

# Business Failure Prediction: The Case of Moroccan SMEs

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**How to cite this paper:** Arzou, N., Kobiyh, M. and Mkik, M. (2025). Business Failure Prediction: The Case of Moroccan SMEs. *Open Journal of Business and Management*, 13, 278-300.

<https://doi.org/10.4236/ojbm.2025.131017>

**Received:** November 19, 2024

**Accepted:** January 7, 2025

**Published:** January 10, 2025

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## Abstract

This research examines the financial challenges faced by small and medium enterprises (SMEs) in Morocco, which play a vital role in the country's economy. However, many SMEs struggle with financial instability, leading to high failure rates. This study focuses on identifying key factors that contribute to business failure. A quantitative approach was applied, utilizing discriminant analysis to assess the differences between successful and failing SMEs. The findings reveal that liquidity and profitability are critical to distinguishing between the two groups, with failing companies showing weaker performance in these areas. This research highlights the importance of financial management practices in mitigating the risk of failure in Moroccan SMEs. It emphasizes the need for effective financial strategies, particularly in managing liquidity and improving profitability, to ensure the sustainability and success of SMEs in the Moroccan context.

## Keywords

SMEs, Financial Management, Failure Prediction, Discriminant Analysis, Business Sustainability

## 1. Introduction

The issue of forecasting company failures has garnered significant attention from both scholars and researchers since Altman's influential study in 1968 (El Manzani & El Manzani, 2018). The aforementioned inclination is evident in the substantial volume of scholarly publications that have been published since 1968. This issue has significant relevance due to two primary factors. To begin with, there has been a significant global surge in the incidence of bankruptcies. Furthermore,

a company failure encompasses a diverse range of individuals who are implicated in the process (Assaad & El-Adaway, 2020). These individuals include workers, owners or shareholders, managers, lenders, suppliers, consumers, the community, the government, and other relevant stakeholders (Cacciotti et al., 2016). The occurrence of bankruptcy incurs a substantial expense due to the involvement of several individuals (Zemis & Demil, 2020).

The economic consequences of business failures are significant, as seen by the drop-in market value of troubled enterprises leading up to their collapse (Beaver, 1966). Under such conditions, it is not just the organization and its workforce who experience immediate consequences, but also a wider range of stakeholders including capital suppliers, investors, and creditors (Altman, 1968).

The identification of organizations that are prone to collapse is a matter of significance for many stakeholders. The prediction of company failure has been a recurring topic in economic study for several decades (Ooghe & De Prijcker, 2008).

The occurrence of business failure suggests that there may have been a misallocation of resources, which is an unfavorable outcome. It is advantageous to recognize in advance the likelihood of such failure, as it would allow for proactive measures to be done in order to avoid its occurrence (Séverin, 2006). Furthermore, the idea of financial distress has been used to elucidate the heightened likelihood of corporate failure in instances when corporations are unable to fulfill their financial commitments (Smida & Gomez-Mejia, 2010).

However, numerous unique elements, such as the development of processes for the prevention of business conflicts, were first implemented in Moroccan law thanks to Law No. 15-95, the Commercial Code. The amount of companies that have failed in Morocco over the last several years is cause for concern. According to the data, the nation set a new record for the number of company failures in 2022 (El Mandili & Elabjani, 2023).

Several scholars have started exploring approaches for estimating default risk in light of the potentially severe and broad implications associated with a firm bankruptcy (Opler & Titman, 1994). In the 1930s, Fitzpatrick (1934) initiated the first studies in this field. Most of the studies conducted in this area throughout the '60s were on refining statistical methods for failure prediction (Crutzen & Van Caillie, 2009; Ferrier et al., 2002).

Financial failure was a subject of research within the realm of financial analysis, particularly in relation to the examination of solvency and the break-even point, until the 1960s (Amankwah-Amoah & Wang, 2019). Based on this particular perspective, the company's bankruptcy may be attributed to specific, non-universal conditions that resulted in abrupt insolvency occurrences (Valaskova et al., 2023). The aforementioned technique underwent a steady evolution as a result of the identification of prevalent statistical patterns in enterprises that have declared bankruptcy.

Ever with Altman's publication of a prominent bankruptcy prediction model in

1968, there has been a proliferation of bankruptcy prediction models in the academic literature (Cohen et al., 2004). This entails not just the escalating quantity of published publications, but also the diverse range of models used for the anticipation of corporate insolvencies. The advancement of statistical techniques and information technology in recent years has facilitated the use of various prediction approaches in the construction of bankruptcy prediction models (Wu et al., 2010). This has resulted in improved accuracy in bankruptcy prediction (Sfakianakis, 2021).

The fundamental issue is how to predict firm cash flow problems and intervene before they spiral out of control (Voda et al., 2021).

The purpose of this article is to talk about these and similar topics. The purpose of this paper is to showcase cutting-edge techniques and resources for predicting a company's collapse. Lastly, we will explain our methodology for data analysis, highlight the most important findings from our study, and speculate on other uses for the information we have uncovered.

In our research, we will delve into the critical issue of preventing business failure, with a specific focus on Moroccan SMEs. This investigation emphasizes the pivotal role that data and methodology play in scientific research, as they are instrumental in ensuring the credibility and reliability of our findings.

Data, in the context of our study, encompass factual information, observations, and measurements collected during our research. These data need to be not only relevant and representative of the targeted population but also precise and dependable to facilitate robust statistical analysis and interpretation.

On the other hand, methodology comprises the comprehensive set of procedures and techniques employed for the collection, measurement, analysis, and interpretation of data in a scientific inquiry. A rigorous, transparent, and reproducible methodology is essential to uphold the validity and reliability of our results, while also guarding against potential systematic errors or biases that might distort our findings.

These foundational principles of data and methodology are paramount in underpinning our scientific research. They serve as the bedrock of our investigation, assuring the credibility and applicability of our results, ultimately allowing for their generalization to the population under study.

This study holds significant relevance in the Moroccan context as it delves into the prevention of business failures, particularly among SMEs, which are a crucial pillar of the country's economy. Previous research has often overlooked providing a comprehensive and up-to-date analysis of this specific issue in Morocco. Our contribution to the literature stands out through rigorous methodological approaches, utilizing precise data, and focusing on the case of the Casablanca-Settat metropolitan area, where we identify both the shortcomings and successes of SMEs while offering valuable insights for public policy and business practitioners.

Our article follows a structured approach, commencing with an extensive literature review, followed by a detailed methodology section, and culminating in the

presentation of results and key conclusions. This sequential organization ensures a comprehensive and coherent presentation of our research findings.

## 2. Review of Literature and the Theoretical Background

A company's failure might have far-reaching effects on the economy and society as a whole, and this is always a possibility. Finding out what goes wrong and what could go wrong in the future has been a major emphasis of this field's study.

### 2.1. Review Theoretical Foundations and Regulatory Approach to Failure

The many attempts to define business failure are highlighted through a survey of the relevant literature. Unfortunately, this phenomenon does not have a single, universally acknowledged term. Internalizing this concept may help us economically, monetarily, legally, and managerially by teaching us to recognise failure in its many forms, identify its symptoms, and probe the causes behind it (Levratto, 2013).

Inaction will only make matters worse. Losing may be a progressive process in which you face more difficult challenges.

There have been attempts to provide a thorough definition of failing enterprises by a number of writers. Everyone suffers when companies choose profits over people and planet over profit (Coulibaly, 2004). Solvency concerns arise when a company's debt level is at or near its maximum, as stated by (Berryman, 1983). According to Malécot (1991), a stressed entity is defined as one that is either influenced by an external risk or is exposed to such a risk.

If these problems aren't fixed, the company could go bankrupt in the long run. Hence, "failure" suggests more serious problems and encompasses a broad range of reasons for the company's demise. To this end, we define failure as the recognition of problems that the company has not been able to resolve (Maricica & Georgeta, 2012). A failing company is a corporation in crisis whose organisational and financial health has deteriorated severely (Hartmann, 2010).

If a corporation is unable to make its contractually agreed upon debt payments, it is considered to be in default under Moroccan law "Law 15-95, Article 560".

The abundance of terms used to characterise a failing organization compels us to investigate the classification of disaster early warning indications.

Repeated deadline extensions, notification of protest, non-payment of tax or social security contributions, refusal of certification of accounts by the auditor, collective redundancies, and loss of three quarters of the capital were identified by the SUDREAU committee in 1975 in France as the most common indicators of failure in bankrupt companies (Martin, 1977).

Cash flow problems and management issues are also included in the AISG's (Accountant International Study Group) list of failure indicators. Several years of negative performance, strained relationships with suppliers, the need to liquidate assets to boost cash flow, and a higher need for working capital than in the past

are all factors identified by the AISG as having an impact on cash flow. The company's market value is falling, prices are stagnant, structural expenses are high, and production is challenging because of inadequate management (Ciampi, 2015).

First-degree deterioration is indicated by negative working capital or a negative net position, as defined by the European Union of Accountants (Messier & Hansen, 1988).

In addition, Argenti (1976), suggests that there are four distinct stages to the failure process. The first is characterised by competent leadership, the second by a string of mistakes made by upper management, and the third by the outside world's view of the company's predicament. The business has exhausted its financial and other resources, so it has filed for bankruptcy. According to Coulibaly (2004), the progression from economic problems to financial difficulties to court after a cessation of payments is what ultimately leads to bankruptcy.

At this point in the economic collapse, the company is no longer profitable and its expenses exceed its income. According to Lee et al., (2022), a decline in value added is the final stage of an economic collapse. Secondly, the company will fail if it is unable to attract enough customers and make money. When a company's assets are insufficient to cover its debts, it declares financial bankruptcy (Kücher et al., 2020). Because of this, the company's financial security may be in jeopardy.

All of these scenarios lead to the inevitable outcome of the corporation breaking an agreement with its creditors. If a commercial court orders a collective receiver or judicial liquidation against a firm, that court has declared the company to be "legally default" (Lee et al., 2021).

A "course of action" meant to forestall a "stoppage of payment" (Morrison, 2021). It's a strategy that might keep problems from escalating out of control and help CEOs navigate through a rough patch in their company's development.

A Moroccan legislator has ordered a tool to check for potential difficulties in an effort to reduce the number of enterprises that fail (Cherqi & Boulaich 2020). In fact, under statute n° 15-95, that together make up this same commercial code and place significant focus on the duties of the company's management in combination with the advice of the auditor and the participation of the partners, the president of the commercial court has the authority to order both internal and external preventative measures.

The Commercial Code's internal preventative method is laid forth in Articles 546 and 547 of Book V. As a first step before enacting further, external preventive measures, this technique may be chosen by the company's director. For the sake of the company's best possible chance of recovery and to avoid arousing the suspicion of its partners, the Moroccan legislator insists that the company's internal preventive strategy be carried out in full secrecy (Zizi et al., 2020). The chief executive officer, the auditor, the board of directors or supervisory board, the annual meeting of shareholders, and, finally, the president of the commercial court is all involved in this safety net.

The manager is the first focus of any preventive measures taken inside the

organization. According to Article 545 of the Commercial Code, the latter's duty as management is to remedy the company's predicament. If a company's chief executive officer (CEO) misses the signs of impending trouble, an auditor will. If the auditor has any reason to believe that the company's operations are not sustainable, they must raise the alarm. The organizational structure of a business determines whether or not an auditor is required to be appointed.

The process consists of four steps. Within eight days of becoming aware of any information that could compromise the company's ability to continue operations, the auditor must notify the board of directors via registered letter with acknowledgment of receipt. Within 15 days of receiving the auditor's request, the company's top executive must convene a meeting of the board of directors or the supervisory board to address the auditor's concerns (Law 15-95, Article 546).

After receiving the certified letter from the auditor, management must comply with their request. The CEO must call a meeting of the board of directors or the supervisory board within 15 days of receiving the request (Section 546 of Act 15-95).

The current method of internal prevention may benefit from the addition of external treatments. As soon as the president of the commercial court issues an order, it will apply to everyone, any business, or any creative endeavors.

After hearing about the company's problems, the president of the commercial court will reach out to company executives to learn more and provide solutions.

After the interview, the president of the commercial court will double-check the facts with the company's auditor, employee representative, government authorities, suppliers, and partners.

Until well into the 1960s, the study of financial failure was primarily focused on financial analysis, particularly solvency and break-even analysis (Contreras et al., 2023). This perspective attributed bankruptcy to singular, non-generalizable factors causing abrupt insolvency events. The paradigm shifted as statistical patterns in bankrupt companies were detected, notably highlighted by Beaver in 1966 (Kim, 2011).

Since Altman published one of the most renowned bankruptcy prediction models in 1968, a plethora of bankruptcy prediction models have inundated the literature, leading not only to a growing number of articles but also a diverse array of models used for predicting business failures (Bayhan, 2023). Thanks to advancements in statistical techniques and information technology, various prediction methods have been applied to establish more accurate bankruptcy prediction models.

Altman's 1968 model, a five-factor multivariate discriminant analysis model, is a highlighted reference. According to Gissel et al. (2007), the main methods for model development include multivariate discriminant analysis (MDA), logit analysis, probit analysis, and neural networks. From the 1990s onwards, researchers increasingly explored artificial intelligence technology, with neural networks becoming one of the most prominent tools (Abidin et al., 2020).

Altman (1968) employed discriminant analysis (DA) to formulate a function that scored and classified observations based on their risk, assessed by five financial ratios. The model revealed a formalized way to assess risk and highlighted the dynamics of financial stress: operational anomalies depleting generated resources and self-financing capacity, leading to desperate survival measures emphasizing cost reduction and increased debt, all contributing to a feedback loop intensifying financial distress. Beaver (1966) had previously predicted that the cash flow-to-debt ratio is a highly reliable indicator of insolvency risk.

Among parametric techniques, logistic regression emerges as a primary alternative to discriminant models. The goal of a logistic model is to estimate the probability of an observation, defined by a specific attribute vector, possessing the studied property, such as experiencing insolvency (Doğan et al., 2022). This approach offers a more realistic assessment of risk since all companies, even seemingly healthy ones, are subject to some degree of risk that must be evaluated and potentially mitigated (Li et al., 2021).

Heuristic models present a radically different approach characterized by an underlying learning process (Bateni & Asghari, 2020). This approach encompasses artificial intelligence tools like artificial neural networks and support vector machines, Bayesian trees, and recursive partitioning techniques, among others (Jabeur & Serret, 2023). These models are generally more effective than their parametric counterparts, mainly due to their inherent capability not only to process data but also to elucidate and formalize hidden patterns in information structures. This grants them a special ability to handle qualitative factors, such as semantic credit rating measures or expressions extracted from audit reports. However, they are computationally more complex, costly, and require larger datasets (Liang et al., 2016).

## 2.2. Factors in Business Failure

As said, the research we evaluated suggests that there are two types of risk variables, those that originate in the broader economic environment and those that are unique to the specific organization under consideration. The distinction between exogenous and endogenous variables is the most common kind of categorization (Hosaka, 2019).

Bankruptcies, we are told, are one of the most dependable negative indicators of the status of the economy for those looking in from the outside (Almamy et al., 2016). In a similar vein, when the economy is in a downturn and customers are unable to spend as freely, corporate revenues may decrease. Similarly, a tighter loan market might cause businesses to delay making important investment choices as interest rates climb (Gepp & Kumar, 2015).

It seems that the management of the company and the circumstances under which it operates are the most important endogenous elements (Gallucci et al., 2023).

Managers are occasionally granted absolute power inside an organization,

allowing them to make whatever choices they see fit in terms of management (Ciampi, 2015). Managers are always there, and it's their abilities that decide whether a project succeeds or fails (Fernando et al., 2020). Another characteristic of failing businesses is the absence of any kind of management control mechanism. The most egregious case of this is when a business does not keep track of its costs in any systematic way and hence has no idea of what it really spends to run (Li et al., 2021).

### 3. Scoring-Based Forecasting Methods

If financial analysis is a popular form of forecasting since it uses a variety of ratios and aggregates to identify issues. The study will primarily concentrate on the grading procedure.

The scoring system is a useful analytical tool for foreseeing the future and assessing potential issues. A general evaluation score or likelihood of failure (or non-failure) may be calculated by weighing the relative weight of many ratios and putting them together (Kou et al., 2021).

There is a simple decision criterion we apply to divide companies into one of our two categories. Using a linear combination of ratios that characterise unhealthy organizations, discriminant analysis may compare a company to a healthy benchmark (Rizzo et al., 2020).

By building a battery of ratios and assigning individual ratios varying weights, the risk of default may be computed directly from the company's financials. By multiplying these weighted ratios, we get a discriminant function (Z function) that provides a rough estimate of the company's bankruptcy risk as a score. The following form describes this function:

With:

$$z = a_0 + a_1R_1 + a_2R_2 + \dots + a_nR_n \quad (1)$$

$a_0$ : Constant;

$a_i$ : Weighting coefficients or weights attached to the ratios;

$R_i$ : Ratios or discriminant variables;

$n$ : Number of ratios.

In addition to the low cost of installation, the automatic generation of the score is a major benefit. A little amount of data is all that's required for the system to operate. With this method, one may determine the average risk and distribution of a portfolio over a given set of parameters, as well as its concentration and statistical risk distribution (Filipe et al., 2016).

### 4. Data and Methodology

Use data and methodology are two very important elements in scientific research, as they ensure the validity and reliability of the results obtained. Data are facts, observations and measurements that are collected during a study (Pituch & Stevens, 2015). These data must be relevant and representative of the population studied in order to be generalized to this population. They must also be sufficiently precise

and reliable to allow for statistical analysis and interpretation (Weber, 2017).

Methodology, on the other hand, is the set of procedures and techniques used to collect, measure, analyze and interpret data in a scientific study. Methodology must be rigorous, transparent and reproducible to ensure the validity and reliability of the results. It also allows for systematic errors or biases that could skew the results to be avoided (Flick, 2015).

The different data and methodology are the foundations of any scientific research. They are essential to ensure the credibility and validity of the results obtained, and to ensure that these results can be generalized to the population studied.

The usual grading procedures are employed. It uses historical data to make projections about the future of a company. The objective is to construct a statistical model from these variables that may foretell the chances of success or failure (Pituch & Stevens, 2015).

#### **4.1. Sampling**

How the sample is generated has a significant impact on how well the prediction works. It's crucial to think about the characteristics of the sample, the duration of the measurements, and the nature of the event being identified.

So, the first step is to label the setback in a way that conforms to accepted terminology. Hence, a variety of results might occur. Comparing the defendant company to others that have had similar legal problems is the most usual strategy. Similarities between successful businesses and those that have fallen behind on payments are easy to see. Some research solely includes insolvent firms in their sample of failing businesses to make a more significant difference. Afterwards, they closed the companies that couldn't make ends meet (Dimitras et al., 1996).

As important as the default definition is the choice of prediction horizon. Past events before the chosen horizon length are not guaranteed to be included in the processed data. Predicting the future is difficult if it is too far away, but worrying about something that is going to happen soon.

is pointless if you can't do anything about it. The typical number of years before default is anything from one to three, according to the studies. There is proof of this in (Aziz & Dar, 2006).

The subsamples selected should be representative of the economy, as a whole, with regards to industry, company size, and the ratio of defaulting to no defaulting businesses. Because of the importance of standardisation in the face of structural diversity, industry-specific models are created (Appiah, 2015).

#### **4.2. Choice of Explanatory Variables**

Several authors have gone against the grain by trying to calculate accounting ratios using data that deviates from the norm. Using concrete facts, like cash flow, is one way to foresee bankruptcy. A corporation is in default when its creditors cease making payments to it because they are not being repaid. It is appropriate to use

cash flows since a company's value equals the present value of all of its predicted future cash flows (Özcan, 2020). A company's financial health may be understood by indicators other than its financial statements (Acosta-González et al., 2019).

### 4.3. Statistical Analysis

When the sample is gathered and the explanatory ratios are chosen, the model is constructed and validated. High placement rates are a common indicator of a successful programme.

- One way to evaluate the efficacy of a discriminant model is to compare its forecasts to real business outcomes.
- The discriminant model may foresee successful enterprises.
- The most hopeless failing company in a collection may be singled out using the discriminant model.
- Discriminant analysis is used to single out a failing firm amid a sea of thriving competitors.
- A firm may be falsely flagged as failing by the system even though it is performing ok.

The model succeeds in accurately classifying in the first two cases because a posteriori classification redistributes companies back to their original sub-groups. Misclassification, or type II mistake, is more common than misclassification, or type I error, when using a classification model (Levratto, 2013).

Default risk may be estimated with the use of econometric models, which are favoured by both specialists and academics because they let the examination of correlations between several factors and the selection of those that best describe the phenomena (Shi & Li, 2019). As ratings are developed in a particular economic environment, there is no one-size-fits-all formula. Changes in the economy would need updating the models, whether by adding new variables or readjusting existing ones.

Focusing on the features of the sample chosen, selecting the explanatory causes for the failure, and the technique of analysis of the data used to construct the statistical forecasting model were all crucial parts of the methodology used to study the data.

### 4.4. The Q-Test

The statistical significance of a small sample of highly rated firms may be analyzed using the Q-press test. It would be wise to conduct an experiment to rule out the possibility that a significant fraction of the highly ranked individuals may be accounted for by factors other than the discriminant function (null hypothesis H0). The calculated value follows a Chi-squared (2) distribution with 1 degree of freedom. The value of a test may be calculated using the following formula:

$$Q_{\text{presse}} = \frac{(n - n_c p)^2}{n(p - 1)}$$

With:

*n*: Number of individuals,

*n<sub>c</sub>*: Number of well classified individuals,

*p*: Number of groups.

## 5. Research Hypotheses and Epistemological Choices

Because Our method is based on positivist principles of inferring reality from hypothetical scenarios. Researchers using this method construct hypotheses on the basis of the aforementioned literature and then test these hypotheses among a statistically significant subset of the population of interest.

Deductive reasoning's major role is in furnishing proof. In this kind of thinking, the conclusion is assumed to be correct if the premises are accepted. The effectiveness of the model will be determined by examining the results of these simulated experiments.

By analyzing the available literature, we found that managerial mistakes are the primary reason why businesses fail, and we unearthed many other factors that contributed to failure as well. From this, our hypotheses for the "Financial management of the firm" section of the research were as follows.

Some businesses thrive while others fail, and this disparity might be due to an uneven financial structure that causes cash flow issues and eventually bankruptcy. A WCR may be covered by a healthy organization if it has enough permanent resources and a sufficient number of secure positions. If they don't coincide, the company won't have enough cash on hand to stay afloat without taking out loans.

The second hypothesis, "The impediments generate an unfavorable dynamic that leads to the extinction of the organization," is unlikely to be valid since there are many other economic reasons for the company's inability to earn operational profits.

Third, we hypothesize that the company's extreme financial independence was a factor in its demise. The firm's inability to escape liquidation is a direct result of the scepticism of investors and lenders. Financial independence is directly related to a business' ability to function independently.

It is possible to tell a successful company apart from an unsuccessful one, contrary to popular belief. Statistical analysis reveals significant differences between the two groups, allowing us to draw this conclusion.

Our method is sensitive to details in data analysis, in the selection of organizations, and in the choice of failure indicators.

### 5.1. Method of Data Processing

Number Fisher's linear discriminant analysis is the statistical method used here. This method yields the best linear combination of parameters for identifying flourishing businesses from those that are floundering. Moreover, multiple studies from the 1990s demonstrated that discriminant analysis provided more precise rankings than competing methods.

## 5.2. Characteristics of the Selected Sample

The Casablanca-Settat metropolitan area is home to 34 of the MSEs we counted. Of the total, 17 are successful enterprises while the other 17 are failing. Due to a lack of qualitative data, we classified businesses as either VSEs (those with annual revenue of less than 3 million MAD) or SMEs (those with annual revenue of between 3 million and 75 million MAD) based on the definitions provided by the National Agency for the Promotion of Small and Medium Enterprises (Morocco SME Agency and General Confederation of Enterprises of Morocco).

Legal failure occurred in 2023 for companies that paid fines as a consequence of litigation. There will be two years till default, since the prediction period begins in 2021. Academic studies have shown that environmental variables may predict a firm's bankruptcy up to three years in advance. Because of this, we've landed on a timeline that's neither too short to produce an accurate prognosis nor too lengthy to let sufficient actions be taken to avert the failure. The most recent year for which financial information for this group of prosperous businesses is available is 2021.

We excluded businesses that hadn't been around for at least five years to prevent any potential "age" bias. This has allowed us to steer clear of the pitfalls that often befall startups in their formative years.

## 5.3. Explanatory Variables

Financial ratios should be seen as only one indicator of financial health. Our continuing focus on the firm's profitability, liquidity, balance sheet structure, and debt level as potential failure indicators is in line with the tenets of financial analysis.

Two years prior to the default, **Table 1** displays the following ratios.

**Table 1.** The list of ratios used as explanatory variables.

Symbol	Type	Heading
B1	Liquidity	Liquidity ratio
B2	Profitability	Operating profitability ratio
B3	Structure	Working capital ratio
B4	Autonomy	Financial autonomy ratio

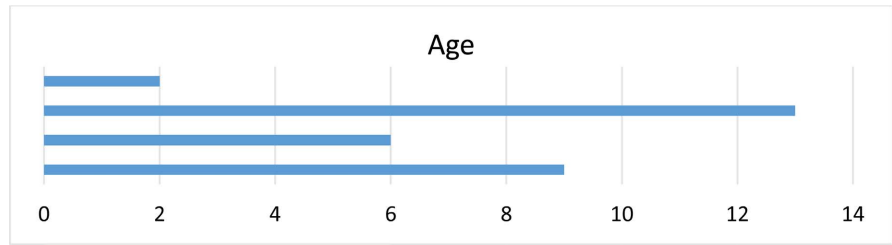
Source: construction author.

## 5.4. Descriptive Statistics

The descriptive statistics for our research are as follows in **Figure 1**.

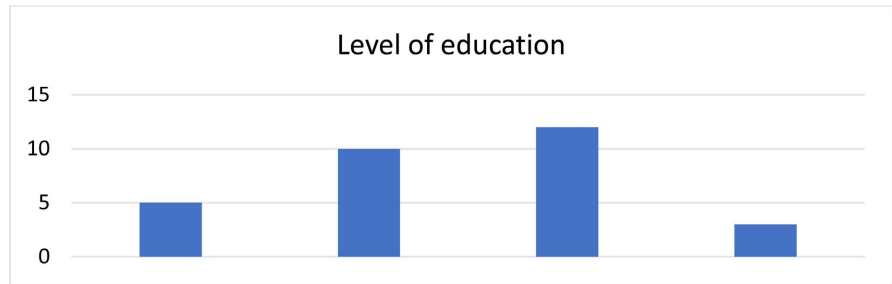
Interestingly, the majority of respondents are under 30 years of age, with a total of 22 out of 30 individuals. Individuals over the age of 40 represent a small proportion of the study population, with only 2 individuals. This may reflect some of the more current cultural tendency to postpone adulthood or to be more flexible in choosing one's life course.

The numbers also suggest that the survey population is quite young, which may have implications for the decisions and interests of the study subjects (**Figure 2**).



Source: Google forms.

**Figure 1.** The age range of the respondent.



Source: Google forms.

**Figure 2.** The educational level of the respondent.

There are a variety of educational levels represented in this list, ranging from Bac to Bac + 5. It is noticeable that there are a large number of students who have obtained a Bac + 2, followed by Bac + 3/Bac + 4. There are also a few students who have attained a higher level of education, with only three people having obtained a Bac + 5. In general, this may reflect the levels of education available in the region or the preferences of students for different programs of study.

### 5.5. Test of Equality of Means

**Table 2** is a summary of our use of the Wilks statistical test to evaluate the explanatory variables' capacity to distinguish between the two groups of businesses.

**Table 2.** Wilks' test for equality of group means.

	F	Sig.
B1	23,498	0.000
B2	88,432	0.000
B3	33,948	0.000
B4	38,345	0.000

Source: SPSS-out.

Under the null hypothesis H0 of mean equality between the two groups and a significance threshold = 5%, our F-statistic has 1 and 32 degrees of freedom, respectively, according to the theoretical Fisher-Snedecor F (1; 32) distribution. Both Wilk's lambda and Fisher's exact agree that all factors should be considered.

A small Wilks' lambda value and a big Fisher F indicate that the null hypothesis  $H_0$  is false, indicating that the average ratios in the two groups are not equal.

According to the results of the equality of means test, failing companies are less liquid than successful ones (B1). Inefficiency and a lack of profitability are hallmarks of bankrupt businesses. The liquidity ratio (B1) is much lower in the failed group as compared to the successful group, lending credence to this hypothesis. Similar to how a high amount of working capital is indicative of thriving operations, a low level of working capital is a hallmark of floundering businesses. Both successful and unsuccessful businesses rely on permanent funding to help fund a part of their operating cycle (B3). A big amount of equity capital is another indicator that a company is doing well and not about to collapse (B4).

In a similar line, the assumption behind discriminant analysis is that removing ratios with little information content will be possible due to low correlation between the explanatory factors. We determined the level of resemblance between each pair of ratios and picked the ones with the lowest value. Examining the ties between our explanatory factors yielded the data in **Table 3**.

**Table 3.** Intra-group correlation matrix.

		B2	B2	B3	B4
Correlation	B1	1.000	-0.783	-0.984	-0.243
	B2	-0.044	1.000	0.495	0.274
	B3	-0.273	0.456	1.000	0.298
	B4	-0.223	0.983	0.230	1.000

Source: SPSS-out.

Examination of the correlation matrices reveals that the independent variables cannot be linearly combined. Weakly negative correlations between (B1/B2), (B1/B3), and (B1/B4), and faintly positive correlations between (B2/B3), (B2/B4), and (B3/B4), are indicative of low multi-collinearity. Discriminating between the two groups is aided by decreasing the correlation between the variables.

Before calculating the discriminant, function coefficients and classifying the firms, we performed one more quality check.

## 5.6. Test of Normality

The assumption of normality in the populations under study is fundamental to Fisher's linear discriminant analysis. The Shapiro-Wilk test was used to determine whether the variables were normally distributed since it yields accurate findings with sample sizes as little as 50. **Table 4** shows the results of our examinations.

As no p-value estimate is less than 0.05, we adopt  $H_0$ , which states that the variables are regularly distributed. When using B1, the false positive rate is 46.9%, while using B2 it is 46.5%, using B3 it is 9.5%, and using B4 it is 6.5%.

**Table 4.** Test of Shapiro Wilk.

	Statistics	Ddl	Sig.
B1	0.898	34	0.469
B2	0.984	34	0.465
B3	0.789	34	0.95
B4	0.948	34	0.065

Source: SPSS-out.

### 5.7. Equivalence Test of Variance-Covariance Matrices

The “Box test,” based on the multivariate Box Statistic M, should use the biggest value of M feasible to test for equality between the variance and covariance matrices.

The F-*p*-value tests should also be somewhat close to 0. You shouldn’t place too much faith in the results if the margin of error is more than 5%. This is a table displaying the test results (**Table 5**).

**Table 5.** Test of Box.

Test of Box	
F	
Ddl 1	10
Ddl 2	6749,894
Sig.	0.034

Source: SPSS-out.

The equality of the variance-covariance matrices is supported by the fact that the significance of the F-test decreases as it approaches 0.

### 5.8. Analysis of the Function

**Table 6** & **Table 7** demonstrate the discriminatory power of the linear function:

**Table 6.** Eigenvalue.

Function	Eigen value	% of variance	Canonical correlation
1	4.948	98.0	0.984

Source: SPSS-out.

**Table 7.** Lambda de wilks.

Test of function	Khi-deux	Sig.
1	67.985	0.001

Source: SPSS-out.

The discriminant function is reliable if and only if the proportion of variance between the two independent variables is exactly 100.

Canonical correlations around 1 are used to determine which model is superior. **Table 6** shows that the canonical correlation value is 98.4 %, validating the linear discriminant function's discriminating capabilities.

**Table 7** of Wilks' lambda analysis shows that the discriminant function is significantly different from zero at the 5% level of significance. We may infer that the discriminant function aids in explaining the differences between the groups since the associated probability is less than 5%.

### 5.9. Presentation of the Resulting Discriminant Function

*z*-scores were computed using SPSS Statistics 22 to provide the following standardised discriminant functions:

$$z = 0.467B_1 + 0.874R_2 + 0.056B_3 + 0.576B_4$$

Discriminant coefficients  $B_1$ ,  $B_2$ ,  $B_3$ , and  $B_4$  illustrate how much emphasis is placed on each grading factor. The liquidity ratio ( $B_1$ ) is the clearest indicator of the disparities between the two groups of organizations; subsequent ratios, including those measuring profitability ( $B_2$ ), financial independence ( $B_3$ ), and working capital, are also informative ( $B_3$ ). The *z*-score algorithm can tell the two types of organizations apart by giving them different values for the financial metrics. By giving each financial signal a varied weight, the *z*-score algorithm may be able to distinguish between the two types of organizations. Many factors contribute to a company's overall well-being, including its access to funding, income stream, organizational stability, and financial independence.

Discriminant scores will be used to categorize individuals into one of two categories. The mean discriminant scores for the two categories are listed below in **Table 8**.

**Table 8.** Group functions.

Failure	Function
0	1.30
1	-1.30

Source: SPSS-out.

When adding a new member to one of the reformed groups, their discriminant score is compared to the average of that group's members to determine where they belong. After controlling for sample size, the assignment cutoff ("Df") is determined by taking the group median. Our methodology allows for assignments up to zero. The likelihood of failure increases for businesses with lower discriminant function scores.

## 6. Results and Discussion

To evaluate the discriminant function's efficacy and the quality of the representation,

the confusion matrix may be used to classify individuals into well-classified and poorly-classified categories. After sorting the data into the two groups, our confusion matrix of the discriminant function looks like this in **Table 9**.

**Table 9.** The confusion matrix.

		Membership of the intended group		
			0	1
Failure		0	32	1
		1	1	32
Original	Effective %	0	78.3	4.3
		1	2.8	88.6

Source: SPSS-OUT.

The discriminant function classification test indicates that 32 of the companies may be safely reassigned to their original group, while the remaining 2 have been incorrectly placed. Our scoring function in the prediction model enables us to classify 88.6% of businesses with high precision two years before default. The error rate for detecting a failing business amongst successful ones (type 1) is 2.8% or less, while the error rate for locating a failing company amid unsuccessful ones (type 2) is 4.3% or less (finding a failing firm among healthy enterprises).

### 6.1. The Q-Test and Standardized Discriminant Function

According to our findings,  $Q$  is equivalent to 26.47. As the calculated Chi-square value (18.49) (with 5% significance and 2 degrees of freedom) is less than the result of the Q-press test, the null hypothesis  $H_0$  is rejected. Hence, discriminant analysis provides reliable groupings.

The above equation represents the standardized discriminant function with four predictor variables  $B_1$ ,  $B_2$ ,  $B_3$  and  $B_4$ . The coefficients assigned to each predictor variable indicate their relative importance in predicting the outcome variable.

To use this equation, the values of the predictor variables for a specific case are entered, and the resulting  $z$ -score reflects the distance between the case values and the mean values of the predictor variables in units of standard deviation.

For example, suppose the predictor variables are age, income, education, and job satisfaction. To predict whether a person is likely to change jobs, the person's age, income, education, and job satisfaction are entered into the equation to calculate the  $z$ -score. If the  $z$ -score is positive, the person is considered to have changed jobs.

If the  $z$ -score is positive, it means that the person is more likely to change jobs based on the values of the predictor variables. If the  $z$ -score is negative, it means that the person is less likely to change jobs.

Overall, this equation can be applied in a variety of contexts to make predictions based on multiple predictors simultaneously.

## 6.2. Recommendations

Here are some research recommendations for our topic:

- 1) Analysis of the current situation of Moroccan SMEs: This research could include an in-depth study of the current situation of Moroccan SMEs in terms of competition, strengths, weaknesses and threats.
- 2) Identification of the risk factors for the failure of Moroccan SMEs: This research could focus on identifying the main factors that lead to the failure of Moroccan SMEs such as competition, regulation, poor financial management, etc.
- 3) Assessment of default prevention measures: This research could examine the different measures taken by Moroccan SMEs to prevent default, such as the adoption of credit insurance, strengthening financial management, reducing costs, etc.
- 4) Analysis of default prevention best practices in other countries: This research could focus on analyzing default prevention strategies that have been successfully implemented in other countries and that can be applied in the Moroccan context.
- 5) Development of recommendations for the prevention of failure of Moroccan SMEs: This research could focus on developing practical and applicable recommendations to help Moroccan SMEs prevent failure, such as improved financial management, expert coaching, business management training, etc.

## 7. Conclusion

In this study, we explored the financial management challenges faced by small and medium enterprises (SMEs) in Morocco, specifically focusing on the factors contributing to their failure. Our research utilized a positivist approach, relying on deductive reasoning to construct hypotheses and test them using quantitative data from a sample of successful and failing SMEs. The study's primary aim was to identify key financial indicators that differentiate thriving businesses from those on the brink of collapse.

Through an analysis of financial ratios such as liquidity, profitability, working capital, and financial autonomy, we found that failing businesses consistently performed worse on these metrics compared to their successful counterparts. Specifically, failed enterprises exhibited lower liquidity, profitability, and working capital, while their financial autonomy was also significantly compromised. These findings were supported by statistical tests, including the Wilks' Lambda and Fisher's exact test, which confirmed that these financial ratios are strong indicators of a company's likelihood of failure.

The study also employed discriminant analysis, which successfully classified businesses based on their financial characteristics. The discriminant function yielded an accuracy rate of 88.6% in predicting which businesses were likely to fail two years in advance. This suggests that financial management, particularly in the areas of liquidity and profitability, is crucial for the survival of SMEs.

Our recommendations include a thorough examination of the current state of Moroccan SMEs, with a particular focus on competition, financial management, and regulatory factors. Additionally, we suggest developing better default prevention

strategies, such as improved financial management training and the adoption of credit insurance, based on best practices observed in other countries.

However, there are limitations in our study, including the lack of qualitative data, which could have provided deeper insights into the causes of failure beyond financial indicators. Furthermore, the study's sample size and focus on businesses in the Casablanca-Settat metropolitan area may limit the generalizability of the findings to other regions of Morocco. Despite these limitations, the study provides valuable insights into the financial health of SMEs and offers practical recommendations for preventing business failure.

## Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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