceptions of entrepreneurship gender disparities in entrepreneurship activities as the integration of

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innovation and technology are all crucial aspects examined respectively by Lahrech et al. (2016), Laabissi et al. (2019), and Benhassine and Braguinsky (2020). Education level also plays a role in shaping the mindset and skills of entrepreneurs.

However, there is a lack of research on using ML models to predict entrepreneurship outcomes in Morocco. Despite having plenty of information on the dynamics of entrepreneurship in the country, we need ML frameworks designed explicitly for Morocco's context. This leads us to discuss prediction models for failure using ML on a scale. Recent studies by Li and Chan (2018), who used Support Vector Machines and Random Forests, and Daskalaki et al. (2019), who applied decision trees and neural networks, demonstrate growing recognition of MLs potential to enhance prediction accuracy by identifying patterns. Keh and Chu (2020) further incorporate social network data to predict business failures.

Previous research gives an overview of how machine learning has evolved in predicting the success or failure of businesses. It also discusses its application in entrepreneurship and examines success factors in developing nations, specifically focusing on entrepreneurs' challenges. Additionally, it emphasizes the increasing significance of machine learning in forecasting failures. This narrative sets the foundation for exploring how machine learning can help address the complex challenges entrepreneurs face in Morocco.

Literature Review

Significant advancements and discoveries in machine learning (ML) have been made to predict a firm's success or failure across various methodologies and industry applications. Pioneering studies by Zavgren (1984) and Beaver (1975) have been turned into classic landmark research, inspiring a plethora of replication and extension studies, most of which attribute a window to the time-series CUSUM of the methodology and an extensive coverage of predictive research conducted during that era. Notable research advances were made in recent works; for example, Xia and Tao (2017) improved bankruptcy prediction by utilizing a data mining technique in conjunction with a fast-clustering algorithm. Jin and Song (2018) use social media analytics and machine learning to forecast organizational competitiveness. In their investigation of predictive analytics in the digital age, Rahman et al. (2018) emphasize the significance of machine learning models in determining a company's competitiveness. According to success factors, Lee et al. (2019) predicts organizational competitiveness, providing insights into the hospitality industry.

Success or failure of entrepreneurship venture can also be predicted using various techniques and models. One method is to build predictive models based on the startup's descriptive features using machine learning algorithms (Piskunova et al., 2022). These models can consider variables like the time elapsed between the establishment and the first funding round, the type and quantity of the first funding round, the activity area, the business model, and applied technologies (Dhochak, Pahal & Doliya, 2022). A hybrid machine-learning, assets, liabilities, and cash-flow bankruptcy prediction model was also presented by Chan et al. (2016). Wang et al. (2017) conducted a highly advanced and recent study that improves the bankruptcy prediction model by using a hybrid feature selection and ensemble learning. Zhang and Luo (2015) investigate machine learning predictive analytics for organizational competitiveness, highlighting its cross-domain applicability. Fathi et al. (2017) examined vital success factors in e-commerce startups. They stated that prioritizing the user experience, achieving product-market fit, putting effective marketing and branding strategies into practice, embracing technology and innovation, streamlining logistics, providing excellent customer service, guaranteeing strong data security, and providing a variety of safe payment options are all essential success factors for e-commerce startups. Dergiades and Milas (2017) concentrate on predicting success in small and medium-sized enterprises (SMEs). They highlighted the importance of strategic management, financial planning, innovation, and successful marketing. According to research, proactive decision-making and flexibility are critical for small and medium-sized enterprises' success (Fatoki, 2014; Wiklund & Shepherd, 2003).

Entrepreneurship Success Factors in Developing Countries

Ongoing research explores the factors contributing to entrepreneurship, in developing countries. When it comes to institutions, Aidis and colleagues (2012) emphasize the role of quality and effective governance.

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Similarly, Klapper, Amit, and Guillén (2010) highlight the significance of having access to capital when studying the impact of banking and financial literacy on business success. Kibler et al. (2014) demonstrate how social networks and cultural values influence efforts in today's discussions. Alves et al. (2018) stress the importance of education and skill development emphasizing the need for targeted educational programs to enhance capabilities in developing countries.

Khan et al. (2020) investigate how regulated organizations and voids impact development operations in poor nations. They place a lot of emphasis on how institutional processes shape the surroundings. The study by Beck, Klapper, and Maksimovic (2018) explores the relationship between advancement and business creation and emphasizes the significance of systems in addressing access-related challenges. Cuevas et al. (2019) explore intention-influencing elements, offering facts about the connection between cultural settings and business ventures. Wyrwich et al. (2021) delve deeply into developing and mastering skills. They provide insight into how education may mold a viewpoint by observing how understudies' motivation to launch their businesses in developing countries may influence their education in business ventures.

Entrepreneurship Research in Morocco

Business disappointment is a complicated problem in Morocco, influenced by social, financial, and hierarchical factors. El Alami and associates (2019) thoroughly analyzed Morocco's geography, emphasizing the value of financial transparency and authoritative building. El Kacemi et al. (2017) point out that financing is tricky for endeavors. In response, the government has established financial assistance programs, as Haddoud and Bouazza (2020) discussed. The more comprehensive socio-social elements deeply ingrained in Moroccan culture directly affect how projects turn out. Lahrech et al. (2016) examined how society views business ventures and demonstrated the implications of these views for the likelihood that a business venture would be a lucrative career choice and for the support that business visionaries get. Besides, Moroccan businesspeople need to coordinate innovation and development to prosper. Benhassine and Braguinsky's (2020) research suggests that entry to rational and creative improvement offices may be restricted.

Bouazza and El Kadiri (2018) emphasize the importance of learning in developing views and capacities for commercial ventures. Increasing the scope of business venture preparation at all stages can give aspiring entrepreneurs the knowledge and tools they require to reduce their failure rate. According to Laabissi et al. (2019), there are differences in sexual orientation in Morocco when it comes to company ownership. Their evaluation underscores the need to unequivocally resolve issues connected with direction, advance consolidation, and make an air that upholds the accomplishments of both male and female business visionaries.

Morocco's funds have worked because of a few regulatory drives, which have boosted organizations and business visionaries to advance development and build occupations. One such program, "Program Moussanada," was presented by MarocPME (Moroccan Organization for the Advancement of Little and Medium-Sized Ventures). It only offers small and medium-sized organizations money, counsel, and preparation. Furthermore, there is the "Maroc Numeric Resource," an urgent drive offering monetary help and assets to computerized ventures in Morocco's development area. Indeed, even with the significance of these activities, further exploration is expected to completely comprehend the impacts of organization possession in Morocco and how computer-based intelligence calculations might be utilized to decide the value of insufficient new pursuits.

Entrepreneurship Failure and Machine Learning Prediction

Artificial intelligence has acquired importance in evaluating the firm possession's downfall because of its capacity to distinguish peril pointers and improve dynamic cycles. Shepherd's conclusive 2003 appraisal is among the principal fundamental distributions to perceive the intricacy of startup disappointment completely. To prepare more specific AI applications, Shepherd's exploration offers primary data on the different viewpoints that lead to innovative disappointment. At first, made by Altman (1968) to estimate

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corporate liquidations, the Z-score model has now been extended to assess the independent company and pioneering monetary well-being, giving an essential instrument for foreseeing the disappointment of enterprising endeavors (Altman, 2017). As per a new examination, AI (ML) approaches can further develop estimating precision and distinguish complex examples that customary formulae could miss.

The exploration by Li and Chan (2018) is critical as it predicts ineffective business adventures utilizing man-made intelligence methods. Their examination yielded exact assessments utilizing Erratic Woods and Support Vector Machines (SVM) strategies, utilizing information from Chinese organizations. Essentially, the 2019 appraisal by Daskalaki et al. zeroed in on foreseeing a business breakdown concerning specific ventures. They used many company data to use machine learning models, such as tree-based models and neural networks, to improve forecasts. Keh and Chu (2020) used machine learning techniques to examine network patterns and find warning signs of approaching business failure to study social network data's expected value. This study enhances the application of predictive analytics to entrepreneurship by taking non-financial elements like social ties into account.

Research Design and Methodology

A representative and diverse sample of business owners was gathered to study the success or failure of Moroccan entrepreneurs' businesses. For an optimum understanding of the entrepreneurial environment, the inclusion criteria considered the sizes of businesses, the industries they belong to, and their geographic locations. Targeting profitable and unsuccessful businesses involved combining random and purposeful sampling techniques. Due to resource constraints, surveys were the only practical method of gathering data. Contacting business owners directly via online government databases and trade associations was one method to facilitate participant recruitment.

Conceptual Framework

A multidimensional method covering financial, environmental, and enterprise dimensions and the entrepreneur's profile will constitute the conceptual framework for analyzing the factors contributing to entrepreneurship success or failure. By identifying and examining these variables, the framework seeks to offer a thorough grasp of the complex elements affecting entrepreneurial success. Meta-independent variables, namely, Entrepreneurial, Enterprise, and Business Environment factors, were selected based on the literature and previous publications. The company's success or failure determines the dependent variable.

Figure 1: Conceptual Framework

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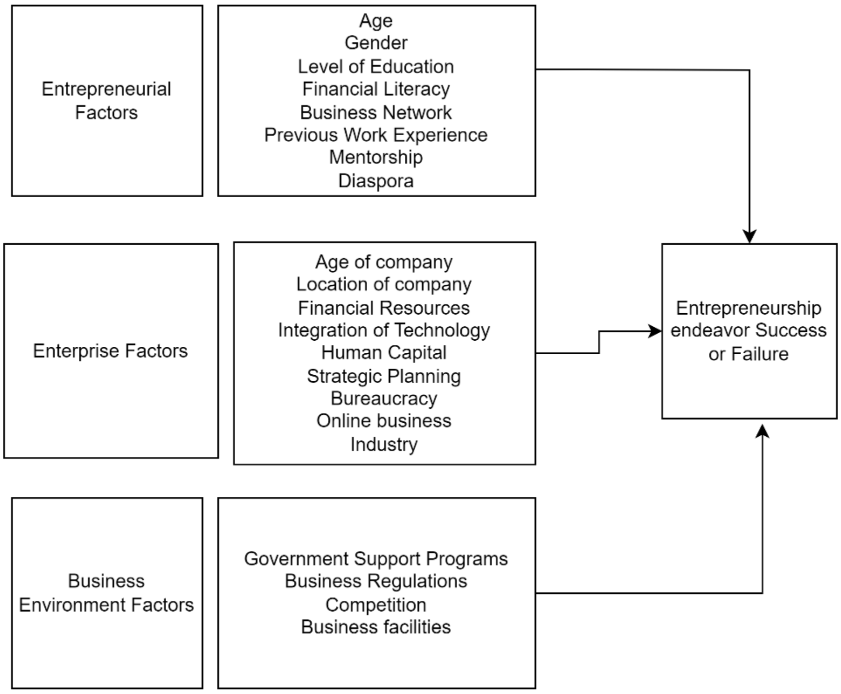

Sampling Strategy and Data Collection Method

A survey has various benefits in this large-scale study setting. It makes it possible to communicate with participants nationwide, including Rabat, the Moroccan capital, Tangier, Fes, Meknes, and Casablanca, the second-busiest business hub in North Africa. It performed incredibly well when obtaining data from a large and diverse sample. The survey provides a standardized data collection method, guaranteeing consistency in the questions and response options due to the nature of this comparative analysis. This standardization simplifies data analysis and makes comparing results across different industries easier.

Participants were contacted via email and randomly selected from government databases. Of the 1875 responses, 1498 were fully completed and usable. A sample of approximately 1500 participants may be deemed adequate in the context of entrepreneurship research. Generally, statistical power increases with larger sample sizes, enabling more thorough analyses and a higher likelihood of identifying real effects or patterns in the data. A representative sample that reflects the diversity of entrepreneurs in terms of industries, regions, and other pertinent characteristics is more likely to be obtained.

Surveys are a reasonably cost-effective way to reach many participants at once. Because of their wide application, fewer resources are required for data collection. The survey also allows for quickly gathering and transforming numerical data to identify patterns and trends using machine learning models. The survey format, response options, and questions are uniform for every participant, ensuring uniform data collection and expediting the analysis process. The distribution of collected answers is displayed in Table 1.

Table 1: Number Of Validated Answers Collected in Each Region.

Casablanca		Rabat		Tangier		Fes		Meknes	
Collected	Valid	Collected	Valid	Collected	Valid	Collected	Valid	Collected	Valid
754	641	525	419	311	247	147	102	138	89

Variables Definition

Existing knowledge guided the initial selection of adequate independent variables for the Moroccan context. Table 2 defines each variable and how it was measured.

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Table 2: Definition Of the Variables

	Variable Name	Description	Measurement
	Entrepreneurial Factor		
1	Age	Age of participant	
2	Gender	Gender of participant	0. Female 1. Male
3	Level of Education		1.Below High School, 2.High School 3.College, 4.Master, 5.Doctorate
4	Financial Literacy	Level of Financial literacy	Likert scale (1.No Literacy to 5.Advanced Literacy)
5	Previous Work Experience	Number of Years in Business	1.<=2 2.>2 & <=5 3.>5 &<=10 4.>10&<=15. 5.>15
6	Mentorship	Support from a mentor (Private or Public)	0. No 1. Yes
7	Diaspora	Belong to the Moroccan Diaspora	0. No 1. Yes
	Enterprise Factor		
8	Age of company	Age of the company since inception	
9	Financial Resources	Enough Financial resources	0. No 1. Yes
10	Integration of Technology	Technology integrated to run the business	Likert scale (1. Very Disagree to 5.Very Agree)
11	Human Capital	Employees skills match business requirements	Likert scale (1. Very Disagree to 5.Very Agree)
12	Strategic Planning	Contribute to fostering a proactive decision-making approach	Likert scale (1. Very Disagree to 5.Very Agree)
13	Bureaucracy	Flexible internal administrative policies	0. Likert scale (1. Very Disagree to 5.Very Agree)
14	Online business	Business fully online?	1. No 1. Yes
15	Industry	Type of Industry (A definition of each sector given to participants)	1. Primary, 2.Secondary, 3. Tertiary, 4. Quaternary
	Business Environment Factors		
16	Government Support Programs	The government provides assistance and support	Likert scale (1. Very Disagree to 5.Very Agree)
17	Business Regulations	Facilitate operations and procedures	Likert scale (1. Very Disagree to 5.Very Agree)
18	Competition	Low Competition	Likert scale (1. Very Disagree to 5.Very Agree)
19	Business facilities	Availability of physical locations, spaces, or structures	Likert scale (1. Very Disagree to 5.Very Agree)
	Dependant variable		
20	Performance	How is the entrepreneur's business performing?	0. Low performance 1. High performance

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Data Processing

To handle missing data, outliers and inconsistencies, this study utilized preprocessing analysis and data preparation techniques. This involves normalizing, scaling, and encoding variables. Machine learning models were employed, including Decision Trees, Random Forests Support Vector Machines (SVMs), Ensemble Models, Logistic Regression and TensorFlow. To address the class imbalance caused by several instances in the variable "Performance", the study utilized the Synthetic Minority Over Sampling Technique (SMOTE). This study used metrics such as precision, recall, accuracy, and F1 score to evaluate the models (Table 3). Additionally, feature importance scores were displayed to identify the variables that significantly influence predictions of business failure through machine learning selection. This research utilized Google Colab as an Integrated Development Environment (IDE). Google Colab offers free GPU (Graphics Processing Unit) resources essential for speeding up computationally demanding tasks. Moreover, it seamlessly integrates with known machine learning libraries, making the implementation of machine learning algorithms easier and ensuring compatibility with used tools in academic research.

Table 3: Description And Use Case of Metrics

Metric	Purpose	Calculation	Use Case
Accuracy	Measures overall correctness	(True Positives + True Negatives) / Total Predictions	Balanced classes; less informative in imbalanced datasets
Precision	Measures accuracy of positive predictions	True Positives / (True Positives + False Positives)	Minimizing false positives (Type I errors)
Recall	Measures the ability to capture all positive instances	True Positives / (True Positives + False Negatives)	Minimizing false negatives (Type II errors)
F1-score	Balanced metric combining precision and recall	2 * ((Precision * Recall) / (Precision + Recall))	Balancing the trade-off between false positives and false negatives

While "precision" emphasizes the accuracy of positive predictions, aiming to minimize false positives, "recall" focuses on capturing all positive instances, aiming to minimize false negatives. There is often a trade-off between precision and recall. Increasing one may decrease the other, depending on the model's threshold for classifying instances as positive.

Precision is crucial when the cost of false positives is high (e.g., misclassifying a non-failure company as a failure case could be costly in support, advising, and unnecessary legal and regulatory Assistance). Recall is critical when missing positive instances is costly (e.g., a company diagnosed as non-failing while facing high business risks of failure may have severe consequences), Scenario of precision evaluation error remains less critical than recall evaluation error.

Ethical Considerations

Participants were fully informed about the purpose, steps, potential risks and benefits, and the option to withdraw from the study without facing any consequences. They willingly agreed to take part in the research. Their independence was respected as they had the freedom to decline participation. Measures were taken to ensure the confidentiality of participants' information with stringent security protocols to prevent data access or disclosure.

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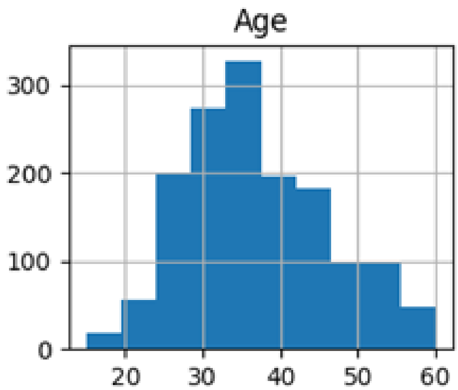
Results

Univariate Comparative Distribution

Statistical exploration begins with univariate analysis, laying the groundwork for more intricate analyses. Figure 2 shows that the distribution of entrepreneurs' age is right-skewed, indicating that most entrepreneurs are below 45. Men represent nearly 60% of the respondents, while 40% are women.

Figure 2: Age Distribution



Frequency analysis shows that 78.4% of respondents have college degrees or higher, and 50.9% have master's or doctorate degrees (Table 4)

Table 4: Level Of Education Frequency

Level of Education	Frequency	Percentag e	Percentage cumulated
Below High School	122	8.1	8.1
High School	202	13.5	21.6
College	412	27.5	49.1
Master	457	30.5	79.6
Doctorate	305	20.4	100
Total	1498	100	

The table illustrates the literacy levels among entrepreneurs, categorizing them into five groups. The majority have low to average literacy, with 34.4% having low literacy and 30.2% having average literacy. Only 5.9% exhibit high literacy. Cumulative percentages show the distribution, emphasizing the prevalence of lower literacy levels in the entrepreneurial population (Table 5).

Table 5: Frequency of Literacy Among Entrepreneurs

Level of Literacy	Frequency	Percentag e	Percentage cumulated
No Literacy	243	16.2	16.2
Low Literacy	516	34.4	50.7
Average Literacy	452	30.2	80.8
Literacy	199	13.3	94.1
High Literacy	88	5.9	100
Total	1498	100	

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The table depicts the distribution of entrepreneurs based on their years of experience. A significant proportion, 26.6%, have 2 to 5 years of experience, while 19.8% and 19.5% fall into the 5 to 10 years and 10 to 15 years categories, respectively. Cumulative percentages reveal the progression of experience levels.

Table 6: Frequency of Years of Experience

Years of Experience	Frequency	Percentage	Percentage cumulated
<=2 years	326	21.8	21.8
>2 & <=5 years	398	26.6	48.3
>5 &<=10 years	296	19.8	68.1
>10&<=15 years	292	19.5	87.6
>15 years	186	12.4	100
Total	1498	100	

The Moroccan diaspora represents 46.1% of respondents. This means that many entrepreneurs who previously worked abroad have returned to Morocco to pursue entrepreneurial endeavors (Table 7).

Table 7: Diaspora Distribution

Diaspora	Frequency	Percentage	Percentage cumulated
No	807	53.9	53.9
Yes	691	46.1	100
Total	1498	100	

The table 8 presents data on monitoring practices, indicating that 47.5% of cases have no monitoring, while 52.5% report having monitoring mechanisms in place. The cumulative percentage reflects a complete coverage of monitoring practices within the examined context.

Table 8: Frequency of Monitoring

Monitoring	Frequency	Percentage	Percentage cumulated
No	712	47.5	47.5
Yes	786	52.5	100
Total	1498	100	

Interestingly, Table 9 shows that the correlation between all variables is close to zero except between mentoring and business performance, where the correlation, despite being low, is r=0.239 (p<001).

Table 9: Correlation between Entrepreneurial Factors

		Gender	Finance Literacy	Level of Education	Years of Previous Business Experience	Mentorship	Moroccan Diaspora	Business Performance
Gender	Pearson Correlation	1	0.008	-.055*	0.025	-0.012	-0.033	-0.043

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	Sig. (bilateral)		0.746	0.033	0.342	0.655	0.199	0.095
	N	1498	1498	1498	1498	1498	1498	1498
Finance Literacy	Pearson Correlation	0.008	1	0.012	.053*	.052*	-0.006	.058*
	Sig. (bilateral)	0.746		0.647	0.041	0.046	0.82	0.025
	N	1498	1498	1498	1498	1498	1498	1498
Level of Education	Pearson Correlation	-.055*	0.012	1	-.067**	-0.032	-0.006	0.048
	Sig. (bilateral)	0.033	0.647		0.009	0.209	0.812	0.064
	N	1498	1498	1498	1498	1498	1498	1498
Years of Previous Business Experience	Pearson Correlation	0.025	.053*	-.067**	1	0.022	-0.016	.053*
	Sig. (bilateral)	0.342	0.041	0.009		0.402	0.534	0.039
	N	1498	1498	1498	1498	1498	1498	1498
Mentorship	Pearson Correlation	-0.012	.052*	-0.032	0.022	1	0.007	**.239****
	Sig. (bilateral)	0.655	0.046	0.209	0.402		0.801	0
	N	1498	1498	1498	1498	1498	1498	1498
Moroccan Diaspora	Pearson Correlation	-0.033	-0.006	-0.006	-0.016	0.007	1	-0.015
	Sig. (bilateral)	0.199	0.82	0.812	0.534	0.801		0.555
	N	1498	1498	1498	1498	1498	1498	1498
Business Performance	Pearson Correlation	-0.043	.058*	0.048	.053*	.239**	-0.015	1
	Sig. (bilateral)	0.095	0.025	0.064	0.039	0	0.555	
	N	1498	1498	1498	1498	1498	1498	1498

The table 10 outlines the alignment of human capital skills with requirements, revealing that 33.6% strongly disagree, 21.8% disagree, and 19.3% are neutral. Conversely, 15.7% agree, and 9.5% strongly agree, indicating varying degrees of agreement on the matching of human capital skills with requirements. The cumulative percentage highlights the overall distribution across these perspectives.

Table 10: Human Capital Skills Matching Requirements

Human Capital	Frequency	Percentag e	Percentage cumulated
Very Disagree	504	33.6	33.6
Disagree	327	21.8	55.5
Neutral	289	19.3	74.8
Agree	235	15.7	90.5
Very Agree	143	9.5	100
Total	1498	100	

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Nearly half of entrepreneurs (49.2%) said they do not have enough financial resources to run their businesses (Table 11), while 51.8% state that strategic planning does not help foster a dynamic and proactive decision-making approach (Table 12)

Table 11: Distribution of Financial Resources Availability

Financial Resources	Frequency	Percentage	Percentage cumulated
No sufficient Resources	737	49.2	49.2
Sufficient Resources	761	50.8	100
Total	1498	100	

Table 12: Distribution of Strategic Planning Influence on Decision-Making

Strategic Planning	Frequency	Percentage	Percentage cumulated
Very Disagree	455	30.4	30.4
Disagree	321	21.4	51.8
Neutral	293	19.6	71.4
Agree	286	19.1	90.5
Very Agree	143	9.5	100
Total	1498	100	

Table 13 provides an overview of the types of industries and their distribution. Primary industries account for 34.7%, secondary industries comprise 27.5%, and tertiary industries represent 14.8%. Quaternary industries contribute 23.0%.

Table 13: Type of Industry Distribution

Type of Industry	Frequency	Percentage	Percentage cumulated
Primary	520	34.7	34.7
Secondary	412	27.5	62.2
Tertiary	221	14.8	77.5
Quaternary	345	23.0	100
Total	1498	100	

Table 14 shows that nearly 70% of entrepreneurs say bureaucracy is rigid, and only 20.3% consider it flexible.

Table 14: Distribution Of How Much Entrepreneurs Consider Bureaucracy Flexible

Bureaucracy	Frequency	Percentage	Percentage cumulated
Very Disagree	661	44.1	44.1
Disagree	381	25.4	69.6
Neutral	151	10.1	79.6
Agree	162	10.8	90.5

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DOI: https://doi.org/10.62754/joe.v3i6.4058

Very Agree	143	9.5	100
Total	1498	100	

Table 15 outlines responses related to technology integration in business and operations. Notably, 31.1% strongly disagree, and 19.6% disagree with this integration. Meanwhile, 18.8% maintain a neutral stance, and 19.5% express agreement, with an additional 11.1% strongly agreeing. These figures underscore diverse attitudes toward incorporating technology into business practices, highlighting the need for nuanced strategies that accommodate varying perspectives on technological integration in entrepreneurial settings.

Table 15: Distribution Of How Much Entrepreneurs Consider Bureaucracy Flexible

Integration of Tech.	Frequency	Percentag e	Percentage cumulated
Very Disagree	466	31.1	31.1
Disagree	293	19.6	50.7
Neutral	281	18.8	69.4
Agree	292	19.5	88.9
Very Agree	166	11.1	100
Total	1498	100	

Table 16 displays the distribution of companies based on their age. About 33.4% of the companies have existed for less than 2 years, 24.0% for more than 2 and up to 5 years, 21.2% for more than 5 and up to 10 years, 12.3% for more than 10 and up to 15 years, and 9.1% for over 15 years. This breakdown provides insights into the composition of companies across different age brackets.

Table 16: Age Of Company Distribution

Age of company	Frequency	Percentag e	Percentage cumulated
<2	500	33.4	33.4
>2&<=5	359	24.0	57.4
>5&<=10	317	21.2	78.6
>10&<=15	186	12.3	90.9
>15	136	9.1	100
Total	1498	100	

Entrepreneurs were also asked about their perception of the environmental factors that influence the course of their business. 50.3% think the government does not provide effective support, while 30.9% say it supports and assists in developing their business (Table 17)

Table 17: Government Support Distribution

Government support	Frequency	Percentag e	Percentage cumulated
Very Disagree	439	29.3	29.3
Disagree	315	21	50.3
Neutral	282	18.8	69.2
Agree	296	19.8	88.9

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Very Agree	166	11.1	100
Total	1498	100	

Statistics reflect that 49.7% of entrepreneurs find business regulations not facilitating operations and procedures (Table 18), while 50% state that the availability of locations, spaces, and structures is a concern (Table 19)

Table1 18: Distribution of How Much Business Regulations Facilitate Business

Business Regulations	Frequency	Percentag e	Percentage cumulated
Very Disagree	458	30.6	30.6
Disagree	286	19.1	49.7
Neutral	319	21.3	71
Agree	293	19.6	90.5
Very Agree	142	9.5	100
Total	1498	100	

Table 19: Distribution of How Much Entrepreneurs Consider the Availability of Physical Resources

Business Facilities	Frequency	Percentag e	Percentage cumulated
Very Disagree	426	28.4	28.4
Disagree	323	21.6	50.0
Neutral	298	19.9	69.9
Agree	296	19.8	89.7
Very Agree	155	10.3	100
Total	1498	100	

Table 20 illustrates the distribution of responses regarding the perceived level of competition. Approximately 29.2% of participants disagree that there is a high level of competition, while 19.6% disagree, 19.3% are neutral, 21.9% agree, and 10.1% very agree. These responses reflect participants' diverse opinions on the competitive landscape, providing insights into their varying perceptions of the intensity of competition in the business environment.

Table 20: Distribution of How Entrepreneurs Evaluate Competition

Competition	Frequency	Percentag e	Percentage cumulated
Very Disagree	437	29.2	29.2
Disagree	293	19.6	48.7
Neutral	289	19.3	68
Agree	328	21.9	89.9
Very Agree	151	10.1	100
Total	1498	100	

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Machine Learning Comparative Metrics

The comparison between different machine learning predictive models offers the possibility to compare metrics, namely, precision, recall, f1-score, and accuracy. The dependent variable (companies' status) will be assessed against the independent variables (or features) to determine which impacts the failure or success of startups the most. Feature importance in machine learning indicates the contribution of each feature (variable) in a model towards making predictions. It provides insights into which features have a more significant influence on the model's output. Generally, higher feature importance suggests a stronger impact on the model's predictions. Table 21 below shows, for each machine-learning model, the metric outcomes. Class 0 represents non-achieving overall business performance while Class 1 represents achieving overall business performance according to entrepreneurs' evaluation.

Table 21: Decision Metrics Outcomes

Decision Trees	Accuracy	precision	recall	f1-score
Class 0	0.76	0.76	0.88	0.82
Class 1		0.75	0.57	0.65
Random Forest	Accuracy	precision	recall	f1-score
Class 0	**0.78**	0.79	**0.89**	**0.84**
Class 1		**0.76**	0.59	0.66
Logistic Regression	Accuracy	precision	recall	f1-score
Class 0	0.74	0.76	0.84	0.80
Class 1		0.69	0.57	0.62
SVM	accuracy	precision	recall	f1-score
Class 0	0.76	0.79	0.85	0.82
Class 1		0.67	0.57	0.62
TensorFlow	Accuracy	precision	recall	f1-score
Class 0	0.72	0.79	0.78	0.79
Class 1		0.59	0.6	0.6
TensorFlow SMOTE	Accuracy	precision	recall	f1-score
Class 0	0.72	0.80	0.76	0.78
Class 1		0.58	0.63	0.60
Ensemble Models Voting Classifier	Accuracy	precision	recall	f1-score
Class 0	**0.78**	0.82	**0.86**	**0.84**
Class 1		**0.70**	0.63	0.66
Ensemble Models Stacking Classifier	Accuracy	precision	recall	f1-score
Class 0	0.74	0.76	0.84	0.80
Class 1		0.68	0.57	0.62

Table 21 shows that Ensemble Models with Voting Classifier and Random Forest have the highest metrics. Indeed, the accuracy of both models is 0.78, and they also have the same f1-score, which is 0.84. However, Random Forest has a Recall score of 0.89 for class 0 while Ensemble Models shows 0.86. On the other hand, Ensemble Models has a procession score of 0.70 for class 1 (companies doing well) while Randon Forest has a score of 0.76. In both classes (0 and 1), Random Forest seems to be the most accurate predictive model for this study.

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Machine Learning Comparative Feature Importances

Essentially, "feature importances" tell how influence different features (independent variables) have on determining the model's output. This concept is especially important in modeling because it helps understand how individual features contribute to the model's decision-making process. For the purpose of simplification, only the first 8 feature importances were compared. Complete feature importance figures are available in the Annexes. The figures show the significance of each feature ranked from the highest weight to the lowest alongside, when available, SHAP (SHapley Additive exPlanations) as a unified approach to explain the output of the machine learning models. SHAP is based on Shapley values from cooperative game theory. It provides a consistent way to distribute the contribution of each feature to the prediction across all possible feature permutations. The two colors, red and blue, represent the direction of the effect of a feature on the model's output. The red color indicates positive SHAP values, signifying an increase in the predicted output. The blue color indicates negative SHAP values, signifying a decrease in the predicted output. Each vertical bar in the plot corresponds to a specific feature, and its length represents the magnitude of the SHAP values. Longer bars (either red or blue) indicate features that have a greater impact on increasing or decreasing the model's output (economic hardship). A comparison between different metrics (Table 4) says that Ensemble Models with Ensemble Model (Voting Classifier) and Random Forest are the most accurate machine learning models in predicting the risk of economic hardship. A comparative summary of feature importance and SHAP is displayed in Table 22 based on figure 3 and 4.

Figure 3: Feature importance of Random Forest Model

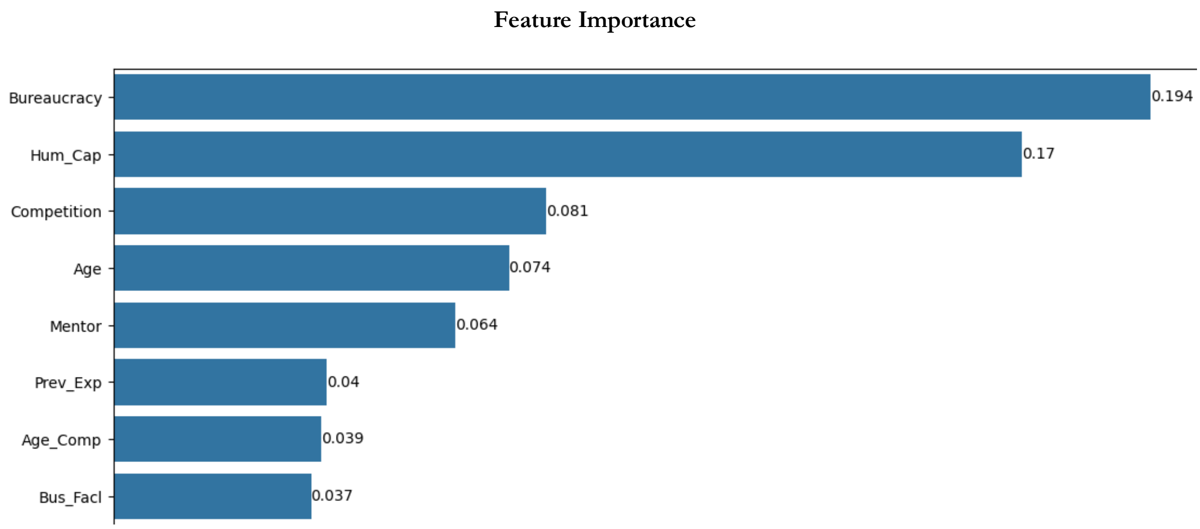

Figure 4: Feature importance of Ensemble Model

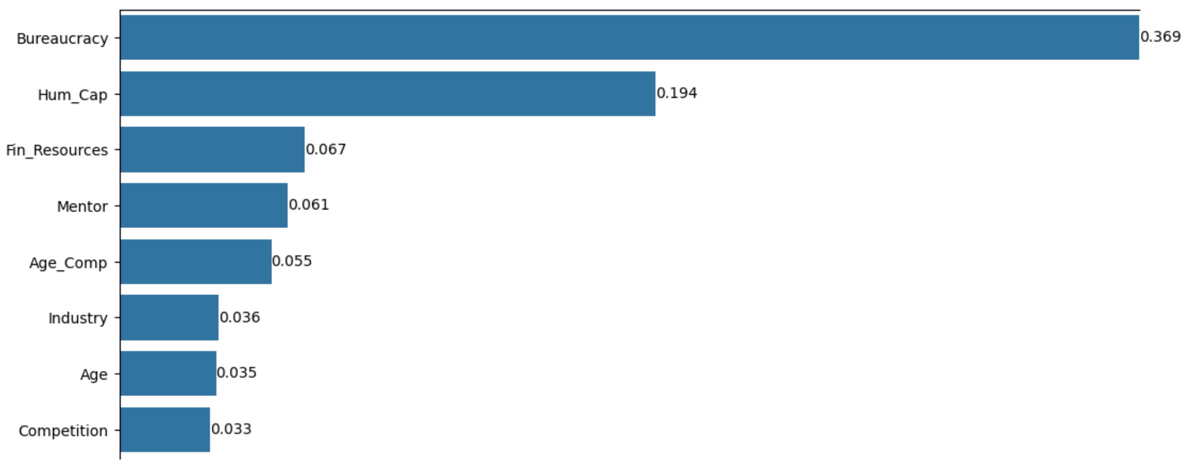

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Table 22: Comparative Analysis of Feature Importance

Model	Feature Importance	Coefficient
Random Forest	1. Bureaucracy	0.194
	2. Human Capital	0.170
	3. Competition	0.081
	4. Age of Entrepreneur	0.074
	5. Mentor	0.064
	6. Previous Experience	0.040
	7. Age of companies	0.039
	8. Business Facilities	0.037
Ensemble Models (Voting Classifier)	1. Bureaucracy	0.369
	2. Human Capital	0.194
	3. Financial Resources	0.067
	4. Mentor	0.061
	5. Age of Companies	0.055
	6. Industry	0.036
	7. Age of Entrepreneurs	0.035
	8. Competition	0.033

Table 22 shows that Random Forest and Ensemble Models (Voting Classifier) rank "Bureaucracy and Human Capital" as the most influential variables to predict companies' performance. However, Random Forest ranks "Competition" as the third most powerful predictor while Ensemble Models puts "Competition" as the number 8 influencer. Ensemble Models considers "Financial Resources' the third most important factor. Random Forest considers the "Age of entrepreneurs," having a "Mentor," and "Previous experience" in business, and the "Age of companies" as contributors to predict companies' performance. Besides the variables just mentioned, Ensemble Models adds the type of Industry as predictor number 6.

Figure 5: Random Forest SHAP Value

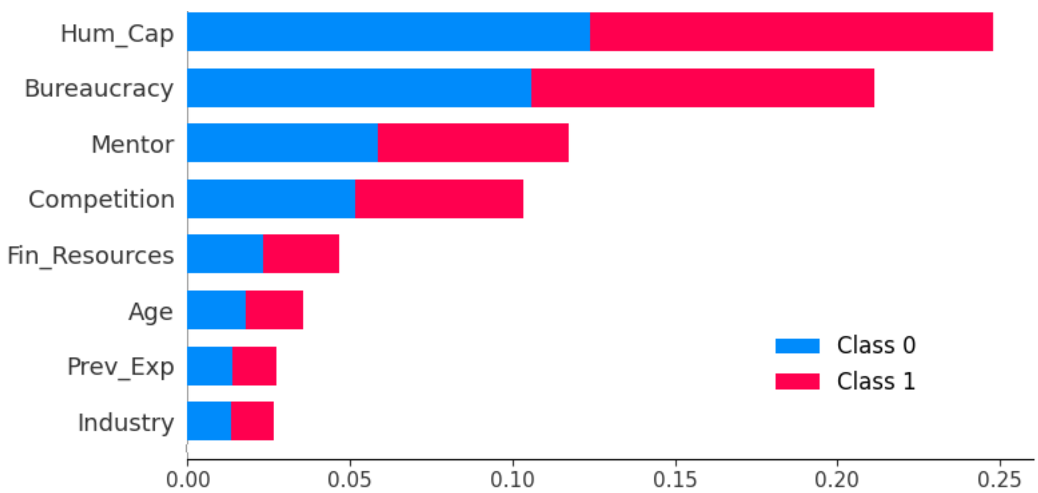

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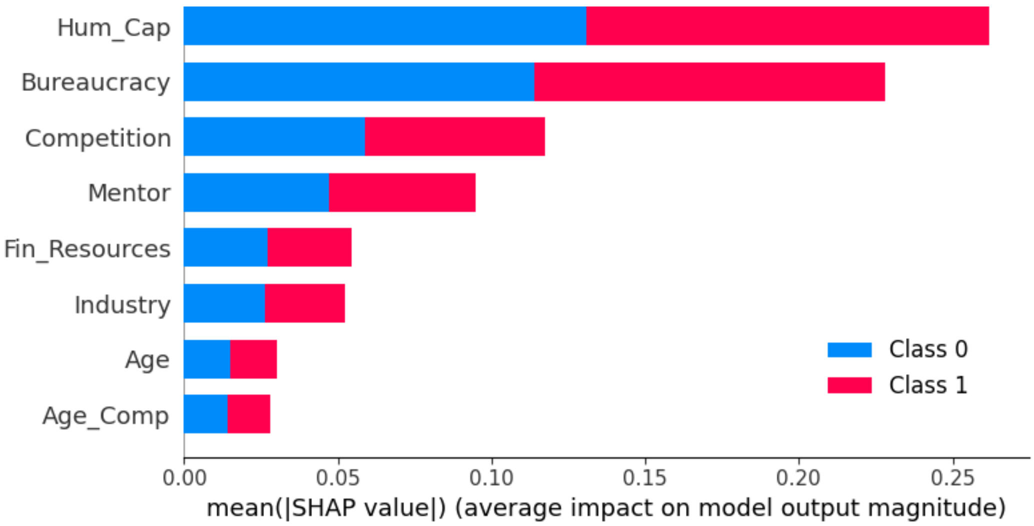
Figure 6: Ensemble Models (Voting Classifier) SHAP Value



On the other hand, both SHAP figures highlight the importance of "Bureaucracy" and "Human capital" as the strongest predictors, but they converge in the third and fourth factors. Ensemble Models considers "Competition as a stronger predictor than Mentor while it is the opposite for Random Forest. Ensemble Models does not mention "Previous Experience" as an influential predictor while Ensemble Models does not mention "Age of Companies".

Discussion

Based on the statistical data analysis related to independent variables and their interactions, it appears that there are no patterns or strong connections that can be used to predict companies' difficulties. The distribution of these variables does not show any trends and correlation analyses involving all the variables. The lack of significant statistical results highlights the complexity of factors influencing companies' performance. Therefore, a nuanced approach becomes essential to understand their dynamics. In this situation, machine learning may provide abilities and adaptability, improving prediction by leveraging data-driven insights and automation surpassing conventional approaches.

Results present the feature importance and coefficients for Random Forest and Ensemble Models (Voting Classifier) in predicting entrepreneurial success. In Random Forest, Bureaucracy holds the highest feature importance (0.194), followed by Human Capital, Competition, Age of Entrepreneur, and Mentor. Ensemble Models, on the other hand, emphasize the Age of Businesses, Human Capital, Finance Resources, Mentors, and Bureaucracy (0.369). The pattern that has been noticed implies that bureaucracy is emphasized in both models, demonstrating that bureaucracy plays a critical role in forecasting the success of businesses. Human resources are increasingly critical as reflected by its constant good position. However, the differences in positions for other aspects, such as economic resources and mentoring, call for further analysis. Ensemble Models give financial resources more weight, indicating that they have a more significant influence.

Differences in data used for training or the fundamental properties of each model may be the cause of ranking discrepancies. Understanding the coefficients of a statistic provides information on how much each attribute contributes. Bureaucracy has the greatest correlation (0.194) according to Random Forest, pointing to a significant influence. With a value of 0.369, bureaucracy is the dominant factor in ensemble models.

All things considered, the critical evaluation indicates that both approaches emphasize bureaucracy and human resources as crucial components. One of the biggest factors depriving firms of performance is internal bureaucracy, which causes issues with effectiveness and agility. Research by Becheikh and Bouaddi (2023), Kamal (2021), and Lecuna et al. (2020) are only two instances of the body of work that emphasizes

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the negative consequences that bureaucratic roadblocks have on companies. The main obstacles to Moroccan enterprises' growth and competitiveness have been described as lengthy and complex administrative processes, complex legislative frameworks, and slow decision-making.

On the other hand, the disparities in coefficients and positions point to subtle variations. The outcomes also show that bureaucracy influences the results of the model in a balanced way. In fact, SHAP uses a 50/50 ratio of red to blue to represent this feature's ability to forecast businesses' success. The shade of red indicates beneficial aid, which enhances the estimate, while the blue color indicates negative contributions, which minimizes the forecast's accuracy. In this instance, bureaucracy both facilitates and hinders business success. The uniform color scheme suggests a complicated interaction between some negative consequences and favorable parts of bureaucracy that boost output. This insight highlights how intimately bureaucratic elements impact the functioning of the entire firm.

As an indicator of businesses' efficiency, the human capital SHAP figure similarly displays a 50/50 balance of both blue and red colors. It represents a complete and diverse impact. Beneficial input, or features of human capital that improve efficiency, are shown by the color red, while negative input, or components that might damage success, are indicated by the color blue. This stability points to a complex connection in which some aspects of human resources may have a beneficial influence on business performance while other elements may have a negative one. The well-balanced representation highlights how important it is to have an in-depth knowledge of all the many parts that make up the human capital build.

The fact that the businesses who provided research for this study are new might be one reason why bureaucracy has less predictive ability than human resources in predicting the success or failure of a business. The perception of bureaucratic organizations is that they make decisions rigidly and adjust slowly, which makes it harder for them to meet the needs of the market. On the other hand, the value of human capital shows how talented, creative, and flexible people can make a difference in a business. As businesses increasingly operate in fluid and uncertain conditions, the ability to harness and develop human capital becomes a crucial factor for success. Prioritizing talents on bureaucratic framework approaches seems more relevant for predicting organizational success.

The factors with low coefficients on business success or failure, as evidenced by Random Forest and Ensemble Models, are attributed to their relatively smaller contribution to the overall predictive model. In this context, factors with lower coefficients, such as "Previous Experience" and "Business Facilities," may have less pronounced effects on the predicted outcome. Although features with lower coefficients may have a weaker influence individually, their collective contribution helps capture nuances in the data and contributes to the overall predictive performance. Indeed, the sum of all other features is equivalent to 0.335 besides bureaucracy and human factors. Nearly 65% of the sum of coefficients goes to Competition, mentoring, and financial resources.

Mentorship, for instance, plays a role in guiding young entrepreneurs. It offers insights and helps entrepreneurs to make informed decisions. Additionally, financial resources act as the lifeblood for startups, allowing them to invest in operations, technology advancements, and acquiring individuals. The study reveals that entrepreneurial success involves making bureaucracy flexible, taking market competition as an impactful factor, learning from mentors, and establishing a solid financial foundation to acquire talented people. These factors empower entrepreneurs to overcome challenges, seize opportunities when they arise, and achieve long-term growth in business environments.

Limitations of Machine Learning Predictive Models

The limitations of machine learning predictions are often discussed in the literature. Machine learning predictive models have some limitations, just like most algorithms. Machine learning models mainly rely on data because biased or insufficient data can lead to inaccurate predictions. The model's perpetuation of biases identified in historical data may lead to unfair or discriminatory outcomes (Obermeyer et al., 2019). Overtly tuned models may capture noise rather than actual patterns in the training set of data. Overfitting or underfitting may limit the model's ability to generalize to new, unobserved data (Roelofs et al., 2019).

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Machine learning predictive models may not function well in situations involving odd occurrences, outliers, or sudden changes since they depend on historical data to generate predictions (Walton, 2018). It is ethical to be concerned about consent, privacy, and potential misuse of personal data. Laws might need help keeping up with the machine learning applications field's rapid changes. Specific deep neural networks and other sophisticated machine learning models are unsuitable for resource-constrained settings because of their high computational requirements for training and inference. Although machine learning models are very good at identifying correlations, they often need help establishing causality. Understanding the cause-and-effect connections between variables is crucial in some applications (Schmidhuber, 2015; Harel & Papadimitriou, 2019).

Conclusion

Understanding the context and underlying assumptions of each model is crucial for accurate interpretation. Additionally, evaluating model performance metrics and conducting sensitivity analyses would enhance the comprehensive assessment of their predictive capabilities in entrepreneurial success prediction. the statistical data analysis highlights the complexity of factors influencing companies' performance, with no clear patterns from independent variables. Machine learning, particularly Random Forest and Ensemble Models, offers an adaptive approach, leveraging data-driven insights for improved prediction. Feature importance and coefficients underscore the significance of bureaucracy and human capital. Bureaucracy, while crucial, exhibits a dual impact on performance, as indicated by SHAP figures, underscoring its intricate relationship. The balanced visualization of human capital suggests a nuanced influence on company performance. The prioritization of human capital over bureaucracy aligns with the agile demands of startups. Lower coefficients for factors like "Previous Experience" and "Business Facilities" signify their smaller individual impact but contribute collectively to overall predictive performance. Mentorship and financial resources emerge as critical contributors, reflecting their pivotal roles in guiding entrepreneurs and sustaining startups. Balancing these factors empowers entrepreneurs to navigate challenges, seize opportunities, and achieve long-term growth. Further reinforcing these points with credibility referencing studies or literature can be beneficial.

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ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
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