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Rocío León-Carlosama; Alba Cevallos-Pineda; Iván Galarza; Rosa Rodríguez-Trejo
Universidad Técnica del Norte
Ibarra - Ecuador
Av, 17 de julio 5-21 y Gral. José María Córdova - Sector El Olivo.
rgleon@utn.edu.ec; agcevallosp@utn.edu.ec; isgalarza@utn.edu.ec; rerodriguez@utn.edu.ec

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Rocío León-Carlosama; Alba Cevallos-Pineda; Galarza Iván; Rosa Rodríguez
Universidad Técnica del Norte
rgleon@utn.edu.ec; agcevallosp@utn.edu.ec; isgalarza@utn.edu.ec; rerodriguez@utn.edu.ec

Abstract

The commercial sector plays a pivotal role in economic development and poverty alleviation. The objective was to predict the risk of financial bankruptcy of small and medium-sized enterprises (SMEs) in the commercial sector of Ecuador. With a quantitative approach, analyzed the financial data of 1.473 companies in the wholesale in the period 2018-2022. Were analyzed using the Altman Z" Score methodology and a probabilistic estimate. The results showed a decrease of five percentage points (63 companies) in the proportion companies classified bankruptcy zone, from 35% in 2018 to 30% in 2022. The probabilistic estimation, employed the financial ratios used by the Altman Z-Score model. The estimation revealed that for each unit increase in the Liquidity ratio, Retained Earnings and productivity decrease the probability of bankruptcy by 72,11%, 95,61% and 62,15% respectively. The study concludes that productivity is the most relevant factor for not going bankrupt, while the leverage ratio did not have a significant impact on the Altman Z"-Score.

keywords

Insolvency, financial ratios, bankruptcy, modelo Altman Z", trade

Resumen

El sector comercial desempeña un papel fundamental en el desarrollo económico y la reducción de la pobreza. El objetivo fue predecir el riesgo de quiebra financiera de las pequeñas y medianas empresas (PYMEs) del sector comercial en Ecuador. El enfoque fue cuantitativo; se analizaron los datos financieros de 1.473 empresas de comercio mayorista del período 2018-2022, empleando la metodología del Altman Z"-Score y una estimación probabilística. Los resultados mostraron una disminución de 5 puntos porcentuales (63 empresas) en la proporción de empresas clasificadas en la zona de quiebra, del 35% en 2018 al 30% en 2022. Para la estimación probabilística empleó ratios financieros del modelo Altman Z-Score. La estimación reveló que, por cada unidad de aumento en el ratio de liquidez, utilidades retenidas y productividad, la probabilidad de quiebra disminuye en un 72,11%, 95,61% y 62,15% respectivamente. El estudio concluye que la productividad es el factor más relevante para evitar la quiebra, mientras que el ratio de apalancamiento no tuvo un impacto significativo en el modelo Altman Z-Score.

Palabras clave

Insolvencia, ratios financieros, quiebra, modelo Altman Z-Score, comercio

Introduction

Small and medium-sized enterprises (SMEs) represent a vital axis for economic advancement and vitality (Carranco, 2017; Montiel et al., 2021), particularly in Latin America, where they constitute 99% of formal enterprises and generate 61% of employment (Dini & Stumpo, 2020). Their adaptability and capacity to respond to the shifting demands of society enable them to fulfill specific requirements and tap into market niches often overlooked by large corporations (Buele et al., 2021). They are multifaceted due to their access to various markets, technology, financial resources, and diverse human capital (Dini & Stumpo, 2020).

Among the activities undertaken by SMEs lies the commerce sector, which is a part of the tertiary or service sector and encompasses a wide array of activities such as transportation, commerce, insurance, communications, government finance, professional services, and real estate.

According to the World Bank, since 1990, global trade has driven 24% of income growth worldwide, with 50% for the poorest 40% of the population, lifted out of poverty through best practices, benefitting over 1 billion people (Banco Mundial, 2022). Global free trade, particularly within the European Union, has evidenced job creation, propelling economic progress supported by enhanced technologies (Rincón et al., 2020).

Ecuador´s wholesale trade sector plays a central role in the national economy. According to the Directory of Enterprises and Establishments (DIEE, 2022), it accounts for 34,5% of all registered enterprises and nearly 37,4% of total national sales. By 2022, the sector had generated close to 97.325 jobs and roughly $ 6 billion in sales revenue (Superintendencia de

Compañías, 2024), consolidating itself as one of the main engines of formal employment. It is not only its scale but its reach. The Banco Central del Ecuador (2023) reports an 11% contribution to Gross Value Added (GVA) in industrial participation. A share that underscores how deeply embedded this sector is across the productive chain. As Horna (2009) and Tung & Phung (2019) have noted, the sector connects a remarkably diverse range of actors, which amplifies its economic and social impact well beyond the numbers alone.

However, the financial stability of these enterprises is threatened by a series of internal and external changes (Carranco, 2017), related to a complex competitive landscape, rife with crises and obstacles (Agustian & Syofyan, 2022), volatility (Telmoudi et al., 2011), with the presence of geopolitical tensions, food insecurity, and financial instability generated by tightening monetary policy (Organización Mundial del Comercio, 2023). In the Ecuadorian context, the challenges faced by this sector include government public expenditure, reduced dynamism of exports in the petroleum sector, labor market deterioration, health crises, supply chain interruptions, cost increases, and shutdowns (CEPAL, 2020).

Economic crises trigger chain reactions that extend well beyond simple market contraction. can induce recession. Štefko et al (2021) and Tung & Phung (2019) warn that they can set off prolonged recessions, while Li & Rahgozar (2012) and Telmoudi et al. (2011) warn of insolvency risk, which translates into the inability to pay debts, causing financial setbacks, or even leading to business failure. This situation can negatively impact stakeholders such as shareholders, creditors, clients, suppliers, workers, and the state itself (Li & Rahgozar, 2012; Qu et al., 2019; Štefko et al., 2021).

Anticipating financial distress is more valuable than reacting after the fact. Vavrek et al. (2021) propose assessing the probability of financial difficulties over time horizons as a monitoring strategy. Among the tools available for this purpose, the model Altman Z-Score stands out for its predictive reliability: its accuracy rate is from 75% to 90% in forecasting corporate bankruptcies, making it one of the most widely validated models in the literature (Abdullah et al., 2020; Agustian & Syofyan, 2022; Isaac-Roque & Caicedo-Carrero, 2023). The model draws on four key indicators: liquidity, retained earnings, efficiency, and leverage, and can flag risk situations up to two years in advance (Isaac-Roque & Caicedo-Carrero, 2023).

The detailed study of business insolvency can aid in problem resolution, as it focuses on determining the factors and their intensity, and identifying their causes (Gregova et al., 2020). If stakeholders are aware that bankruptcy may occur in the coming years, they will be better prepared to safeguard their assets (Galarza et al., 2023; Li & Rahgozar, 2012), mitigate significant impacts on the profitability of the economic unit (Telmoudi et al., 2011), and ensure its continued presence in the market (Buele et al., 2021).

In this context, the following research question What is the level of bankruptcy risk for companies in the wholesale trade sector in Ecuador?. This research aims to contribute to the knowledge of predicting financial failure in the wholesale trade sector in emerging markets. The results provide relevant empirical evidence to make informed public policy decisions at the sector and firm level (Isaac-Roque & Caicedo-Carrero, 2023; Mavengere & Gumede, 2024; Muzanni & Yuliana, 2021), to financial resource planning (Maulana, 2024), and to understand financial fragility in crisis situations (Keller, 2022).

The integration of the Altman Z"-Score model with probabilistic estimation establishes a framework for forecasting the failure of SMEs in the commercial sector, taking into account the influence of liquidity, Retained Earnings, productivity, and Leverage.

This academic inquiry was prompted by the scarce research in the trade sector within the Latin American context. It is noteworthy that the majority of studies addressing this sector have primarily focused on regions such as China, the USA, Taiwan, South Korea, and Spain (Shi & Li, 2019).

The research follows this structure: the introduction outlines the scope of the study; the second section delves into a literature review on bankruptcy prediction. The third section details the methodology, emphasizing data analysis. Findings are outlined in the fourth section. Lastly, conclusions, discussions, limitations, and avenues for future research are explored in the fifth section.

Literature Review

Small and medium-sized enterprises (SMEs) are entities engaged in primary, secondary, or tertiary activities, playing a crucial role in the economies of various countries (Eggers, 2020; Madan, 2020), with those focusing on the commerce sector being more prevalent in the Latin American economy (Dini & Stumpo, 2020). Trading companies act as intermediaries between producers and consumers, engaging in the purchase and sale of goods under duly accepted commercial norms. They can operate as retailers or wholesalers, as individual entities or corporations, with some conducting business on a small scale while others operate on a large scale (Kerubo et al., 2020).

Due to global crises stemming from economic turbulence, wars, pandemics, or international policies, the business sector has had to address and manage financial aspects such as liquidity, indebtedness, and profitability (Mazaraki & Zubko, 2022), to avoid disruption in operations (Xu et al., 2023) and to sustain their presence in the market (Dwi, 2020).

Bartik et al., (2020) assert that SMEs exhibit financial fragility, which may lead to systemic instability (Médici, 2020). Abdullah & Achsani (2020)suggest that the risk is elevated within the retail trade sector due to its heightened vulnerability relative to other sectors. Lewaru & Loupatty (2021)state that, in times of crisis, the most affected sectors are commerce, services, and investment. Lastly, Lamia et al. (2019)emphasize the notion that commercial enterprises often demonstrate poor performance in commercial policy, thereby failing to generate sufficient profitability to confront challenges (Zhang et al., 2016), particularly during economic crises (Bartik et al., 2020).

Bankruptcy risk, at its core, reflects the probability that a firm will be unable to meet its immediate financial commitments (Brito, 2018). More specifically, it points to the possibility that cash flow will fall short of what is needed to sustain financial stability over time (Valaskova, Kliestik, Svabova, et al., 2018). This is why identifying, assessing, and anticipating is not merely good practice, but a necessary condition for business survival in volatile environments (Gregova et al., 2020; Zhang et al., 2016).

Financial risk management is primarily concerned with identifying situations that could adversely affect economic stability (Vavrek et al., 2021) and mitigating risks through the utilization of tools that facilitate readiness for changes (Préstamo et al., 2021), such as the application of various methods (Zvarikova et al., 2017) and bankruptcy risk prediction models

(Qu et al., 2019). Bankruptcy can occur in three forms: 1) bankruptcy, representing involuntary market exit, 2) liquidation due to various circumstances, and 3) inactivity for reasons other than the former (Amendola et al., 2015).

Prediction models serve as preemptive alert systems for potential issues (Valaskova, Kliestik, & Kovacova, 2018), safeguarding interests and assets (Tung & Phung, 2019), discerning disparities between declared and recorded data (Oliveira et al., 2017), guiding stakeholders on performance (Arini et al., 2020; Gregova et al., 2020; Karim et al., 2021), forecasting forthcoming financial challenges (Štefko et al., 2021; Vavrek et al., 2021), estimating the likelihood of bankruptcy (Alaka et al., 2018; Antunes et al., 2017; Zvarikova et al., 2017), mitigating productivity-threatening vulnerabilities (Telmoudi et al., 2011), averting insolvency (Karim et al., 2021), facilitating informed decision-making, and harnessing financial metrics as prognostic instruments (Burksaitiene & Draugele, 2018). These models should incorporate the unique conditions of the country, the capital market, and the economic and financial status of the company (Ibarra, 2010).

Prediction models likely originated with William Beaver's univariate analysis in 1966-1968 (Beaver, 1966; Qu et al., 2019), which led to Edward Altman's multivariate studies in 1968 (Almamy et al., 2016; Álvarez-Ferrer & Campa-Planas, 2020; Tung & Phung, 2019). These investigations laid the groundwork for advancing financial risk prediction studies (Shi & Li, 2019), with Altman's Z-Score model being the most widely used due to its demonstrated accuracy (Damayanti et al., 2019; Del Castillo, 2021; Sharma & Bodla, 2022).

The original Z-Score model is a reliable financial analysis tool (Tung & Phung, 2019), employing financial indicators (Antunes et al., 2017; Arini et al., 2020), to predict bankruptcy

in both manufacturing and non-manufacturing companies, whether publicly traded or not (Li & Rahgozar, 2012; MacCarthy, 2017). The model uses multiple discriminant analysis, a statistical technique that allows observations to be classified using mathematical equations. This considered financial indicators: liquidity, retained earnings, productivity, and leverage (Altman, 2018). The academic literature was demonstrates that model bankruptcy prediction accuracy ranging from 90% to 95% in the initial year post-analysis and from 70% to 82% in the subsequent year (Abdullah et al., 2020; Agustian & Syofyan, 2022; Prasetiyani & Sofyan, 2020; Tung & Phung, 2019).

Li & Rahgozar (2012) and Laitinen et al.(2023) point out that the model has not been without its criticisms, including concerns about dependence on unadjusted accounting data, limited sample sizes, and outdated information. Despite these reservations, this model remains the predominant tool for measuring financial distress (Altman et al., 2017; Del Castillo, 2021; Kim et al., 2020).

Altman developed three versions of the model to address different organizational contexts. The original Z-Score was designed for publicly traded manufacturing firms; the Z’-Score adapted that framework for privately held manufacturing companies; and the Z”-Score extended its applicability to service and non-manufacturing firms that are not listed on stock exchanges (Arini et al., 2020; Tahu, 2019; Tung & Phung, 2019). This last version is the one adopted in the present study, given its alignment with the characteristics of trading firms operating in the service sector (Sharma & Bodla, 2022).

Table 1

Altman Z" Score Model

Z’’=6,567X1+3,26X2+6,727X3+1,05X4		
Variable	**Formula**	**Description**
X1 Liquidity	WC/TA	Ability to generate working capital to cover short-term obligations.

X2 Retained Earnings	RE/TA	Ability to generate retained earnings from assets.
X3 Productividad	EBIT/TA	Ability to manage total assets to generate earnings before interest and taxes, measures operational efficiency.
X4 Leverage	Equity/TL	Measures the degree of equity commitment to fulfill obligations.

Discrimination Zones

Z > 2,60 Safe Zone	Z = 2,60 y 1,10 Gray Zone	Z < 1,10 Bankruptcy Zone

Note. Liquid assets, or the gap between current assets and current liabilities, are measured by working capital (WC). The company's rights and assets are represented by its total assets (TA). Retained Earnings (RE) are profits retained for reinvestment or cumulative profits or losses over time. Earnings Before Interest and Taxes (EBIT-TA) is a measure of the true productivity of assets. Equity (E) is the company's liability to owners (including the owner contributions) and includes earnings; it is the difference between assets and liabilities. Total Liabilities (TL) are the company's external funding from third parties. They are composed of short-term and long-term liabilities.
Source: (Agustian & Syofyan, 2022; Altman et al., 2017; Arini et al., 2020; Castañeda, 2022)

The Altman Z"-Score model considers three discrimination zones: a) safe zone, where the business is financially sound and the likelihood of the company facing financial difficulties is low; b) gray zone, where there is less likelihood of the company facing financial difficulties in the short term; c) bankruptcy zone, with a high probability of the company facing financial difficulties in the short term (Mostofa et al., 2016).

On the other hand, a useful model for identifying the probability of bankruptcy for SMEs is the Logit model, which allows determining the relationship between success and failure, or records the probabilities of the occurrence or non-occurrence of an event (in its binary sense). The diffusion of the model in the econometric field was led by D.R. Cox, who in 1970 published his book The Analysis of Binary Data, thus formalizing Logit models when dealing with binary phenomena.

Studies involving the probabilities of preferences in individuals received a definitive boost with the work of the 2000 Nobel Prize in Economics laureate, economist McFadden, who in 1973 linked Logit models with Discrete Choice Theory(McFadden, 1973), which states that a discrete choice model in which the probability of choosing an alternative is defined as the

probability that this alternative has the highest utility among the set of possible alternatives(Martínez, 2008). Discrete choice models allow modeling qualitative variables. For this process, the study variable must be converted into codes or values that can be treated with regression techniques.

Materials and Methods

This study uses a quantitative technique and a prediction strategy for the period 2018-2022. Employs secondary data collected by the Superintendence of Companies, Securities and Insurance, which centers on the financial information of SMEs working in the wholesale trade industry (CIIU 4.0 G46 code) in Ecuador, with the exception of the automotive and motorcycle industries. The purposive sampling strategy was utilized, and the sample involved the rejection of companies: 1) that lacked key values for the model, and 2) that had outlier data. It looked at 1,473 companies in the industry a year. 7,364 observations were analyzed for the period from 2018 to 2022.

The calculations were done per year using the Altman Z”-score model, which is designed for non-manufacturing service companies within the emerging markets (Z’’=6,567X1+3,26X2+6,727X3+1,05X4). To verify if there are significant differences between the averages of the subgroups in the commerce sector, the Kruskal-Wallis test was used.

In order to strengthen the examination of the financial susceptibility of enterprises, a binomial logistic model was designed based on the available information, considering financial variables (liquidity, accrued profits, productivity and leverage) as independent. The

dummy variable was based on the generated Altman Z"-Score model with the following values:

Z = 1 (High chance of insolvency)

Z = 0 (Low chance of bankruptcy)

If the dependent variable is dichotomous, logistic regression is used. The value of the Z"-Score model has been measured in high risk (bankruptcy zone), medium risk (gray zone) and low risk (safe zone) categories, but they are reclassified into two categories: 1 - high probability of bankruptcy (for the medium and high risk categories) and 0 - low probability of bankruptcy (for the low risk categories).

A notable practical advantage of logistic regression compared to discriminant analysis is its robustness; it does not necessitate multivariate normality or homogeneity of variance-covariance matrices among groups. The interpretation of coefficients and diagnostics is analogous to linear regression, indicating suitable use, despite its equivalence to discriminant analysis of two groups.

The model estimation process based on the dichotomous dependent variable (which points to the occurrence or non-occurrence of an event; in this study high probability of bankruptcy - low probability of bankruptcy) forecasts an estimation of the occurrence or non-occurrence of the phenomena. The logistic coefficient (Bi) is derived by comparing the chance that the event occurs to the probability that it does not. The interpretation of the data includes the

study of marginal effects, i.e., the changes in the probability of a certain outcome (success or failure) as a consequence of a one unit change in the independent variables, maintaining all other variables constant. These marginal impacts are measured in terms of likelihood.

The marginal effects are determined through the derivation of the probability function for each independent variable, and then evaluated at the mean values of the variables. These marginal effects might be stated as coefficients or as extra or decremental probabilities in percentages.

Goodness of fit is assessed by the coefficient of determination (R2) and its probabilistic nature is taken into account. This coefficient shows the partial increase between the outcome variable and each predictor, which ranges from -1 to 1(Berkson, 1944). A positive value indicates that the likelihood that the event will occur grows as the predictor variable increases. Conversely, a negative coefficient means that reducing the predictor variable reduces the odds of the event happening.

Results

Table 2 shows a distribution of SME subsectors engaged in wholesale trade in Ecuador by type of product, which provides an indication of the country’s consumption and production priorities. These categories include medications and medical equipment, metals and metal ores. In particular, the top three subsectors, each accounting for 12% of the total, are pharmaceutical items, machinery and equipment, and commission/consignment services.

The results reveal a diversified economy in the context of domestic wholesale trade with strong demand for health care products, industrial machinery, and commercial intermediary

services. About 10% of wholesale trade is in food, beverages, and tobacco, showing their substantial importance. Construction materials, hardware, and IT equipment are other important sectors (9% and 8% of the total, respectively).

Some subsectors, such as agriculture, telephones, and agricultural equipment, have lower participation, all below 3%. Similarly, metals and minerals are important resources for the economy, although they constitute 1%. This can be a sign of lower manufacturing or industrial activity that depends on these inputs. See table 2

Table 2 *Wholesale Domestic Trade Economic Activities.*

Wholesale Selling Activities - SMEs	Total	%
Pharmaceuticals, Medicinal Products, Medical Materials, Perfumery, and Cosmetics.	181	12%
Other Types of Machinery and Equipment	179	12%
Change of a commission or by contract	173	12%
Food, Beverages, and Tobacco	140	10%
Construction materials, hardware, equipment, plumbing materials, and heating.	133	9%
Computers, Equipment, and Software	111	8%
Waste, Scrap, Junk, and Other	97	7%
Various Unspecialized Products.	90	6%
Textiles, Clothing, and Footwear.	71	5%
Household Electrical Appliances, Furniture, Mattresses, Carpets, and Home Lighting Appliances.	63	4%
Other Household Items.	60	4%
Agricultural Raw Materials	55	4%
Electronic Equipment, Parts, and Telecommunications.	49	3%
Agricultural Machinery, Equipment, and Materials.	29	2%
Solid, Liquid, and Gaseous Fuels and Related Products	27	2%
Metals and Metal Ores	15	1%

Figure 1 shows the percentage of enterprises falling into three bankruptcy-risk groups according to the Altman Z-Score model from 2018 to 2022. The data shows a reduction in the number of firms in the bankruptcy zone from 35% in 2018 to 30% in 2022. This fall is showing improvement in the financial situation of the analyzed firms. The share of firms operating in the gray zone has slightly reduced from 22% in 2018 to 18% in 2022.

This drop can be seen as a positive trend, meaning that fewer enterprises are in a precarious financial situation. Finally, the safe zone has little chance of insolvency. This group has been expanding from 43% in 2018 to 51% in 2021 and remaining at that level in 2022. This is a good sign; it means that more than half of the enterprises evaluated are in a relatively safe financial situation, and the chance of insolvency is lower.

The trend during this period could be interpreted as a direct response not only to the experienced crises but also to emerging opportunities, such as online commerce (CECE, 2023) . The latter has experienced notable growth in Ecuador, breaking the barriers imposed by the crisis and surpassing the traditional preference for in-person purchases. Faced with decreased purchasing power and stagnant sales, various companies were forced to adapt to digital channels (Zambrano et al., 2021).

On the other hand, the predominant role of social networks has been an important factor for this type of transaction(Cajamarca-Ramos et al., 2023). According to Zambrano et al., (2021) 36% correspond to food and groceries, 26% to personal goods, 16% to games and entertainment, and 25% to non-personal goods, strengthened by the increasingly frequent use of the internet that promotes non-in-person purchases. Thus, during the year 2018, 12.70% of e-commerce corresponded to domestic purchases and 87% to international purchases (CECE, 2018). The pandemic demanded greater participation in e-commerce, increasing the frequency of purchases even to once a month for 19% of the population, executed by an age group younger than 26 years old. (CECE, 2020).See Figure 1

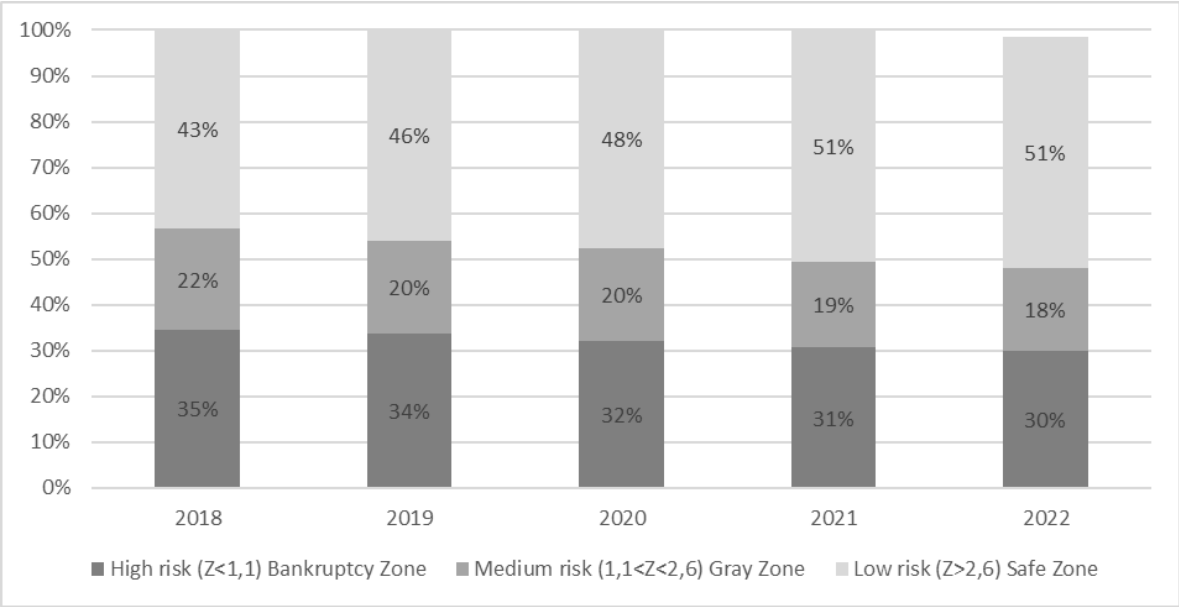

Figure 1. *Score according to Altman Z-Score Model*

Descriptive Statistics

The average Altman Z-Score of the 1,473 enterprises surveyed is 2.41, showing a modest probability of insolvency. The highest was 9.97, and the lowest was -9.88. In addition, the median score is 2.43, which means that half of the organizations had scores above this value and half had scores below. The highest number of scores is 3.02, which means that the majority of the SMEs have a minimal risk of bankruptcy. On the other hand, the standard deviation of the measurements from the mean is 3.09, which indicates some dispersion in the scores due to varied business activities of the SMEs.

In terms of financial metrics, the examined SMEs have low liquidity (average of -0.0021) and excessive leverage. Based on the analysis of the method, it is concluded that a lot of enterprises have poor liquidity, accumulated earnings, and indications of productivity. The standard deviation of leverage is large (18.5), and this implies a high dispersion of leverage

among SMEs, which affects their final scores given the diversity of their activities. Table 3 below presents the descriptive statistics for the variables.

Table 3 Descriptive Statistics

	Z	Liquidity	Management	Productivity	Leverage
Mean	2.41	-0.0021	0.112	0.0404	1.60
Median	2.43	0.0466	0.0728	0.0240	0.349
Mode	-3.02 [a]	-0.490 [a]	0.00	0.00	0.0978 [a]
Standard Deviation	3.09	0.370	0.307	0.186	18.5
Variance	9.57	0.137	0.0944	0.0345	341
Minimum	-9.88	-3.71	-3.84	-10.4	-460
Máximum	9.97	1.14	14.9	1.81	759

[a] There is more than one mode, only the first one is reported |

Non-parametric Kruskal Wallis tests were applied to 16 independent samples from sub-sectors of the commerce sector to determine if the Z-values are different. It was observed that in the year 2020, there are fewer companies in the zone at risk of financial bankruptcy, meaning the scores increased from the threshold of 2.60 and were situated in a safe zone. The following hypotheses were proposed:

H0: All means are equal.

H1: There is at least one significant difference in the Z scores among the subgroups of commerce.

Table 4 *Result of Kruskalwallis test*

Test Statistics[a,b]	
Z Risk Level	
H de Kruskal-Wallis	38,090
df	15
Asymptotic Sig.	,001

a. Kruskal-Wallis Test

b. Grouping Variable: Group

To complement the analysis of the ratings of companies logistic regression was conducted using Stata 16 statistical software, considering the score obtained from the Altman Z"-Score model as the dependent variable, and liquidity, accumulated profits, productivity, and leverage as independent variables. The results are detailed in Table 4.

Description of variables:

Dependent variable

- Y: Dichotomous variable (Low probability of bankruptcy – High probability of bankruptcy). Z Score rating reclassified obtained by SMEs when applying the Altman Z"-Score methodology A.

Independent variables:

- X1: Liquidity: Difference between current assets and liabilities, related to total assets. Speed at which a financial asset can be converted into a means of payment without losing value.
- X2: Retained earnings: Ratio of retained earnings to total assets. Capacity to generate retained earnings from assets.
- X3: Productivity: Ratio of earnings before interest and taxes to total assets. Capacity of SMEs to achieve operational efficiency.
- X4: Leverage: Ratio of equity to total liabilities. Degree to which companies can meet obligations.

The results of the marginal effects of the logistic regression are as follows:

Table 5 *Logistic regression – Marginal Effects*

Average marginal effects — Number of obs = 7.364
Model VCE: OIM

Expression: Pr(Z), predict()
dy/dx w.r.t. : Liquidity Management Productivity Leverage

X	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
Liquidity	-0.721131	0.0149284	-48.31	0.00	-0.750391	-0.691872
Accumulated Profits	-0.621543	0.0219706	-28.29	0.00	-0.664605	-0.578481
Productivity	-0.956077	0.0333232	-28.69	0.00	-1.02139	-0.890765
Leverage	-0.000948	0.0002894	-3.28	0.00	-0.001515	-0.000381

To measure the goodness of fit of the model, and as it is probabilistic, the R-squared of the model was used through the classification truth table 6 to establish the percentage of correct and incorrect forecasts in the model, resulting in a prediction percentage of 79.63%, which is an acceptable prediction percentage.

Tabla 6 *Adjustment of the Logistic Model for Z*

Logistic model for Z

	True		
Classified	D	~D	Total
+	3160	818	3978
-	682	2704	3386
Total	3842	3522	7364

Classified + if predicted Pr(D) >= .5
True D defined as Z != 0

Sensitivity	Pr(+| D)	82.25%
Specificity	Pr(-|~D)	76.77%
Positive predictive value	Pr(D| +)	79.44%

Negative predictive value	Pr(~D| -)	79.86%
False + rate for true ~D	Pr(+|~D)	23.23%
False - rate for true D	Pr(-| D)	17.75%
False + rate for classified	+ Pr(~D| +)	20.56%
False - rate for classified	- Pr(D| -)	20.14%
Correctly classified		79.63%

The marginal effects of the regression model yield the following results:

- For each unit increase in the productivity indicator, the probability of SME bankruptcy decreases by 95.61%.
- For each unit increase in the liquidity indicator, the probability of SME bankruptcy decreases by 72.11%.
- For each unit increase in the accumulated profits indicator, the probability of SME bankruptcy decreases by 62.15%.
- For each unit increase in the leverage indicator, the probability of SME bankruptcy decreases by 0.09%.

Discussion

This research focused on forecasting the financial susceptibility of a sample of Small and Medium-sized Enterprises (SMEs) operating in the wholesale trade sector of Ecuador. The utilization of the Altman Z"-Score model, coupled with logistic estimation, facilitated this endeavor. The study outcomes revealed a predictive accuracy of 79,63%, derived from meticulous analysis employing the R-squared This finding aligns with prior research employing the Altman Z" Score model (Abdullah et al., 2020; Agustian & Syofyan, 2022; Damayanti et al., 2019; Isaac-Roque & Caicedo-Carrero, 2023; Prasetiyani & Sofyan, 2020). Similar results were reported in a Slovenian study, where the prediction level achieved 71.21%

reliability at the Z”-Score model threshold (Dolinšek & Kovač, 2024), and 74.29% in predicting the bankruptcy of retail companies listed on the Indonesia Stock Exchange (Viciwati, 2020).

Companies are categorized as high, medium, and low risk of financial failure. Stakeholders and investors can analyze financial health and risk of failure across the industry. The literature on finance uses bankruptcy models to anticipate financial dynamics and to make educated judgments (Alcalde et al., 2022; Reza et al., 2023; Wibowo & Hidayah, 2023).

In this research, the main predictor of financial insolvency was productivity (X3). This result emphasizes that the bigger the profit margins, the more the bankruptcy constraints. This result differs from a study in commercial enterprises in Colombia, where it was found that the accumulated profitability (X2) and the decrease in leverage (X4) contribute favorably to a better performance. Moderate debt combined with good liquidity (Ramli et al., 2019), supports investment in R&D and innovation, leading to enhanced efficiency, which is positively associated with business performance (Galarza et al., 2023). The results of the present study are compatible with the results of other studies carried out in Poland, in 20 nations of the European Union, and in 3 non-European countries. In particular, leverage showed a relatively small contribution to the probability of bankruptcy in linear and logistic regression models (Lubawa & Louangrath, 2016). This is a common feature of the business sector, because the greatest leverage is often through suppliers, hence reducing financial expenses.

Although the Altman Z-Score model has limitations in considering political, economic, social, and strategic variables in predicting financial vulnerability (Abdullah et al., 2020;

Abidin et al., 2021; Isaac-Roque & Caicedo-Carrero, 2023), it is still accessible and useful as a predictive tool.

Finally, the empirical research of the wholesale sector in Ecuador provides a useful framework for national and worldwide society, since in many countries, small and medium-sized firms (SMEs) face similar difficulties regarding financial fragility and economic stability. The methodology and results are applicable in different situations, especially in developing countries, where small and medium-sized firms are important for economic growth and job creation (Kapounek et al., 2022). The Altman Z"-Score model and the accepted predictive variables have a strong basis for assessing financial risk and strategic decision-making worldwide. The Altman Z"-Score model and the identified predictive variables form a strong basis for assessing the financial risk and designing strategic decisions across the globe.

Conclusions

This study shows that the wholesale sector has several sub-sectors, 16 of which were analyzed. The analysis of five years of data shows that companies have reduced their probability of bankruptcy by 5 percentage points, equivalent to 63 companies. This improvement could be attributed to the rise of e-commerce, the widespread use of social networking platforms, the facilitation of online transactions, and the contribution of strategic sectors such as pharmaceuticals, machinery and equipment, food and beverages, and technology.

The Kruskal-Wallis test was used to determine which subgroups show differences in the Z score in 2022, which showed that there are significant differences between the categories of

two groups. A post hoc test was performed, which shows differences in the subgroups: Wholesale of food, beverages and tobacco and Wholesale of other machinery and equipment.

In this particular test, using Stata version 16 and the R-squared statistic, it was found that the model achieves a predictive accuracy of 79,63%, which is similar to what is reported in the literature (Abdullah et al., 2020; Agustian & Syofyan, 2022; Damayanti et al., 2019; Dolinšek & Kovač, 2024; Isaac-Roque & Caicedo-Carrero, 2023; Prasetiyani & Sofyan, 2020). The reliability of the Altman Z" Score model and the identified predictive factors provide a sound basis for financial risk assessment and strategic decision-making at the global level.

Among the predictor variables in the Altman Z-score model, productivity is the most important factor. The results indicate that for every unit increase in liquidity ratio, retained earnings, and productivity, the probability of bankruptcy decreases by 72,11%, 95,61%, and 62,15%, respectively. In this study, leverage had no significant effect on Alman Z-score.

In conclusion, this empirical study conducted in an emerging-market country is useful for future discussions on small and medium-sized enterprises (SMEs), as many countries face similar challenges related to financial vulnerability and economic stability (Kapounek et al., 2022).

Referencias

Abdullah, A., Achsani, N. A., & Suhendi. (2020). Bankruptcy analysis of National airlines companies in regional Asia after Covid-19 Pandemic. *Jurnal Aplikasi Manajemen Dan Bisnis*, *6*(3), 691.

Abidin, J. Z., Abdullah, N. A. H., & Khaw, K. L.-H. (2021). Bankruptcy prediction: SMEs in the hospitality industry. *International Journal of Banking and Finance*, *16*(2), 51–80.

Agustian, V., & Syofyan, R. (2022). Analisis Potensi Kebangkrutan Perusahaan Sub Sektor Transportasi yang Terdaftar di BEI Sebelum dan Selama Pandemi Covid-19. *Journal Ecogen*, *5*(3), 487. https://doi.org/10.24036/jmpe.v5i3.13725

Alaka, H. A., Oyedele, L. O., Owolabi, H. A., Kumar, V., Ajayi, S. O., Akinade, O. O., & Bilal, M. (2018). Systematic review of bankruptcy prediction models: Towards a framework for tool selection. *Expert Systems with Applications*, *94*, 164–184.

Alcalde, R., de Armiño, C. A., & García, S. (2022). Analysis of the Economic Sustainability of the Supply Chain Sector by Applying the Altman Z-Score Predictor. *Sustainability (Switzerland)*, *14*(2), 1–13. https://doi.org/10.3390/su14020851

Almamy, J., Aston, J., & Ngwa, L. N. (2016). An evaluation of Altman's Z-score using cash flow ratio to predict corporate failure amid the recent financial crisis: Evidence from the UK. *Journal of Corporate Finance*, *36*, 278–285. https://doi.org/10.1016/j.jcorpfin.2015.12.009

Altman, E. (2018). A fifty-year retrospective on credit risk models, the altman z-score family of models and their applications to financial markets and managerial strategies. *Journal of Credit Risk*, *14*(4), 1–34. https://doi.org/10.21314/JCR.2018.243

Altman, E., Iwanicz-Drozdowska, M., Laitinen, E., & Suvas, A. (2017). Financial Distress Prediction in an International Context: A Review and Empirical Analysis of Altman's Z-

core Model. In *Journal of International Financial Management & Accounting* (Vol. 28, Issue 2, pp. 131–171).

Álvarez-Ferrer, A., & Campa-Planas, F. (2020). The prediction of business failure in the hospitality business. *Cuadernos de Turismo*, *45*, 33–59. https://doi.org/10.6018/turismo.426031

Amendola, A., Restaino, M., & Sensini, L. (2015). An analysis of the determinants of financial distress in Italy: A competing risks approach. *International Review of Economics & Finance*, *37*, 33–41. https://doi.org/https://doi.org/10.1016/j.iref.2014.10.012

Antunes, F., Ribeiro, B., & Pereira, F. (2017). Probabilistic modeling and visualization for bankruptcy prediction. *Applied Soft Computing*, *60*, 831–843. https://doi.org/http://dx.doi.org/doi:10.1016/j.asoc.2017.06.043

Arini, Handayati, P., & Naruli, A. (2020). *Analysis of the Method of Altman Z-Score to Predict the Potential of Bankruptcy in Advertising, Printing and Media Companies Listed on the IDX*. *Irceb 2018*, 230–236. https://doi.org/10.5220/0008783702300236

Banco Central del Ecuador. (2023). *Boletín Analítico del Índice de Actividad Económica Coyuntural No. 44 1.* (Issue 44).

Banco Mundial. (2022). *Aviso de privacidad*. https://www.bancomundial.org/es/about/legal/privacy-notice

Bartik, A., Bertrand, M., Cullen, Z., Glaeser, E., Luca, M., & Stanton, C. (2020). The impact of COVID-19 on small business outcomes and expectations. *Proceedings of the National Academy of Sciences*, *117*(30), 17656–17666. https://doi.org/10.1073/PNAS.2006991117

Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research*, 71–111. https://doi.org/https://doi.org/10.2307/2490171

Berkson, J. (1944). Application of the Logistic Function to Bio-Assay. *Journal of the*

American Statistical Association, *39*(227), 357–365. https://doi.org/10.2307/2280041

Brito, D. (2018). El riesgo empresarial. *Revista Universidad y Sociedad*, *10*(1), 272–280.

Buele, I., Mora, A., & Solano, S. (2021). Ecuadorian wholesale and retail trade companies: analysis of the financial situation and bankruptcy forecast under Altman Z-score. *Academy of Accounting and Financial Studies Journal*, *25*(1), 1–11.

Burksaitiene, D., & Draugele, L. (2018). Capital structure impact on liquidity management. *International Journal of Economics, Business and Management Research*, *2*(1), 110–127.

Cajamarca-Ramos, E., Delgado-Garrido, J., & Zamora-Campoverde, A. (2023). *El Impacto del E-Commerce the Impact of E-Commerce as a Marketing Strategy for Micro-Enterprises in the City of Machala*.

Carranco, R. (2017). La aportación de las pequeñas y medianas empresas (pymes) en la economía ecuatoriana. *Universidad Internacional de Ecuador*, 12.

Castañeda, A. (2022). *Ratios Financieros* (2da. Edición). E-Book.

CECE. (2018). *Comportamiento de las transacciones no presenciales en Ecuador 2018*. 72.

CECE. (2023). *Estudio de transacciones no presenciales en Ecuador*.

CEPAL. (2020). *Ecuador Rasgos generales de la evolución reciente*.

Damayanti, N. A., Nurhayati, N., & Prasetyaningtyas, S. (2019). Analisis Perbandingan Model Prediksi Kebangkrutan Altman Z-Score dan Zmijewski di BEI Periode 2011-2015. *E-Journal Ekonomi Bisnis Dan Akuntansi*, *6*(2), 171–174.

Del Castillo, A. (2021). *Modelos de predicción de insolvencia: Un análisis de variables no financieras y de selección muestral*. Universidad de Málaga.

DIEE. (2022). *Boletín Técnico*.

Dini, M., & Stumpo, G. (2020). MIPIMES en América Latina: Un frágil desempeño y nuevos desafíos para las MIPYMES. In *Cepal*.

Dolinšek, T., & Kovač, T. (2024). Application of the Altman Model for the Prediction of Financial Distress in the Case of Slovenian Companies. *Organizacija*, *57*(2), 115–126. https://doi.org/10.2478/orga-2024-0008

Dwi, R. (2020). Impact of Covid 19 on trade, FDI, real exchange rate and era of digitalization: Brief review global economy during pandemic. *Journal of Developing Economies*, *5*(2), 86–90. https://doi.org/http://dx.doi.org/10.20473/jde.v5i2.23597

Eggers, F. (2020). Masters of disasters? Challenges and opportunities for SMEs in times of crisis. *Journal of Business Research*, *116*, 199–208.

Galarza, I. S., León-Carlosama, R. G., Cevallos-Pineda, A. G., & Martínez-Gómez, M. (2023). Innovation in the tourism sector, organizational learning and performance. *Academia Revista Latinoamericana de Administración*. https://doi.org/10.1108/ARLA-06-2023-0090

Gregova, E., Valaskova, K., Adamko, P., Tumpach, M., & Jaros, J. (2020). Predicting financial distress of slovak enterprises: Comparison of selected traditional and learning algorithms methods. *Sustainability (Switzerland)*, *12*(10). https://doi.org/10.3390/SU12103954

Horna, L., Guachamín, M., & Cevallos, T. (2009). Análisis de mercado del sector comercio al por mayor y al por menor, código CIIU sección G, bajo un enfoque de concentración económica en el caso ecuatoriano durante el período 2000 - 2008. *Revista Politécnica*, *30 (1)*(January), 217–229.

Ibarra, A. (2010). *Desarrollo del análisis factorial multivariable aplicado al análisis financiero actual*. Eumed. net.

Isaac-Roque, D., & Caicedo-Carrero, A. (2023). Relationship between the financial indicators of the Altman Z-model and the Z-Score. *RETOS. Revista de Ciencias de La*

Administración y Economía, *13*(25), 139–158.

Kapounek, S., Hanousek, J., & Bílý, F. (2022). Predikční Schopnost Altmanova Z-Skóre Evropských Soukromých Společností*. *Politická Ekonomie*, *70*(3), 265–287. https://doi.org/10.18267/j.polek.1353

Karim, M. R., Shetu, S. A., & Razia, S. (2021). COVID-19, liquidity and financial health: empirical evidence from South Asian economy. *Asian Journal of Economics and Banking*, *5*(3), 307–323. https://doi.org/10.1108/ajeb-03-2021-0033

Keller, A. (2022). Vulnerability in Financial Regulation: The Case of SMEs. *European Business Law Review*, *33*(5).

Kerubo, S., Muathe, S., & Wamugo, L. (2020). Financial risk and financial performance: evidence and insights from commercial and services listed companies in Nairobi securities exchange, Kenya. *International Journal of Financial Studies*, *8*(3), 51.

Kim, H., Cho, H., & Ryu, D. (2020). Corporate default predictions using machine learning: Literature review. *Sustainability (Switzerland)*, *12*(16), 1–11. https://doi.org/10.3390/SU12166325

Laitinen, E., Camacho-Miñano, M.-M., & Muñoz-Izquierdo, N. (2023). *A review of the limitations of financial failure prediction research*. *26*(2), 255–273.

Lamia, J., Meriem, J., Monia, B., & Raied, A. H. (2019). Modeling and Analysis of Business Failures: Application to Moroccan SMEs. *Stud*, *2*(6), 131. https://doi.org/10.12691/ijbrm-2-1-4

Lewaru, T. S., & Loupatty, L. G. (2021). Prediction of Financial Distress as the Impact of the Covid¬-19 Pandemic on Trade, Services and Investment Companies in Indonesia Using Altman Z-Score Discriminant Analysis. *International Journal Of Multi Science*, *2*(08), 37–56.

Li, J., & Rahgozar, R. (2012). Application of the Z -Score Model with Consideration of Total

Assets Volatility in Predicting Corporate Financial Failures from 2000-2010. *Journal of Acc*, *12*(2), 11–20.

Lubawa, G., & Louangrath, P. (2016). Using Altman Z-Score to Assess the Financial Effects of Multiple Loans on SMEs. *International Journal of Research & Methodology in Social Science Inter. J. Res. Methodol. Soc. Sci*, *2*(1), 63–63. https://doi.org/10.5281/zenodo.1315187

MacCarthy, J. (2017). Using Altman Z-score and Beneish M-score models to detect financial fraud and corporate failure: A case study of Enron Corporation. *International Journal of Finance and Accounting*, *6*(6), 159–166.

Madan, N. (2020). *A review of access to finance by micro, small and medium enterprises and digital financial services in selected Asia-Pacific least developed countries*.

Martínez, E. (2008). Logit Model como modelo de elección discreta: origen y evolución. *Anuario Jurídico y Económico Escurialense*, 469–484.

Maulana, F. (2024). Financial Distress Assessment Through Altman Z-Score. *Journal of Economics and Business UBS*, *13*(1), 227–240. https://doi.org/10.52644/joeb.v13i1.1493

Mavengere, K., & Gumede, P. (2024). Financial Distress Prediction Competence of the Altman Z Score and Zmijewski Model: Evidence From Selected Zimbabwe Stock Exchange Firms. *Pressacademia*, *11*, 9–15. https://doi.org/10.17261/pressacademia.2024.1892

Mazaraki, A., & Zubko, T. (2022). Stability of production and trading companies considering their economic security. *Management*, *20*(1), 445–458. https://doi.org/http://dx.doi.org/10.21511/ppm.20(1).2022.36

McFadden, D. (1973). Conditional Logit Analysis of Qualitative Choice Behavior. *UC Berkeley*, 1–59.

Médici, F. (2020). Financial instability in peripheral economies: an approach from the

balance-of-payments constraint. *Journal of Post Keynesian Economics*, *43*(4), 515–539.

Montiel, U., José, A., Garcia, B., Vitorio, E., Ordóñez, G., & Inés, A. (2021). *Función empresarial y concentración de*. *26*.

Mostofa, S., Rezina, S., & Hasan, S. (2016). *Predicting the Financial Distress in the Banking Industry of Bangladesh: A Case Study on Private Commercial Banks*. *January 2016*, 20–22.

Muzanni, M., & Yuliana, I. (2021). Comparative Analysis of Altman, Springate, and Zmijewski Models in Predicting the Bankruptcy of Retail Companies in Indonesia and Singapore. *TIJAB (The International Journal of Applied Business)*, *5*(1), 81. https://doi.org/10.20473/tijab.v5.i1.2021.81-93

Oliveira, M. D. N. T., Ferreira, F. A. F., Pérez-Bustamante Ilander, G. O., & Jalali, M. S. (2017). Integrating cognitive mapping and MCDA for bankruptcy prediction in small- and medium-sized enterprises. *Journal of the Operational Research Society*, *68*(9), 985–997. https://doi.org/10.1057/s41274-016-0166-3

Organización Mundial del Comercio. (2023). Perspectivas del comercio mundial y estadísticas. In *Perspectivas del comercio mundial y estadísticas*. https://doi.org/10.30875/9789287075598

Prasetiyani, E., & Sofyan, M. (2020). Bankruptcy analysis using Altman Z-score model and Springate model in retail trading company listed in Indonesia Stock Exchange. *Ilomata International Journal of Tax and Accounting*, *1*(3), 139–144.

Préstamo, F., Cordero, A., & Zúñiga, J. (2021). Administración del riesgo y planeación financiera como estrategias de las Pymes del sector tecnológico en Costa Rica ante la pandemia del Covid-19. *Revista Metropolitana de Ciencias Aplicadas*, *4*(1), 16–25.

Qu, Y., Quan, P., Lei, M., & Shi, Y. (2019). Review of bankruptcy prediction using machine learning and deep learning techniques. *Procedia Computer Science*, *162*(Itqm 2019), 895–899. https://doi.org/10.1016/j.procs.2019.12.065

Ramli, N. A., Latan, H., & Solovida, G. T. (2019). Determinants of capital structure and firm financial performance—A PLS-SEM approach: Evidence from Malaysia and Indonesia. *The Quarterly Review of Economics and Finance*, *71*, 148–160.

Reza, M. J., Pagalung, G., & Damayanti, R. A. (2023). Bankruptcy Prediction With the Altman Z-Score, Springate, Zmijewski, and Grover Models. *Contemporary Journal on Business and Accounting*, *3*(02), 118–135. https://doi.org/10.58792/cjba.v3i02.40

Rincón, E., Suriaga, M., & Barzola, L. (2020). La competencia y el impacto del comercio internacional en los mercados de los países en desarrollo. *E-Idea*, *2*(4), 35–44.

Sharma, S., & Bodla, B. S. (2022). Review and comparison of Altman and Ohlson model to predict bankruptcy of companies. *Anvesak*, *September*.

Shi, Y., & Li, X. (2019). A bibliometric study on intelligent techniques of bankruptcy prediction for corporate firms. *Heliyon*, *5*(12), 1–12. https://doi.org/10.1016/j.heliyon.2019.e02997

Štefko, R., Horváthová, J., & Mokrišová, M. (2021). The Application of Graphic Methods and the DEA in Predicting the Risk of Bankruptcy. *Journal of Risk and Financial Management*, *14*(5), 220. https://doi.org/10.3390/jrfm14050220

Superintendencia de Compañías, V. y S. (2024). *Ranking*. Portal Oficial de La Superintendencia de Compañías, Valores y Seguros. https://appscvsmovil.supercias.gob.ec/ranking/reporte.html

Tahu, P. G. (2019). Predicting Financial Distress of Construction Companies in Indonesia: a Comparison of Altman Z-Score and Springate Methods. *International Journal of Sustainability, Education, and Global Creative Economic (IJSEGCE)*, *2*(2), 7–12.

Telmoudi, F., El Ghourabi, M., & Limam, M. (2011). RST–GCBR-Clustering-Based RGA–SVM Model for Corporate Failure Prediction. *Intelligent Systems in Accounting, Finance and Management*, *18*(2–3), 105–120.

Tung, D. T., & Phung, V. T. H. (2019). An application of Altman Z-score model to analyze the bankruptcy risk: Cases of multidisciplinary enterprises in Vietnam. *Investment Management and Financial Innovations*, *16*(4), 181–191. https://doi.org/10.21511/imfi.16(4).2019.16

Valaskova, K., Kliestik, T., & Kovacova, M. (2018). Management of financial risks in Slovak enterprises using regression analysis. *Oeconomia Copernicana*, *9*(1), 105–121. https://doi.org/https://doi.org/10.24136/oc.2018.006

Valaskova, K., Kliestik, T., Svabova, L., & Adamko, P. (2018). Financial risk measurement and prediction modelling for sustainable development of business entities using regression analysis. *Sustainability*, *10*(7), 2144. https://doi.org/https://doi.org/10.3390/su10072144

Vavrek, R., Vozárová, I. K., & Kotulič, R. (2021). Evaluating the financial health of agricultural enterprises in the conditions of the slovak republic using bankruptcy models. *Agriculture (Switzerland)*, *11*(3). https://doi.org/10.3390/agriculture11030242

Wibowo, D. T., & Hidayah, N. (2023). Model Formula Altman Z Score Dalam Memprediksi dan Menilai Kinerja Keuangan. *Dialektika : Jurnal Ekonomi Dan Ilmu Sosial*, *8*(1), 86–98. https://doi.org/10.36636/dialektika.v8i1.2260

Xu, H., Zhang, D., & Zhang, Z. (2023). The Impact of Covid-19 on International Trade in China-Industry Review in the YRD and the PRD. *Journal of Education, Humanities and Social Sciences*, *8*, 1763–1769.

Zambrano, B., Castellanos, E., & Miranda, M. (2021). El E-Commerce en las empresas ecuatorianas. *Revista Publicando*, *8*(29), 13–20. https://doi.org/10.51528/rp.vol8.id2176

Zhang, L., Zhang, S., & Tao, N. (2016). Financial system risk tolerance capacity and economic growth: Evidence from a cross-country analysis.Español. *Global Economic Review*, *45*(2), 97–115.

Zvarikova, K., Spuchlakova, E., & Sopkova, G. (2017). International comparison of the

relevant variables in the chosen bankruptcy models used in the risk management. *Oeconomia Copernicana*, *8*(1), 145–157.