Artículos de investigación

Application of the Zavgren Model for Assessing Financial Insolvency in the Construction Industry (2018–2022)

Aplicación del modelo Zavgren en el análisis de la insolvencia financiera en el sector constructor entre 2018-2022

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Abstract: **Objetivo**: identificar la viabilidad del uso del modelo Zavgren en empresas del sector constructor colombiano para medir la probabilidad de insolvencia financiera entre los años 2018 y 2022.
Diseño/metodología: la investigación se desarrolla con un enfoque cuantitativo de tipo exploratorio y descriptivo. Este alcance de investigación busca medir la viabilidad del modelo Zavgren como herramienta de predicción en empresas del sector constructor de Colombia; para tal fin se analizan 734 empresas que reportaron información financiera de forma sistemática entre 2018-2022.
Resultados: más del 80 % de las empresas evaluadas se ubicaron en la zona de quiebra, lo que refleja una vulnerabilidad significativa en el sector. Sin embargo, se observaron variaciones interanuales en los niveles de riesgo de insolvencia financiera, mostrando que, aunque el modelo marca un riesgo elevado, existe heterogeneidad en las condiciones de insolvencia financiera de las empresas.
Conclusiones: hay una alta proporción de empresas en riesgo de insolvencia financiera y una heterogeneidad significativa en los resultados que sugiere variaciones en los niveles de riesgo de quiebra entre las empresas. Este patrón de resultados muestra que el modelo es efectivo para señalar el riesgo global de insolvencia en el sector, pero su capacidad para descifrar entre diferentes niveles de riesgo es limitada. Esto se debe a factores específicos y características del sector que no son capturadas por el modelo.
Originalidad: esta investigación, primera en aplicar el modelo Zavgren en Colombia, evidencia su relevancia y sus limitaciones en el entorno nacional. El estudio contiene análisis estadísticos transversales y longitudinales en una ventana de observación de cinco años, lo que permite una comprensión de las dinámicas de insolvencia financiera y el impacto de variables endógenas empresariales. La investigación pone en evidencia la importancia de adaptar modelos de predicción de insolvencia para las características específicas de mercados emergentes como el colombiano.
Keywords: financial insolvency, financial management, Zavgren model, financial analysis, bankruptcy prediction, **JEL codes**: C53, G33.

Resumen: **Objective**: To identify the feasibility of applying the Zavgren model for estimating the probability of financial insolvency among Colombian construction firms between 2018 and 2022.

Design/Methodology: Adopting a quantitative, exploratory, and descriptive approach this study examines the predictive capacity of the Zavgren model within the context of the Colombian construction industry. To this end, a sample of 734 firms that systematically reported financial information from 2018 to 2022 was analyzed.

Findings: More than 80 % of the firms assessed were classified in the bankruptcy zone, which reflects significant financial vulnerability within the industry. However, year-over-year variation in insolvency risk was also observed, suggesting that despite the model's indication of elevated overall risk, insolvency conditions across firms are heterogeneous.

Conclusions: The findings reveal a high proportion of firms at risk of insolvency, as well as substantial heterogeneity in risk levels across the sample. While the Zavgren model proves effective in identifying overall insolvency risk within the industry, its ability to discriminate between different levels of risk remains limited, likely due to industry-specific factors and characteristics not accounted for in the model.

Originality: This is the first study to apply the Zavgren model in the Colombian context, offering insights into its relevance and limitations. It combines cross-sectional and longitudinal statistical analyses over a five-year period, enhancing understanding of financial insolvency dynamics and the impact of firm-level endogenous variables. The study also underscores the importance of adapting insolvency prediction models to the specific conditions of emerging markets such as Colombia.

Palabras clave: insolvencia financiera, gestión financiera, modelo Zavgren, análisis financiero, predicción de quiebra, **Códigs JEL**: C53, G33.

Highlights

- The Zavgren model effectively signals financial insolvency risk but does not clearly capture its level.
- Variations in insolvency risk levels among the firms assessed were observed.
- This is the first study in Colombia to apply the Zavgren model for predicting financial insolvency in the construction industry.

Highlights

- El modelo Zavgren alerta del riesgo de insolvencia financiera, pero no mide claramente la intensidad.
- Se detectaron diferencias en el riesgo de insolvencia entre las empresas.
- Este es el primer estudio en Colombia que usa el modelo Zavgren como método de predicción de la insolvencia financiera en el sector de la construcción.

1. INTRODUCTION

The Colombian construction industry plays a vital role in the country's economic and social development, acting as a catalyst for growth in other industries (Sarmiento Rojas et al., 2022). It makes a significant contribution to the Gross Domestic Product (GDP), generates employment, and supports progress toward a more equitable and sustainable society (Urazán-Bonells et al., 2024).

However, this industry faces considerable challenges due to rising raw material costs, driven by supply-demand factors in the post-pandemic recovery period. These price increases have reached unprecedented levels, directly affecting the operational capacity of construction firms. According to the Cámara Colombiana de la Construcción (2022), the pandemic's aftermath is evident in the increased cost of construction, as reflected in the Housing Construction Cost Index (abbreviated ICCV in Spanish).

Additionally, the Bank of the Republic of Colombia's decision to raise interest rates has increased the cost of financing, which limits access to affordable credit for construction firms. This scenario presents a critical challenge, as firms must navigate escalating input costs while maintaining sustainable economic development (International Monetary Fund, 2022).

Therefore, this context compels Colombian construction firms to adopt innovative yet robust financial strategies to counter the effects of rising inflation. The current outlook for this industry underscores the need for a comprehensive approach to financial management, aimed at promoting sustainable economic development and minimizing the risk of financial insolvency (Anton et al., 2025).

The proactive identification of insolvency signs is essential for ensuring corporate continuity and stability, particularly in volatile economic environments (Klaudiusz Tomczak, 2023; Mehmood & De Luca, 2023). In this regard, scholars emphasize the importance of integrating insolvency prediction models into financial planning processes. These models support timely debt restructuring and enable firms to take preventive measures. They also offer stakeholders a reliable means of assessing a company's financial health (Kušter et al., 2023).

Building on this perspective, Dasilas and Rigani (2024) argue that insolvency prediction is a key concern for different stakeholders, given the wide-ranging consequences of bankruptcy—including substantial financial losses, unemployment, and systemic instability. Consequently, the ability to anticipate financial distress is critical for informed decision-making, effective risk mitigation, and the broader resilience of the economy (Shi & Li, 2019a).

Given the critical importance of anticipating financial distress, recent research has focused on identifying analytical tools that enhance early detection. Internationally, studies have aimed to improve the predictive accuracy of insolvency models in the construction industry through diverse methodological approaches. For instance, Im et al. (2018) compared construction firms in Korea, Japan, and the United States using bankruptcy prediction models, and concluded that regulatory frameworks and public policy significantly influence corporate stability. Their findings also highlight the limitations of traditional models in accounting for structural differences across economies.

A further application of insolvency models is seen in Ethiopia, where Wassie and Lakatos (2024) demonstrated that the volume and content of Key Audit Matters (KAMs) disclosed by auditors serve as important indicators of financial distress. This study introduces a novel perspective by incorporating qualitative data derived from professional judgment, which emphasizes the value of non-financial information in risk assessment.

Similarly, Wang et al. (2025) proposed an ensemble-based machine learning model in China, integrating financial ratios, firm characteristics, and macroeconomic indicators. Their research identifies two major gaps in the literature: the overreliance on single classifiers and the insufficient incorporation of non-financial variables. They also critique existing models for being developed under economically stable conditions, which may reduce their relevance in volatile environments .

In Latin America, Bermeo Chiriboga and Armijos Cordero (2021) applied the Altman Z-Score Model to housing construction firms in Ecuador and found it effective for categorizing firms into risk zones. However, they acknowledge the limited accuracy of the model in emerging markets due to its exclusive reliance on historical accounting data, which restricts its applicability in highly volatile scenarios.

Similarly, Peña Ortiz et al. (2018) used the Z-Score Model to evaluate insolvency risk in companies listed on the Colombian and Mexican stock markets (2012–2016). While the model successfully predicted insolvency in Mexican firms—revealing a negative correlation between financial strength and stock price—it failed to identify a similar relationship in Colombian firms. This contrast highlights the challenges in adapting the model to local economic contexts.

International and national research reflects growing concern about financial distress in the construction industry, driven by the recurrent nature of bankruptcy in market economies (Dankiewicz, 2020). In this regard, Balina et al. (2021) emphasize the vulnerability of firms in this industry, exacerbated by factors such as delayed payments, dependency on bank loans and fluctuating interest rates, lack of capital, and absence of regulatory frameworks (Enshassi et al., 2006).

Given the interdependence of the construction industry with multiple areas of the economy, the ability to foresee financial instability is essential for safeguarding both construction firms and their workforce. Considering Colombia's current economic volatility and the specific challenges of its construction industry, this study proposes the application of the Zavgren model to predict insolvency risk in Colombian construction firms for the period 2018–2022. This approach aims to address the shortcomings of prior models by focusing on endogenous variables that better capture the internal financial dynamics of these organizations, offering a more context-sensitive and robust predictive framework.

The rest of this paper Is structured as follows: A review of the literature on the use of the Zavgren model as a financial insolvency prediction tool is provided. The methodology applied during the research is then introduced. Following this section, the results, discussion, and conclusions of the study are presented.

2. THEORETICAL OR REFERENCE FRAMEWORK

Bankruptcy is widely recognized as a disruptive event (Dasilas & Rigani, 2024), typically triggered by a range of internal and external factors (Wicaksono et al., 2022). When a firm becomes insolvent, it risks operational discontinuity, which directly affects key stakeholders such as creditors, shareholders, suppliers, and employees (Shi & Li, 2019b). Therefore, the early prediction of financial distress should be adopted as a preventive strategy to mitigate risks and reduce the likelihood of bankruptcy (Wahyuni et al., 2024).

Kristanti (2019) emphasizes that financial distress can be assessed using predictive insolvency models. Traditionally, bankruptcy forecasting has relied on financial ratios and quantitative methods, which often fail to capture complex, nonlinear patterns in financial data (Dasilas & Rigani, 2024). With advancements in statistical techniques and information technology, more sophisticated prediction methods have emerged, aiming to improve accuracy (Shi & Li, 2019b; Vásquez-Serpa et al., 2025). While their evolution has progressed from basic statistical methods to advanced machine learning techniques (Radovanovic & Haas, 2023), many models focus solely on binary outcomes—solvency versus insolvency—overlooking the broader economic, social, and financial consequences of misclassification.

In response to this limitation, Beade et al. (2024) maintain that interpretability must be a core component of insolvency prediction models. Accuracy alone is insufficient; decision-makers must be able to understand the rationale behind predictions to apply them appropriately in financial planning and risk management.

While insolvency models are primarily designed to predict bankruptcy (Narvekar & Gua, 2021; Lin et al., 2025), Isaac Roque and Caicedo Carrero (2021) argue for their broader use as complementary tools in corporate financial analysis. From the theoretical perspective of shareholder value maximization, these models can help firms adapt more effectively to market conditions. However, for these models to be practical and functional, they must be supported by transparent and accurate accounting practices, as their reliability depends on the quality of financial data used as input (Roque & Caicedo Carrero, 2022).

Within the field of finance, a wide variety of insolvency prediction models have been developed (Prusak, 2018). According to Kliestik (2018), these models can be categorized into three main groups:

I. Statistical models: These rely on techniques such as univariate analysis, risk indices, Multiple Discriminant Analysis (MDA), and conditional probability. They typically use financial ratios and quantitative indicators to estimate the likelihood of insolvency.

II. Artificial Intelligence (AI) models: This group includes survival analysis, decision trees, and artificial neural networks, which aim to replicate human reasoning in assessing a company's financial stability.

III. Alternative models: These encompass approaches such as fuzzy logic classification, chaos theory, dynamic event analysis, and expert systems. They often integrate both qualitative and quantitative methodologies to enhance predictive accuracy.

Kliestik (2018) emphasizes that each model has specific advantages and limitations, and their selection should depend on the research context, data availability, and intended predictive goals. From the perspective of Isaac-Roque and Caicedo-Carrero (2023), insolvency prediction models also fall into parametric and non-parametric categories, further illustrating the complexity of forecasting corporate financial distress. Therefore, selecting an appropriate model requires careful consideration of a company's unique characteristics, its economic environment, and the sector in which it operates (Isaac-Roque et al., 2023).

Among the various families of insolvency prediction models, statistical models remain prominent, with MDAs emerging as one of the most widely used techniques for bankruptcy forecasting (Karas & Režnáková, 2012; Alaka et al., 2018). Despite its popularity, MDA has notable limitations, which have led to the adoption of logit and probit models for predicting financial distress (Prusak, 2018). Several significant models have been developed using these statistical approaches, including those by Ohlson (1980), Zavgren (1985), Keasey and Watson (1987), Aziz et al. (1988), Platt and Platt (1990), Sheppard (1994), and Charitou et al. (2004). Among them, Zavgren's model stands out for its adaptability in forecasting financial insolvency (Andriani et al., 2023).

Designed to predict bankruptcy in U.S. companies up to five years in advance, Zavgren's (1985) model calculates insolvency probability based on empirically selected financial variables. It has proven effective in identifying financially vulnerable firms, thereby reducing uncertainty and providing early-warning signals. This predictive capability is particularly valuable for researchers, financial analysts, and managers focused on early intervention and strategic planning (Zavgren, 1985). However, a key limitation of the model is its reliance on historical financial data, which restricts its applicability to firms with incomplete accounting records or those undergoing liquidation (Kanapickiene & Marcinkevicius, 2014).

According to Bohórquez Alfonso (2019), logit regression is well-suited for building early-warning models of corporate insolvency because it offers precise discrimination between distressed and solvent firms. The model incorporates financial indicators such as the ratio of ordinary income to equity, ordinary income to non-operating assets, and total liabilities to equity. These metrics reflect profitability, operational efficiency, and capital structure, respectively. Additionally, the integration of Receiver Operating Characteristic (ROC) curves enhances the model's classification accuracy, marking a significant advancement in the prediction of corporate financial failure.

One notable application of the Zavgren model is the study by Talebnia et al. (2016) on firms listed on the Tehran Stock Exchange. The researchers compared logit regression and MDA techniques, adjusting Zavgren's coefficients to reflect Iran's economic context. Their findings revealed variations in predictive accuracy, which underscores the importance of adapting bankruptcy models to local market conditions.

Another relevant study is that by Wardayani and Maksum (2020), who applied the Zavgren model and the Altman Z-Score to Indonesian cosmetics companies from 2016 to 2018. The authors found that the Zavgren's model was less robust in environments where asset growth and profitability diverged, therefore its sensitivity to emerging financial risks is limited.

Similarly, Rivendra et al. (2021) compared the Zavgren and Altman models across various Indonesian firms from 2013 to 2017. Although Zavgren achieved an accuracy rate of 82%, Altman demonstrated superior performance, particularly in non-manufacturing sectors, due to its greater adaptability. The study concluded that while Zavgren can identify broad insolvency trends, it struggles with accuracy in industries characterized by high volatility.

Lisnawati et al. (2021) examined retail companies in Indonesia (2015–2019) using five models: Altman Z-Score, Zavgren, Springate, Grover, and Zmijewski. Altman's model showed the highest accuracy at 82%, while Zavgren's accuracy was significantly lower at 46%. Despite its weaker predictive power, Zavgren enabled granular analysis using indicators like inventory and asset turnover. However, its 54% error margin limits its reliability for strategic decision-making.

Indriyanti and Gustyana (2021) assessed several insolvency prediction models in the Indonesian retail sector for the same period. They reported that Zavgren performed worse than both Springate and Altman Z-Score, a shortfall attributed to digital market disruption and declining consumer demand. Nonetheless, Zavgren proved useful for preliminary evaluations, particularly for firms with comparable structural profiles.

Janrosl et al. (2022) analyzed coal companies listed on the Indonesian stock exchange from 2017 to 2020—an industry highly sensitive to global commodity price fluctuations. The study compared the predictive effectiveness of the Altman Z-Score and Zavgren models. Zavgren achieved an accuracy rate of 54% for insolvent firms and 60% for solvent ones, which shows a relatively higher utility in this industry. In contrast, the Altman model correctly predicted 51 %

of bankruptcies and showed similar performance in identifying financially stable companies.

In India, the Zavgren model has also been applied to firms listed on the national stock exchange. Sebastian (2023) evaluated its predictive effectiveness by comparing it with MDA techniques and models such as Altman Z-Score and Springate. Using data from both solvent and bankrupt firms, the study offered a detailed assessment of Zavgren's capacity to detect early signs of financial distress.

Andriani et al. (2023) examined the model's performance in Indonesia during the COVID-19 pandemic. Their findings showed that Zavgren outperformed Altman Z-Score, Springate, Grover, and Zmijewski in predicting insolvency, because it achieved 100% accuracy in the multi-industry manufacturing sector. Unlike traditional MDA-based approaches, the Zavgren model proved highly reliable in periods of economic turbulence, which demonstrates its adaptability for risk assessment under adverse market conditions.

Dukalang et al. (2024) compared several bankruptcy prediction models in Indonesian manufacturing firms between 2017 and 2021. While the Zavgren model showed moderate accuracy (approximately 82%), it was surpassed by newer models such as the CA-Score, which reached 97% accuracy. This study underscores Zavgren's continued relevance as an early warning tool, although its predictive strength is more limited compared to modern approaches that include corporate governance variables and macroeconomic indicators.

Similarly, Rizqon and Yunita (2024) applied the Zavgren model to Indonesian tourism sector firms during the COVID-19 pandemic (2018–2022). Zavgren exhibited the lowest predictive accuracy (28%) among the models tested, indicating limited effectiveness in capturing insolvency risks during atypical, high-volatility periods. Nevertheless, it is still valuable in assessing long-term structural and macroeconomic trends.

Overall, these studies demonstrate the broad applicability of the Zavgren model across diverse industries and geographical contexts given its consistent ability to detect general insolvency trends. However, it is important to consider both the adaptability and restrictions of the Zavgren model as a prediction tool within the set of financial insolvency prediction models. Principio del formulario

3. METHODOLOGY

This research employs an exploratory and descriptive quantitative approach. To meet the research objectives, the Zavgren model is applied as a financial indicator to assess the probability of insolvency among construction firms in Colombia.

The sample comprises Colombian construction companies that consistently reported financial information between 2018 and 2022 in the Integrated Corporate Information System (abbreviated SIIS in Spanish) of the Colombian Superintendency of Companies. Using an imputation technique, a total of 734 companies meeting these criteria were identified for analysis.

The selected period holds significant economic and social relevance for Colombia. During these years, the construction industry experienced notable fluctuations driven by events such as the global economic slowdown and the COVID-19 pandemic, which disrupted market dynamics within the industry. These conditions provide a suitable context to analyze how external pressures impact financial soundness and to test the Zavgren model's predictive capacity under stress conditions .

Table 1 presents the distribution of these companies based on asset values expressed in current monthly legal minimum wages for 2022.

Table 1

Distribution of firms included in the study

Type of Firm	No. of Firms	%
Micro	1	0.1 %
Small	39	5.3 %
Medium	328	44.7 %
Large	366	49.9 %
Total	734	100.0 %

Tabla 1. Distribución empresas incluidas en este estudio

Source: Own work.

Based on the sample, 94.6% of the firms are classified as medium and large enterprises according to their 2022 asset values. This predominance highlights the significant role these companies play within Colombian broader economy. After defining the target firms, the seven variables established by Zavgren are calculated, incorporating liquidity indicators, operating profitability, and capital structure. Applying the original version of the model ensures adherence to its mathematical formulation, maintaining consistency and enabling comparisons with previous studies in other industries and contexts. The calculation structure for the financial indicators within the Zavgren model is outlined below:

Variable X_1 measures the proportion of prior-year results (retained earnings or accumulated losses) relative to total sales. A higher value indicates that retained earnings represent a significant portion of sales volume for the period analyzed. The calculation structure for Variable X_1 is presented in Equation (1)

$$X_1 = \left(\frac{\text{Retained Earnings}}{\text{Revenue From Core Business Operations}}\right)$$

(1)

Variable X_2 compares a firm's total liabilities to its accumulated retained earnings. A higher value indicates that the firm carries a significant level of debt relative to its retained earnings, which signals potential financial vulnerability. The calculation structure for X_2 is shown in Equation (2)

$$X_2 = \left(\frac{\text{Total Liabilities}}{\text{Retained Earnings}}\right)$$

(2)

Variable X_3 measures liquidity by comparing cash and cash equivalents to retained earnings from the most recent period. A higher value suggests that greater liquidity relative to earnings reduces the risk of insolvency. The calculation structure for X_3 is displayed in Equation (3)

$$X_3 = \left(\frac{\text{Cash and cash equivalents}}{\text{Retained Earnings}}\right)$$

(3)

Variable X_4 represents the ratio of cash and cash equivalents to current liabilities (short-term obligations), which indicates the firm's ability to meet immediate obligations using its most liquid assets. The calculation structure for X_4 is exhibited in Equation (4)

$$X_4 = \left(\frac{\text{Cash and Cash Equivalents}}{\text{Current Liabilities}}\right)$$

(4)

Variable X_5 serves as a measure of operating efficiency, comparing operating income to net working capital. This ratio reflects how effectively the firm's operations generate earnings per unit of working capital. The calculation structure for X_5 is presented in Equation (5)

$$X_5 = \left(\frac{\text{Ganancia (pérdida) por actividades de operación}}{\text{Capital de trabajo}}\right) \tag{5}$$

Variable X_6 measures the ratio of total assets to current liabilities, indicating the firm's capacity to meet short-term obligations using its total asset base. The calculation structure for X_6 is shown in Equation (6)

$$X_6 = \left(\frac{\text{Total Assets}}{\text{Current Liabilities}}\right) \tag{6}$$

Variable X_7 represents the ratio of revenue from core business operations to net profit for the accounting period. A lower value suggests that the company efficiently converts sales into profit. The calculation structure for X_7 is displayed in Equation (7)

$$X_7 = \left(\frac{\text{Revenue From Core Business Operations}}{\text{Net Profit (Loss) for the Accounting Period}}\right) \tag{7}$$

Once all financial indicators comprising the Z-Score model are calculated, the Zavgren model is applied using the following Equation (8)

$$Z = 0.11X_1 + 1.58X_2 + 10.78X_3 - 3.07X_4 - 0.49X_5 + 4.35X_6 - 0.11X_7 - 0.24 \tag{8}$$

The probability of financial insolvency is then estimated using Equation (9)

$$P = \frac{1}{1+e^{-z}}$$

(9)

where *e* is Euler's number (2.7182818284).

To interpret the Zavgren model results, the three categories of bankruptcy presented by Stankevičienė and Prazdeckaitė (2021) are applied:

- If P > 0.6, the firm is supposed to go bankrupt.
- If 0.3 ≤ P ≤ 0.6, the firm is in the gray area.
- If P < 0.3, the firm is financially healthy.

Following the classification, the dispersion of results is evaluated using the measurement scale proposed by Vargas Franco (2007):

- If CV ≤ $0.3\bar{X}$, the data set is homogeneous relative to the mean.
- If $0.3\bar{X}$ < CV ≤ $0.7\bar{X}$, the data set is heterogeneous relative to the mean.
- If CV > $0.7\bar{X}$, the data set is highly heterogeneous relative to the mean.
- *Note: CV stands for Coefficient of Variation.*

To validate the consistency of the Z-Score model results, two hypothesis tests are proposed:

1. Cross-sectional hypothesis testing evaluates, year by year, whether there is statistical evidence that construction firms in Colombia, on average, exhibit a high probability of insolvency.

2. Longitudinal hypothesis testing examines whether, across the observation period, construction firms in Colombia consistently show signs of financial insolvency.

The null and alternative hypotheses for the cross-sectional test are as follows:

H_0= The average Zavgren model score for construction firms in Colombia in year is equal to or greater than 0.6.

H_1= The average Zavgren model score for construction firms in Colombia in year is less than 0.6.

The significance level for hypothesis validation is 5% (α = 5%). Therefore, the non-rejection value of H_1 will be if Z < -1.64. Based on the above, Equation (10) applies:

$$Z_a = \frac{(\bar{x}_a - \mu)}{\left(\frac{\sigma_a}{\sqrt{n_a}}\right)} \tag{10}$$

where:

Z_a = Test statistic for year .

$\bar{x}_a$= Average Zavgren model score for construction firms in Colombia in year a.

μ= Expected threshold score for the Zavgren model (0.6).

σ_a = Standard deviation of Zavgren scores for construction firms in Colombia in year a.

$\sqrt{n_a}$ = Number of construction firms in Colombia analyzed in year a.

To complement this analysis, a longitudinal hypothesis test is performed for each firm across the period 2018–2022:

$\boldsymbol{H}_0$ = The average Zavgren model score for firm e is equal to or greater than 0.6 during 2018–2022.

$\boldsymbol{H}_1$ = The average Zavgren model score for firm e is less than 0.6 during 2018–2022.

Since the analysis covers five years (n < 30), a Student's t-test is applied, using a 5% significance level (α = 5 %) with n−1 degrees of freedom. Therefore, the non-rejection value for H_1 will be if t < -2.1318. The test statistic is calculated as shown in Equation (11)

$$t_e = \frac{(\bar{x}_e - \mu)}{\left(\frac{\sigma_e}{\sqrt{n_e}}\right)} \; (n-1)GL \tag{11}$$

t_e = Test statistic for firm e.

$\bar{x}_e$ = The average Zavgren model score for firm e during 2018–2022.

μ = Expected threshold score for the Zavgren model (0.6).

σ_e = Standard deviation of Zavgren scores for firm e during 2018 – 2022.

n_e = Number of years analyzed for firm e.

The application of the statistical methods described above enables the analysis of both temporal variations and persistence in financial insolvency, which reveals underlying dynamics within the construction industry.

To evaluate the relevance and significance of the variables within the Zavgren model, logistic regression analyses were conducted for each year during the 2018–2022 period. This technique systematically assesses the explanatory power of each variable in relation to the probability of financial insolvency. Data processing and analysis were performed using Stata, a software recognized for its robustness in econometric modeling and its capacity to handle large datasets.

Logistic regression was selected due to its effectiveness in modeling binary outcomes, such as the presence or absence of insolvency, which enables the direct interpretation of the relationship between explanatory variables and bankruptcy risk. To ensure result robustness, sensitivity analyses were conducted by introducing variations in financial variables and observing their impact on estimated probabilities. This approach identified the most influential predictors of insolvency and confirmed the consistency of the Zavgren model when applied to firms within the Colombian construction industry.

It is important to acknowledge the limitations of this research when analyzing and interpreting the results. First, the Zavgren model was applied in its original form, without specific adjustments to the Colombian context. Second, although the sample includes firms reporting data to the ICCV between 2018 and 2022, firms with incomplete data that did not meet the imputation criteria were excluded, which may affect the findings. Additionally, the analysis is based solely on financial statements, restricting the scope to internal quantitative indicators while excluding exogenous factors such as regulatory uncertainty, macroeconomic conditions, and corporate governance quality. Finally, the logistic regression applied to validate the model exhibited low predictive sensitivity, thus the potential need for hybrid models or more advanced statistical techniques in future research stands out.

4. RESULTS

Based on the selected sample, the Zavgren model was applied to the 734 firms in the Colombian construction industry. As shown in Table 2, the distribution of results considers the percentages of firms in the Colombian construction industry that are in the bankruptcy, gray, and healthy areas during the 2018–2022 period.

Table 2

Results of the Zavgren model

Area	2018	2019	2020	2021	2022
Bankruptcy	83.8 %	86.0 %	65.8 %	84.1 %	80.2 %
Grey	2.0 %	1.1 %	1.9 %	1.6 %	2.2 %
Healthy	14.2 %	12.9 %	32.3 %	14.3 %	17.6 %
Total	100.0 %	100.0 %	100.0 %	100.0 %	100.0 %

Tabla 2. Resultados del modelo Zavgren
Source: Own work.

Over the five-year period, a significant proportion of firms consistently fell within the bankruptcy area, with percentages exceeding 80%, except in 2020. This trend suggests that, according to the model, most construction firms in Colombia face a high risk of insolvency, which indicates potential structural or cyclical vulnerabilities within the industry. The gray area, representing financial uncertainty, accounted for only 1.1% to 2.2% of firms during this period, showing that few firms exhibited borderline financial conditions according to the model. Conversely, firms classified in the healthy area represented a minority, with a notable increase to 32.3% in 2020, likely reflecting temporary improvements or industry adjustments during that year. However, this proportion declined in subsequent years and returned to levels similar to those observed in 2018 and 2019.

The predominance of firms in the bankruptcy area and their limited representation in the healthy area raise concerns regarding the financial resilience of the industry. These findings may point to underlying structural challenges, market dynamics, or potential limitations of the Zavgren model in capturing the specific financial characteristics of Colombian construction firms.

Table 3 presents the heterogeneity analysis of the Zavgren model results for the Colombian construction industry from 2018 to 2022.

Table 3

Heterogeneity analysis of the average probability of insolvency

Measure	2018	2019	2020	2021	2022
Average	0.84	0.86	0.66	0.84	0.80
Standard Deviation	0.34	0.33	0.45	0.35	0.37
Coefficient of Variation	40.9 %	38.6 %	68.4 %	41.3 %	46.4 %
Interpretation	Heterogeneous				

Tabla 3. Análisis de heterogeneidad del promedio de probabilidad de insolvencia
Source: Own work.

The average scores indicate a consistent trend toward the bankruptcy area (scores > 0.6) in 2018, 2019, 2021, and 2022, with respective averages of 0.84, 0.86, 0.84, and 0.80, while 2020 shows a temporary decline to 0.66. Standard deviations range from 0.33 to 0.45, and coefficients of variation range from 38.6% to 68.4%, which reflects moderate to high dispersion in the scores across firms each year. This heterogeneity (CV > 30%) reveals that, despite the general trend toward insolvency risk, there is considerable variability in the financial health among construction firms. Such variability may reflect differences in financial strength and risk management practices among firms within the industry.

The highest heterogeneity was observed in 2020, with a CV of 68.4%, possibly influenced by the effects of industry-specific or external factors during that year. These results suggest that while the Zavgren model classified a large proportion of firms at risk of insolvency, the actual industry situation may be more balanced.

Table 4 presents the results of the cross-sectional hypothesis test conducted for each year from 2018 to 2022.

Table 4

Cross-sectional hypothesis test results

Measure	2018	2019	2020	2021	2022
Sample Mean	0.84	0.86	0.66	0.84	0.80
Expected Mean	0.60	0.60	0.60	0.60	0.60
Standard Deviation	0.34	0.33	0.45	0.35	0.37
No. of Firms			734		
Rejection Value			-1.64		
Test Statistic	18.99	21.04	3.79	18.69	14.69
Decision			Reject H_1		

Tabla 4. Resultado prueba de hipótesis transversal

Source: Own work.

The results of the cross-sectional hypothesis tests indicate that firms in this industry exhibited a high probability of insolvency. The test statistics for all years exceeded the critical value of 1.64, leading to the rejection of the alternative hypothesis (H_1) in favor of the null hypothesis (H_0). This means that the average insolvency probability significantly exceeded the threshold of 0.6 each year, indicating a persistently high level of financial vulnerability. Additionally, the sample means ranged from 0.66 (2020) to 0.86 (2019), with standard deviations between 0.33 and 0.45, reinforcing the conclusion that Colombian construction firms faced consistently elevated insolvency risks throughout the study period.

Table 5 presents the results of the longitudinal hypothesis test, which evaluates insolvency risk across the five-year period at the firm level.

Table 5

Longitudinal hypothesis test results

Decision	No. of Firms	Percentage
Reject H_1	704	95.9 %
Fail to Reject H_1	30	4.1 %
Total	734	100.0 %

Tabla 5. Resultado prueba de hipótesis longitudinal
Source: Own work.

The results show that among the 734 firms examined, 95.9% (704) had an average insolvency score of 0.6 or higher over the five-year period, thereby refuting the alternative hypothesis. This finding further reinforces the conclusion that most construction firms in Colombia maintained a high level of financial vulnerability during the study period. Conversely, an average score below the threshold was attained by only 4.1% (30) of firms, indicating a more stable financial condition for this minority group.

To assess the model's accuracy, official data from the Colombian Superintendence of Companies were consulted to identify firms that underwent business reorganization between 2018 and 2022. Table 6 summarizes the findings.

Table 6

Construction firms in Colombia under business reorganization

Concept	2018	2019	2020	2021	2022
No. of Firms	4	4	3	8	11

Tabla 6. Empresas del sector constructor de Colombia en reorganización empresarial
Source: Own work.

According to the Superintendence's insolvency module, 30 firms from the sample entered reorganization proceedings during the study period, which confirms that a considerable number of firms were facing financial distress. However, the discrepancy between the number of firms flagged by the Zavgren model as financially vulnerable and those formally undergoing reorganization raises questions about the model's suitability or the precision of its variables in predicting insolvency.

To assess the relevance of the Zavgren model's variables, firms were classified into two categories: those that underwent reorganization were assigned a value of 1, and those without financial difficulties were assigned a value of 0. This classification allowed for an evaluation of the variables' predictive ability regarding insolvency in the Colombian construction industry.

2018 Logistic Regression Model

The low χ^2 value in the 2018 model indicates that its predictive performance does not significantly differ from that of a model without independent variables. This suggests that the variables included in the model do not exhibit a strong collective relationship with the probability of insolvency in the construction industry during the year under analysis. Th R^2 value indicates that the model explains only 15.4 % of the variability in insolvency outcomes (see Table 7). This means that other important factors not accounted for in the model contribute to explaining financial insolvency in these firms.

Table 7

Logistic regression results for the probability of insolvency in the Colombian construction industry (2018)

Logistic Regression				No. of Obs. =		734
				LR chi^2(7)=		7.65
				Prob > chi^2 =		0.3643
Log-likelihood =		-21.011884		Pseudo R^2=		0.154
R2018	**Coefficient**	**SE**	**z**	**P > z**	**[95 % CI]**	
X1	0.00019	0.00018	1.07	0.283	-0.00016	0.00053
X2	-0.00151	0.00555	-0.27	0.786	-0.01240	0.00937
X3	-0.00303	0.04207	-0.07	0.943	-0.08548	0.07943
X4	-18.54721	14.07057	-1.32	0.187	-46.12501	9.03059
X5	-0.02494	0.24289	-0.10	0.918	-0.50099	0.45110
X6	1.27280	1.08958	1.17	0.243	-0.86274	3.40835
X7	-0.00183	0.00608	-0.30	0.763	-0.01375	0.01008
_cons	-4.41143	0.88659	-4.98	0.000	-6.14911	-2.67375
Note: 128 prediction errors and 0 correct classifications.						

Tabla 7. Resultado modelo de regresión logístico de probabilidad de insolvencia sector constructor de Colombia (2018)
Source: Own work.

An examination of the coefficients and their respective significance levels revealed that none of the variables reach conventional levels of statistical significance ($p < 0.05$). This means that, individually, these variables do not offer a reliable basis for predicting financial insolvency among Colombian construction firms in 2018. The coefficients for X2, X3, X4, X5, and X7 are negative, while X1 and X6 are positive. The magnitude of some coefficients—particularly that of X4 (−18.54721)—suggests that changes in these variables could have substantial effects on the probability of insolvency, although such effects are not statistically significant in this model (see Table 8).

Table 8

Marginal effects of explanatory variables on the probability of insolvency in the Colombian construction industry (2018)

	Delta Method					
	dy/dx	SE	z	P > |z|	[95 % CI]	
X1	0.00000	0.00000	0.96	0.339	0.00000	0.00000
X2	-0.00001	0.00003	-0.27	0.787	-0.00007	0.00005
X3	-0.00002	0.00022	-0.07	0.943	-0.00046	0.00042
X4	-0.09908	0.08871	-1.12	0.264	-0.27294	0.07479
X5	-0.00013	0.00130	-0.10	0.918	-0.00268	0.00241
X6	0.00680	0.00660	1.03	0.303	-0.00614	0.01974
X7	-0.00001	0.00003	-0.30	0.765	-0.00007	0.00005

Tabla 8. Cambios marginales en las variables explicativas probabilidad de insolvencia (2018)
Source: Own work.

Changes in the probability of insolvency associated with variables X1 through X7 are not statistically significant, underscoring their limited predictive power. The slight increase linked to X1 (0.00000101) and the relatively greater increase linked to X6 (0.0067991) both lack statistical significance ($p = 0.339$ and $p = 0.303$, respectively), suggesting that these variables are not reliable predictors of insolvency.

Similarly, the marginal decreases in the probability of insolvency associated with increases in X2, X3, X4, X5, and X7 reflect a trend toward reduced financial risk as these variables rise. However, these effects are also statistically insignificant (p = 0.787, 0.943, 0.264, 0.918, and 0.765, respectively). These findings call into question the relevance and effectiveness of the variables employed in the Zavgren model as reliable indicators of financial distress.

The confusion matrix for the 2018 model reveals a complete absence of both true positives and false positives, indicating that the model failed to correctly identify any insolvent firms (see Table 9). This lack of sensitivity suggests that the model is ineffective for detecting cases of financial insolvency—a major limitation when the objective is to flag financially distressed firms. Although the model exhibits 100 % specificity, correctly classifying financially sound firms, this result should be interpreted with caution. The absence of true positives may reflect either an actual lack of insolvent firms in the sample or a flaw in the model's ability to distinguish between solvent and insolvent firms.

Table 9
Confusion matrix (2018)

Classification	D	~D	Total	
+	0	0	0	
-	4	730	734	
Total	4	730	734	
Classification + Prediction if probability of (D) > = .5				
True D is defined as R2018! = 0				
Sensitivity			Pr(+| D)	0.00 %
Specificity			Pr(-|~D)	100.00 %
Positive predictive value			Pr(D| +)	.%
Negative predictive value			Pr(~D| -)	99.46 %
False + True positive rate ~D			Pr(+|~D)	0.00 %
False - True positive rate D			Pr(-| D)	100.00 %
False + Classification rate +			Pr(~D| +)	.%
False - Classification rate -			Pr(D| -)	0.54 %
Correctly classified			99.46 %	

Tabla 9. Matriz de confusión (2018)
Source: Own work.

Furthermore, the high negative predictive value (99.46 %) indicates that when the model predicts financial soundness, it is generally correct. However, the positive predictive value is not applicable in this case due to the complete absence of both true positives and false positives. In contrast, the high false negative rate suggests that the model tends to misclassify insolvent firms as solvent. Although the overall classification accuracy of 99.46 % may appear satisfactory, it is overshadowed by the model's inability to identify firms at risk of insolvency—an essential function in financial distress analysis.

2019 Logistic Regression Model

The χ^2 value for the 2019 model remains low, indicating that this model does not significantly enhance the prediction of financial insolvency compared to a null model (see Table 10). The R^2 value is slightly lower than that of the previous year, reinforcing the notion that other variables not included in the model may be relevant in explaining insolvency outcomes.

Table 10
Logistic regression results for the probability of insolvency in the Colombian construction industry (2019)

Logistic Regression				No. of Obs. =		734
				LR $chi^2(7)$=		6.86
				Prob > chi^2 =		0.4435
Log-likelihood =		**-21.407449**		**Pseudo R^2=**		**0.1381**
R2019	**Coefficient**	**SE**	**z**	**P > z**	**[95 % CI]**	
X1	0.00147	0.14500	0.01	0.992	-0.28272	0.28566
X2	-0.00130	0.00475	-0.27	0.784	-0.01060	0.00800
X3	-0.00130	0.00550	-0.24	0.813	-0.01207	0.00947
X4	-0.14234	0.26416	-0.54	0.590	-0.66008	0.37539
X5	2.80965	1.50147	1.87	0.061	-0.13316	5.75247
X6	4.36053	1.73652	2.51	0.012	0.95701	7.76404
X7	0.00328	0.00456	0.72	0.472	-0.00567	0.01222
_cons	-7.96657	1.54922	-5.14	0.000	-11.00298	-4.93016
Note: 2 prediction errors and 0 correct classifications.						

Tabla 10. Resultado modelo de regresión logístico de probabilidad de insolvencia sector constructor de Colombia (2019)
Source: Own work.

Variables X5 and X6 exhibit significance levels of 0.061 and 0.012, respectively. X6, in particular, emerges as statistically significant ($p < 0.05$), suggesting a potential relationship with financial insolvency. Variable X5 also approaches the conventional significance threshold, pointing to a potentially relevant influence. In contrast, variables X1, X2, X3, X4, and X7 do not reach statistical significance, as was also the case in the 2018 model. This implies that, individually, they are not reliable predictors of insolvency. While the 2019 model shows a modest improvement in the statistical relevance of some variables, it continues to exhibit limited overall predictive power for firms in the Colombian construction industry.

In 2019, X6 is the only variable approaching conventional statistical significance ($p = 0.097$), indicating that increases in X6 are marginally associated with a higher probability of insolvency, although the relationship is weakly significant (see Table 11). The remaining variables (X1 through X5 and X7) exhibit marginal changes in the probability of insolvency, but their high p-values (ranging from 0.496 to 0.992) indicate that none of these associations are statistically significant. Notably, variable X5 shows a positive marginal effect (0.0148436), implying a slight increase in the probability of insolvency as this variable rises. However, its significance remains limited ($p = 0.156$).

Table 11

Marginal effects of explanatory variables on the probability of insolvency in the Colombian construction industry (2019)

Delta Method						
	dy/dx	SE	z	P > |z|	[95 % CI]	
X1	0.00001	0.00077	0.01	0.992	-0.00149	0.00151
X2	-0.00001	0.00003	-0.27	0.786	-0.00006	0.00004
X3	-0.00001	0.00003	-0.24	0.814	-0.00006	0.00005
X4	-0.00075	0.00144	-0.52	0.600	-0.00357	0.00206
X5	0.01484	0.01046	1.42	0.156	-0.00565	0.03534
X6	0.02304	0.01389	1.66	0.097	-0.00418	0.05025
X7	0.00002	0.00003	0.68	0.496	-0.00003	0.00007

Tabla 11. Cambios marginales en las variables explicativas probabilidad de insolvencia sector constructor de Colombia (2019)
Source: Own work.

Compared to the 2018 model, which did not identify any significant variables, the 2019 model shows a slight improvement in detecting potentially relevant predictors. Nonetheless, the general absence of statistical significance across most variables in both years suggests that the Zavgren model's variable set may not adequately capture the key determinants of financial distress within the Colombian construction industry.

The overall predictive performance of the 2019 model mirrors that of 2018. As with the previous year, the model failed to identify any true positives or false positives, resulting in 0% sensitivity and 100% specificity (see Table 12). This consistent inability to detect insolvent firms (true positives) in both years means that the model is ineffective in identifying financial distress, despite its strong performance in classifying financially sound firms.

Table 12

Confusion matrix (2019)

Logistic Model for R2019				
Classification	**D**	**~D**	**Total**	
+	0	0	0	
-	4	730	734	
Total	4	730	734	
Classification + Prediction if probability of (D) > = .5				
True D is defined as R2019! =0				
Sensitivity			Pr(+| D)	0.00 %
Specificity			Pr(-|~D)	100.00 %
Positive predictive value			Pr(D| +)	.%
Negative predictive value			Pr(~D| -)	99.46 %
False + True positive rate ~D			Pr(+|~D)	0.00 %
False - True positive rate D			Pr(-| D)	100.00 %
False + Classification rate +			Pr(~D| +)	. %
False - Classification rate -			Pr(D| -)	0.54 %
Correctly classified			99.46 %	

Tabla 12. Matriz de confusión (2019)
Source: Own work.

The model's negative predictive value remains high (99.46%), indicating a strong likelihood that firms classified as solvent are indeed financially sound. However, the absence of true positives and the presence of false negatives (4 in both years) point to a critical limitation in the model's capacity to detect actual cases of insolvency.

2020 Logistic Regression Model

As in the models estimated for previous years, the χ^2 value for 2020 is low, suggesting that the model does not significantly improve the prediction of financial insolvency compared to a null model (see Table 13). However, the R^2 value of 0.3101 represents an increase relative to earlier years, indicating an improvement in the model's capacity to explain variability in insolvency outcomes. Despite this increase, the R^2 remains at a modest level, which underscores the continued influence of factors not included in the model.

Table 13

Logistic regression results for the probability of insolvency in the Colombian construction industry (2020)

Logistic Regression				**No. of Obs. =**		**734**
				LR chi^2(7)=		**12.09**
				Prob > chi^2 =		**0.0977**
Log-likelihood =		**-13.449024**		**Pseudo R^2 =**		**0.3101**
R2020	**Coefficient**	**SE**	**Z**	**P > z**	**[95 % CI]**	
X1	-0.02471	0.17488	-0.14	0.888	-0.36746	0.31805
X2	-0.00005	0.00523	-0.01	0.993	-0.01029	0.01020
X3	0.00759	0.01661	0.46	0.648	-0.02496	0.04015
X4	-0.67811	1.67486	-0.40	0.686	-3.96078	2.60456
X5	0.09553	0.17512	0.55	0.585	-0.24770	0.43876
X6	-0.00192	0.02125	-0.09	0.928	-0.04358	0.03974
X7	-0.00739	0.00432	-1.71	0.088	-0.01586	0.00109
_cons	-5.52303	0.85975	-6.42	0.000	-7.20812	-3.83795
Note: 23 prediction errors and 0 correct classifications.						

Tabla 13. Resultado modelo de regresión logístico de probabilidad de insolvencia sector constructor de Colombia (2020)
Source: Own work.

Consistent with previous years, none of the variables included in the 2020 model achieve conventional significance levels, reinforcing the conclusion that these variables are not individually reliable predictors of insolvency for construction firms during this period. Unlike in 2019, where X6 showed marginal significance, all variables in 2020 display high p-values, indicating no statistically significant association with financial insolvency.

The lack of consistency in the statistical significance of variables across years may imply that the risk factors for financial insolvency are variable or that industry-specific market conditions shift from year to year. While the increased pseudo R^2 in 2020 points to enhanced explanatory power, this gain remains modest. Overall, the 2020 results extend the trend observed in 2018 and 2019, where none of the variables exhibit a statistically significant influence on the probability of insolvency (see Table 14).

Table 14

Marginal effects of explanatory variables on the probability of insolvency in the Colombian construction industry (2020)

Delta Method						
	dy/dx	SE	z	P > |z|	[95 % CI]	
X1	-0.00007	0.00049	-0.14	0.888	-0.00103	0.00089
X2	0.00000	0.00001	-0.01	0.993	-0.00003	0.00003
X3	0.00002	0.00005	0.45	0.656	-0.00007	0.00011
X4	-0.00189	0.00483	-0.39	0.696	-0.01135	0.00758
X5	0.00027	0.00052	0.51	0.609	-0.00075	0.00128
X6	-0.00001	0.00006	-0.09	0.928	-0.00012	0.00011
X7	-0.00002	0.00002	-1.24	0.217	-0.00005	0.00001

Tabla 14. Cambios marginales en las variables explicativas probabilidad de insolvencia sector constructor de Colombia (2020)
Source: Own work.

In 2020, the marginal effects indicate that small fluctuations in these variables have minimal impact. Specifically, small decreases in the probability of insolvency are associated with increases in X1, X2, X4, X6, and X7 (with marginal effects of -0.0000687, -0.000000132, -0.0018857, -0.00000534, and -0.0000205, respectively). Moreover, slight increases are observed for X3 and X5 (0.0000211 and 0.0002656, respectively). Nonetheless, the high p-values, ranging from 0.217 to 0.993, suggest that these changes are not statistically significant. When compared with the results from 2018 and 2019, the 2020 model reflects the consistent lack of statistical significance across variables over the three-year period.

The confusion matrix analysis for the 2020 model reveals an improvement in predictive performance relative to previous years. Unlike the 2018 and 2019 models, which failed to correctly identify any insolvent firms, the 2020 model successfully classified one true positive (i.e., one insolvent firm). This result yields a sensitivity of 33.33%, representing a notable enhancement in the model's ability to detect financial insolvency (see Table 15).

Table 15

Matriz de confusión (2020)

Logistic Model for R2020				
Classification	**D**	**~D**	**Total**	
+	1	0	1	
-	2	731	733	
Total	3	731	734	
Classification + Prediction if probability of (D) > = .5				
True D is defined as R2020! = 0				
Sensitivity			Pr(+| D)	33.33 %
Specificity			Pr(-|~D)	100.00 %
Positive predictive value			Pr(D| +)	100.00 %
Negative predictive value			Pr(~D| -)	99.73 %
False + True positive rate ~D			Pr(+|~D)	0.00 %
False - True positive rate D			Pr(-| D)	66.67 %
False + Classification rate +			Pr(~D| +)	0.00 %
False - Classification rate -			Pr(D| -)	0.27 %
Correctly classified			99.73 %	

Table 15. Confusion matrix (2020)
Source: Own work.

Although the number of insolvent firms in the sample is small, the model's ability to avoid false positives and to maintain 100% specificity—correctly classifying all solvent firms—is noteworthy. The resulting positive predictive value of 100% and negative predictive value of 99.73%, along with an overall classification accuracy of 99.73%, reinforce the model's ability to predict financial soundness. However, the false negative rate of 66.67% indicates that the model continues to misclassify some insolvent firms as solvent, although this rate has decreased compared to the previous two years. This progress in identifying insolvent firms in 2020—though still limited—constitutes a step forward compared to 2018 and 2019, when the model failed to detect any true positives.

2021 Logistic Regression Model

In the 2021 model, the value of χ^2 increased compared to previous years but remains low, indicating that the model does not significantly improve the prediction of insolvency relative to a null model (see Table 16). However, the pseudo R^2 value of 0.0446 is the lowest among the models estimated for 2018 to 2021, suggesting that the 2021 model has the weakest explanatory power in accounting for variability in insolvency outcomes.

Table 16

Logistic regression results for the probability of insolvency in the Colombian construction industry (2021)

Logistic Regression				No. of Obs. =		734
				LR $chi^2(7)$=		3.93
				Prob > chi^2 =		0.7874
Log-likelihood =		-42.14222		Pseudo R^2 =		0.0446
R2021	**Coefficient**	**SE**	**Z**	**P>z**	**[95 % CI]**	
X1	-0.00006	0.00128	-0.04	0.965	-0.00256	0.00245
X2	0.00003	0.00031	0.10	0.918	-0.00058	0.00064
X3	-0.00455	0.01857	-0.24	0.807	-0.04095	0.03186
X4	-0.67097	0.89085	-0.75	0.451	-2.41700	1.07506
X5	0.46373	0.34852	1.33	0.183	-0.21936	1.14682
X6	1.03636	0.60811	1.70	0.088	-0.15551	2.22824
X7	-0.00020	0.00302	-0.06	0.948	-0.00611	0.00571
_cons	-4.73571	0.57213	-8.28	0.000	-5.85705	-3.61436
Note: 10 prediction errors and 0 correct classifications.						

Tabla 16. Resultado modelo de regresión logístico de probabilidad de insolvencia sector constructor de Colombia (2021)
Source: Own work.

As in previous years, none of the variables reach conventional levels of statistical significance, confirming that, individually, they are not reliable predictors of insolvency for construction firms in 2021. Variable X6 exhibits a p-value of 0.088—the closest to statistical significance among all variables—but still falls short of the standard threshold. The variation in statistical significance observed across years suggests that either the relevant risk factors for insolvency change over time or the model fails to adequately capture them. Overall, the 2021 results continue the trend established in 2018–2020, in which variables X1 through X7 do not exert a statistically significant influence on the probability of insolvency (see Table 17).

Table 17

Marginal effects of explanatory variables on the probability of insolvency in the Colombian construction industry (2021)

	Delta Method					
	dy/dx	**SE**	**z**	**P > |z|**	**[95 % CI]**	
X1	0.00000	0.00001	-0.04	0.965	-0.00003	0.00003
X2	0.00000	0.00000	0.10	0.918	-0.00001	0.00001
X3	-0.00005	0.00020	-0.24	0.807	-0.00044	0.00034
X4	-0.00715	0.00979	-0.73	0.465	-0.02633	0.01204
X5	0.00494	0.00397	1.24	0.214	-0.00285	0.01273
X6	0.01104	0.00725	1.52	0.128	-0.00316	0.02524
X7	0,00000	0.00003	-0.06	0.948	-0.00007	0.00006

Tabla 17. Cambios marginales en las variables explicativas probabilidad de insolvencia sector constructor de Colombia (2021)
Source: Own work.

The marginal effects for 2021 indicate that, although there are variations in the probability of insolvency associated with each variable, these are not sufficiently robust to be considered predictive. Specifically, marginal decreases are linked to increases in X1, X3, X4, and X7 (-0.0000006, -0.0000484, -0.0071462, and -0.00000208, respectively), while increases are linked to X2, X5, and X6 (0.000000342, 0.004939, and 0.0110379, respectively). These variations suggest possible trends, but their significance levels (P = 0.965, 0.807, 0.465, 0.214, 0.128, and 0.948) reveal limited statistical robustness. These results are consistent with earlier models, both in terms of the lack of statistical significance and the small magnitude of marginal effects.

The confusion matrix for 2021 mirrors the patterns observed in 2018 and 2019, confirming the model's limited ability to identify insolvent firms (see Table 18).

Table 18

Confusion matrix (2021)

Logistic Model for R2021				
Classification	**D**	**~D**	**Total**	
+	0	0	0	
-	8	726	734	
Total	8	726	734	
Classification + Prediction if probability of (D) > = .5				
True D is defined as R2021! = 0				
Sensitivity			Pr(+| D)	0.00 %
Specificity			Pr(-|~D)	100.00 %
Positive predictive value			Pr(D| +)	. %
Negative predictive value			Pr(~D| -)	98.91 %
False + True positive rate ~D			Pr(+|~D)	0.00 %
False - True positive rate D			Pr(-| D)	100.00 %
False + Classification rate +			Pr(~D| +)	. %
False - Classification rate -			Pr(D| -)	1.09 %
Correctly classified			98.91 %	

Tabla 18. Matriz de confusión (2021)
Source: Own work.

Unlike the 2020 model, which identified one true positive, the 2021 model detected none, yielding 0% sensitivity. This inability to detect insolvency, combined with the absence of false positives and 100% specificity, indicates that the model is highly effective at classifying solvent firms but fails to identify those at risk. In addition, the number of false negatives increased to eight, reflecting a decline in the model's accuracy, as demonstrated by a negative predictive value of 98.91% and an overall correct classification rate of 98.91%. This decline in predictive performance relative to 2020 suggests inconsistency in the model's effectiveness across years.

2022 Logistic Regression Model

In the 2022 model, χ^2 remains low, confirming that the model does not improve the prediction of insolvency compared to a null model (see Table 19). Moreover, the pseudo R^2 value of 0.0446 is the lowest across all years analyzed, implying that this model has the weakest explanatory power for variability in financial insolvency probability.

Table 19

Logistic regression results for the probability of insolvency in the Colombian construction industry (2022)

Logistic Regression				No. of Obs. =		734
				LR $chi^2(7)$=		3.64
				Prob > chi^2 =		0.8204
Log-likelihood =		-55.304866		Pseudo R^2 =		0.0318
R2022	**Coefficient**	**SE**	**Z**	**P > z**	**[95 % CI]**	
X1	-0.02958	0.07356	-0.40	0.688	-0.17376	0.11459
X2	-0.00075	0.00278	-0.27	0.786	-0.00620	0.00469
X3	-0.00077	0.00517	-0.15	0.881	-0.01090	0.00935
X4	-0.43073	0.66336	-0.65	0.516	-1.73090	0.86943
X5	1.24743	0.79246	1.57	0.115	-0.30576	2.80063
X6	0.38777	0.80004	0.48	0.628	-1.18029	1.95583
X7	0.00016	0.00045	0.35	0.730	-0.00073	0.00104
_cons	-4.30007	0.51826	-8.30	0.000	-5.31584	-3.28431
Note: 7 prediction errors and 0 correct classifications.						

Tabla 19. Resultado modelo de regresión logístico de probabilidad de insolvencia sector constructor de Colombia (2022)
Source: Own work.

None of the variables reach conventional levels of statistical significance, indicating that, individually, they do not effectively predict insolvency in Colombian construction firms for 2022. Variable X5, with a p-value of 0.115, is the closest to the threshold, though it remains statistically insignificant. These results are consistent with previous years and reinforce the overall trend of limited predictive capacity, with the 2022 model exhibiting the weakest performance.

As in earlier models, the lack of consistent statistical significance among variables highlights either the dynamic nature of risk factors over time or the model's inability to capture key determinants of insolvency. Moreover, the continued decline in pseudo R^2 values across the five-year period suggests a diminishing capacity of the model to explain financial insolvency in the construction industry.

The marginal effects estimated for 2022 again reveal a lack of statistical significance of variables X1 through X7 (see Table 20). The trend is similar to that observed in earlier years, with minor changes in the probability of insolvency that do not reach statistical significance: decreases associated with increases in X1, X3, X4, and X7 (-0.0000006, -0.0000484, -0.0071462, and -0.00000208, respectively) and slight increases with X2, X5, and X6 (0.000000342, 0.004939, and 0.0110379). The p-values related to these estimates (0.965, 0.918, 0.807, 0.465, 0.214, 0.128, and 0.948) confirm a lack of statistical robustness in the relationship between these variables and financial insolvency.

Table 20

Marginal effects of explanatory variables on the probability of insolvency in the Colombian construction industry (2022)

Delta Method						
	dy/dx	SE	z	P > |z|	[95 % CI]	
X1	-0.00043	0.00108	-0.40	0.689	-0.00256	0.00169
X2	-0.00001	0.00004	-0.27	0.787	-0.00009	0.00007
X3	-0.00001	0.00008	-0.15	0.881	-0.00016	0.00014
X4	-0.00631	0.00988	-0.64	0.523	-0.02567	0.01305
X5	0.01827	0.01252	1.46	0.144	-0.00627	0.04280
X6	0.00568	0.01182	0.48	0.631	-0.01748	0.02884
X7	0.00000	0.00001	0.34	0.731	-0.00001	0.00002

Tabla 20. Cambios marginales en las variables explicativas probabilidad de insolvencia sector constructor de Colombia (2022)
Source: Own work.

Over the five-year period from 2018 to 2022, the analysis of marginal effects consistently reveals that none of the variables serve as statistically significant predictors of insolvency. Despite small year-over-year fluctuations, none of the observed effects reach significance, calling into question the ability of the variables employed in the Zavgren model to capture the true determinants of financial distress in the construction industry.

The confusion matrix for 2022 continues to reflect the model's limitations in predictive performance (see Table 21). As in previous years, the 2022 model fails to identify any true positives, resulting in 0% sensitivity. While specificity remains at 100% due to the absence of false positives, indicating accurate classification of financially sound firms, the model does not detect any firms at risk of insolvency.

Table 21

Matriz de confusión (2022)

Logistic Model for R2022				
Classification	**D**	**~D**	**Total**	
+	0	0	0	
-	11	723	734	
Total	11	723	734	
Classification + Prediction if probability of (D) > = .5				
True D is defined as R2022! = 0				
Sensitivity			Pr(+| D)	0.00 %
Specificity			Pr(-|~D)	100.00 %
Positive predictive value			Pr(D| +)	. %
Negative predictive value			Pr(~D| -)	98.50 %
False + True positive rate ~D			Pr(+|~D)	0.00 %
False - True positive rate D			Pr(-| D)	100.00 %
False + Classification rate +			Pr(~D| +)	. %
False - Classification rate -			Pr(D| -)	1.50 %
Correctly classified			98.50 %	

Table 21. Confusion matrix (2022)
Source: Own work.

The model's negative predictive value of 98.50% suggests that firms predicted to be solvent are indeed likely to be financially sound. However, the growing number of false negatives (11 in 2022 compared to 4 in 2018, 2 in 2020, and 8 in 2021) signals a decline in the model's accuracy. The persistence of these issues over the years indicates that, while the model may reliably identify financial soundness, its practical usefulness is limited by its inability to detect key insolvency risks—an essential aspect for its application in financial analysis.

5. DISCUSSION

The results obtained from applying the Zavgren model to the Colombian construction industry between 2018 and 2022 reveal that a high proportion of firms—approximately 80% annually, except in 2020—were at risk of insolvency. This pattern is consistent with findings from previous studies, such as that by Lisnawati et al. (2021), in which the Zavgren model also identified a majority of financially distressed firms, although with limited predictive accuracy (46%). By contrast, in the mining sector, Janrosl et al. (2022) reported a modestly higher accuracy (54%) for identifying bankrupt firms, highlighting the model's dependency on the structural and economic characteristics of the industry under analysis.

These findings underscore the importance of complementing the Zavgren model with additional tools for monitoring financial health, particularly in industries highly exposed to external risks. This recommendation aligns with that of Rizqon and Yunita (2024), who advocated combining predictive insolvency models with vertical financial analysis and macroeconomic trend evaluations to improve forecasting capabilities in crisis-affected industries. In the Colombian context, the results point to the need for public policy and industry-specific strategies to mitigate structural vulnerabilities, especially given the limitations of the Zavgren model.

Similarly, the model's low sensitivity in detecting financially distressed firms in the Colombian construction industry represents a significant shortcoming. This issue is consistent with the findings of Rivendra et al. (2021) in the Indonesian plantation sector, where the model was unable to account for commodity price volatility. Additionally, the lack of statistical significance among the independent variables in this study aligns with the observations of Rizqon and Yunita (2024), who reported that the Zavgren model had the lowest predictive performance among several models applied to the tourism industry during the COVID-19 pandemic. These results suggest that the model may be less effective in contexts characterized by high uncertainty or structural variability.

This study provides an empirical assessment of the Zavgren model in a key economic sector in Colombia, offering insights into both its strengths and limitations. In comparison to studies by Lisnawati et al. (2021) in the retail sector and Janrosl et al. (2022) in mining, the present findings illustrate how the model's effectiveness can vary depending on the economic context. The result heterogeneity observed among Colombian construction firms echoes the findings of Rivendra et al. (2021), who reported considerable variation in the model's accuracy depending on industry-specific and market-related conditions.

Unlike studies in other sectors—such as retail (Lisnawati et al., 2021) or tourism (Rizqon & Yunita, 2024)—this research demonstrates how characteristics specific to the construction industry, including dependence on long-term projects and sensitivity to public policy, may significantly affect the model's applicability and accuracy. In line with Janrosl et al. (2022), who emphasized the need to adapt financial insolvency prediction models to the specific dynamics of the mining industry, this study highlights the importance of methodological refinements to the Zavgren model to better reflect the financial realities of construction firms in Colombia.

Based on these findings, future lines of research should aim to deepen the understanding of financial insolvency through comparative and integrative approaches. In the first place, recalibrating the Zavgren model to fit the Colombian context—through the adjustment of coefficients based on industry-specific characteristics—could enhance its predictive accuracy. Additionally, comparative intersectoral studies could be conducted to evaluate the model's performance across economic sectors with diverse capital structures, leverage ratios, and risk exposure levels.

A second line of research should explore the integration of macroeconomic indicators into prediction models to account for the potential impact of exogenous variables on organizations' financial stability. Moreover, incorporating non-financial variables into bankruptcy risk analysis could offer a more comprehensive perspective on the phenomenon of financial insolvency.

As a third line of research, the implementation of hybrid models—combining the multivariate approach of the Altman Z-score with the logistic regression technique of the Zavgren model—could offer improved accuracy. It would also be valuable to compare the performance of classical models with alternative approaches based on artificial intelligence and machine learning within the Colombian context. Such comparisons could help assess the adaptability and predictive power of these techniques in emerging markets characterized by high uncertainty and volatility.

6. CONCLUSIONS

The COVID-19 pandemic exposed the Colombian construction industry's high vulnerability to exogenous shocks, resulting in increased operational costs, reduced productivity, and adverse effects on projects of significant social value. In this context, implementing financial strategies that reduce insolvency risk and promote the financial stability of firms is essential. Predictive models of financial insolvency play a critical role in supporting business continuity, as they facilitate the early identification of financial distress and enable the adoption of preventive measures to reinforce organizational financial health.

Given the construction sector's deep interdependence on other areas of the economy, firms in this industry must adopt an integrated and proactive approach to financial management. This includes effective working capital management, the strategic use of financial leverage, and the design of an optimal capital structure to reduce insolvency risk. The combined exposure to endogenous and exogenous factors demands flexible and adaptive financial strategies capable of responding to dynamic market conditions. As such, the use of predictive tools becomes indispensable for ensuring the long-term sustainability of firms operating in volatile environments.

Throughout the 2018–2022 period, the Zavgren model demonstrated limited predictive capacity when applied to the Colombian construction industry. Low χ^2 values consistently indicated no significant improvement in predicting insolvency compared to a null model. The findings suggest that the financial variables incorporated in the model do not adequately capture the key determinants of insolvency in this sector. Moreover, the lack of statistically significant results ($p < 0.05$) for most variables indicates inconsistencies in their individual contributions to predicting insolvency, reinforcing the need to revise or supplement the model with additional financial indicators.

The model's performance, as reflected in the confusion matrix analysis, was characterized by low sensitivity and limited ability to identify true positives during the study period. Although it consistently achieved high specificity, its failure to detect financially distressed firms, especially in 2021 and 2022, raises concerns about its practical applicability. This limitation is exacerbated by the model's reliance on true negatives for accurate classification. In addition, the marginal effects analysis further confirms the limited explanatory power of the variables used, as changes in the predicted probability of insolvency were consistently statistically insignificant. These findings point to the need to include additional explanatory factors and highlight the importance of reviewing or expanding the model's structure to enhance its predictive power.

The results demonstrate that the Zavgren model serves as an early warning tool, albeit with limitations in capturing structural factors specific to the Colombian context. This limitation is largely due to its reliance solely on financial variables, without considering macroeconomic or industry-specific structural factors. Consequently, there is a clear need to design hybrid models that integrate firms' financial indicators with macroeconomic variables such as inflation, interest rates, business cycles, and GDP performance. Such integration would enhance the model's predictive and explanatory capacity, particularly in emerging economies where firms are more vulnerable to external shocks.

This study offers both theoretical and practical contributions. From a theoretical perspective, it demonstrates the inadequacy of the Zavgren model's financial variables to explain insolvency risk in the Colombian construction sector, highlighting the importance of developing or adapting models that account for sectoral specificities and exogenous influences. From a practical standpoint, the findings emphasize the need for managers, shareholders, investors, and policymakers to reassess their approaches to insolvency risk management. Likewise, it is essential to implement more comprehensive analytical tools that incorporate financial, operational, and legal dimensions. Doing so would strengthen firms' resilience to economic adversity and support the development of more robust insolvency prediction models, ultimately fostering sound financial practices that contribute to the country's economic and social progress.

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Notes

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CONFLICTS OF INTEREST

The authors declare that they have no financial, professional, or personal conflicts of interest that could have inappropriately influenced the results or interpretations presented in this study.

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AUTHOR CONTRIBUTIONS

All authors contributed substantially to the development of this research, as outlined below:

Andrés Caicedo Carrero: Conceptualization and design of the study; data collection, analysis, and interpretation; drafting of the manuscript.

Daniel Isaac Roque: Conceptualization and design of the study; data collection, analysis, and interpretation; drafting of the manuscript.

Información adicional

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