Financial Determinants of Firm Survival in the Belgian Tourism Sector: Insights for Sustainable and Resilient Futures

Mustapha Ahachmi, Xavier Brédart, and Abdelhaq Lahfidi

Abstract The predictive models of bankruptcy in academic literature are extensive, yet they frequently exhibit inconsistencies, particularly within the tourism sector. This paper investigates the viability of SMEs in the tourism industry, emphasizing how financial predictors influence their sustainability and capacity to implement resilient practices. Utilizing logistic regression to analyze financial data from 1070 SMEs, including 535 that declared bankruptcy between 2018 and 2022, the study identifies asset tangibility as a critical determinant of resilience, particularly during periods of crisis. Furthermore, elevated profitability, as indicated by the return on assets (ROA) and the working capital ratio, is shown to reduce the likelihood of bankruptcy. Firm-level attributes such as size and age are also significant, contributing to greater financial stability and enhancing businesses' ability to endure economic disruptions. This research advances the understanding of bankruptcy risk factors in the Belgian tourism context and underscores the crucial role of effective financial management and sustainable practices in securing long-term profitability. The findings provide strategic insights essential for fostering resilience and sustainability within the tourism industry, contributing to the shaping of more robust and future business models.

Keywords Bankruptcy · Prediction model · Logistic regression · Touristic SMEs · Belgium

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1 Introduction

Investing in tourism focuses on risk reduction and profit maximization. Shi and Li [81] emphasize the critical importance of this for financial planning. They highlight the sector's potential for profitability despite its inherent volatility. This has become increasingly relevant as recent events have underscored the need for thorough financial health assessments to avert both business and consumer bankruptcies. As such, the use of accurate forecasting tools has become indispensable.

In Belgium, tourism significantly impacts both employment and GDP. It accounts for 3.3% of the country's jobs and was expected to contribute 2.62% to GDP in 2022. However, the sector faces challenges, such as the significant drop in passenger traffic at Brussels Airport in 2020 and the varying contribution of travel and tourism to Brussels' GDP. These fluctuations underscore the sector's unstable demand, impacting related services such as accommodations, dining, and travel bookings.

The growing importance of understanding financial health, as highlighted by Shetty et al. [43], is pivotal in shaping the future of tourism. This knowledge is essential for a diverse group of stakeholders, including business owners, investors, financial institutions, suppliers, and customers, as it supports informed decision-making related to investments, loans, and overall business sustainability. Bankruptcy prediction, a key component of financial management, is especially critical in the tourism sector, where early detection of financial distress can enable preemptive actions, safeguarding both the cultural and economic assets vital to the industry. SMEs in Belgium, particularly those in tourism, are highly vulnerable to economic shifts and disruptions.

Despite challenges in accessing comprehensive financial data, various prediction methods have emerged, ranging from traditional statistical models to innovative applications of AI and machine learning [5]. This research focuses on developing tailored bankruptcy prediction models for Belgium's tourism sector. By leveraging logistic regression, we explore the intricate relationships between key financial factors and their impact on business resilience and continuity.

The study aims to deepen the understanding of bankruptcy risk and organizational resilience within the tourism industry, offering insights that are crucial for navigating the sector's evolving economic and societal challenges. Ultimately, our goal is to design a predictive model specifically adapted to the Belgian context, which will serve as a strategic tool for businesses and stakeholders, addressing current and future challenges in creating more sustainable and innovative tourism futures.

The document is structured into five main sections. It begins with an in-depth literature review, followed by a detailed explanation of our data collection and analysis methodology. We then compare our findings with those of previous studies, highlighting the key insights gained. This structured approach demonstrates our commitment to making a meaningful contribution to the body of research, as well as addressing the specific issues encountered by the Belgian tourism industry.

2 Literature Review and Hypothesis Development

2.1 Overview of *Predicting Bankruptcy Models*

The field of financial literature, particularly in bankruptcy prediction, has evolved considerably since Fitzpatrick's seminal work in 1932. This area of study has branched into two main streams: traditional statistical models and advanced artificial intelligence (AI) and machine learning (ML) approaches.

Traditional statistical models have been foundational in bankruptcy prediction. For instance, Ohlson's logistic and probit models, introduced in 1980, use logistic functions and a cumulative normal distribution function, respectively, to estimate the probability of bankruptcy. This distinction highlights these models' ability to handle non-linear relationships with simplicity and precision. Additionally, Beaver's univariate analysis [11] and Altman's multivariate discriminant analysis model [6], which culminates in a composite Z-score for predicting bankruptcy likelihood, represent significant contributions to this stream. Furthermore, the Hazard model, introduced by Aalen in 1978 [1], leverages survival analysis techniques to assess bankruptcy risk as a function of changing risk factors over time, adding a dynamic component to bankruptcy prediction.

The emergence of AI and ML has brought forth a new wave of models, enhancing the accuracy and reliability of bankruptcy prediction. Lennox's neural network model [65], which mimics human brain functionalities to detect complex patterns, and the Kalman support vector machine [40], which classifies data using hyperplanes, are notable examples. Additionally, decision tree frameworks developed by Hunt et al. [49] and Quinlan [18], alongside Shin and Lee's genetic algorithm [68], Zadeh's fuzzy logic [46], and Pawlak's rough set theory (2012–1991), have significantly advanced the field. These models offer sophisticated tools for data classification, hierarchical decision-making, and the analysis of imprecise data.

Recent research continues to highlight the relevance of combining traditional and modern models for improved bankruptcy prediction. Studies by Shi and Li [81] and Durica et al. [30] emphasize the effectiveness of logistic regression models and neural networks [20], and the combination of multiple discriminant analysis, logit models [60], and neural network back-propagation, respectively. This integrated approach aims to enhance the accuracy and reliability of financial distress forecasts, indicating a nuanced method for bankruptcy forecasting.

Moreover, research by Yu et al. [82] on the Leave-One-Out-Incremental Extreme Learning Machine (LOO-IELM) model focuses on financial parameters essential for assessing bankruptcy risks, employing a systematic learning approach for accurate and swift forecasts. Similarly, studies by Tobback et al. [44] have incorporated connectivity data and industry-specific characteristics into bankruptcy prediction models. This integration of relational and financial data has been shown to improve the models' performance in forecasting high-risk enterprises.

This ongoing research evolution demonstrates a sophisticated approach to bankruptcy prediction, underlining the importance of combining various models for more accurate and reliable forecasting. The integration of traditional statistical methods with cutting-edge AI and ML techniques offers a comprehensive toolkit for navigating the complexities of financial distress prediction.

Over the last century, bankruptcy forecasts have become a key component of financial studies, providing a link between financial theory and market development. These forecasts help to understand economic crises and to plan for the tourism sector.

2.2 Focus on the Belgium's Context

Belgium's economic performance has been a subject of considerable interest, particularly in light of its recovery from the COVID-19 crisis. In 2022, the nation's GDP was ranked 25th globally by the World Bank, amounting to a total of $578.6 billion. This marked a significant rebound, with a 5.9% increase in GDP, culminating in a 3% growth rate. Despite this economic recovery, Belgium experienced a notable rise in corporate bankruptcies, climbing from 6533 cases in 2021 to 10,243 in 2023, as reported by Statista [57]. This increase occurs within Belgium's complex linguistic and cultural landscape, comprising Wallonia, Flanders, and Brussels, presenting a unique opportunity to apply and evaluate a variety of analytical methods within academic literature to enhance bankruptcy prediction models.

The intricate economic environment of Belgium serves as an excellent backdrop for integrating traditional economic research with advanced analytical techniques. Cultrera et al. [27] utilized logistic regression to predict insolvency among Belgian SMEs based on financial metrics. Although specific ratios and their impacts were not detailed, related studies have indicated that financial ratios particularly those related to liquidity, profitability, and solvency are significant predictors of bankruptcy. These studies generally conclude that declining profitability, increased indebtedness, and liquidity issues escalate the risk of bankruptcy.

Further exploring the potential of logistic regression and machine learning for bankruptcy prediction, Brédart [15, 16] concentrated on financial statistics. These studies propose that financial ratios effectively distinguish between bankrupt and solvent companies, with particular emphasis on ratios reflecting operational efficiency, financial leverage, and liquidity. Both logistic regression and machine learning models were employed to elucidate how these financial indicators influence bankruptcy risk, focusing on key metrics such as return on assets, current ratio, and solvency ratios.

In a comprehensive study by Cultrera and Brédart [26], logistic regression was applied to assess the predictive power of financial ratios over a decade across 7152 Belgian SMEs. This research utilized ratios like debt to equity, quick ratio, and net margin to evaluate financial health, measuring a firm's ability to meet its obligations and maintain operational efficiency and sustainable growth. The findings underscore the importance of these financial health indicators in forecasting financial distress.

Shetty et al. [43] further advanced this line of inquiry by employing sophisticated machine learning techniques to predict bankruptcy among Belgian SMEs, using return on assets, current ratio, and solvency ratio. The high predictive accuracy (82–83%) of these ratios underscores their significance in bankruptcy prediction, highlighting the importance of profitability, liquidity, and solvency as critical indicators.

The body of Belgian research suggests that financial indicators can effectively predict bankruptcy, and that different data sources and analysis methodologies are useful. This study explores the complex link between financial measures such as profitability, liquidity, and solvency, and their ability to predict bankruptcy in the Belgian economy, thereby enhancing both academic and practical knowledge of financial distress indicators [16]. The use of subject matter experts and data from large companies provides a comprehensive economic picture and in-depth information. This helps stakeholders understand how financial health indicators evolve across company size and industry sectors, enabling them to adapt their strategies and operations [27].

2.3 Bankruptcy Prediction in the Tourist Industry: Highlighting Research Gaps

The advancement of bankruptcy prediction models for the tourism sector has become a significant area of academic focus, especially in the aftermath of the COVID-19 pandemic [39]. Researchers García and Miguélez [34] devised a model specifically for the tourism industry, targeting businesses such as hotels, restaurants, and travel agencies. They analyzed data from 406 Spanish companies using sophisticated artificial neural network techniques, finding that their comprehensive model surpassed other specialized models in predicting business failures. Similarly, Goh et al. [38] explored the effectiveness of financial ratios in forecasting bankruptcies within the tourism and hospitality sectors. By applying Altman's Z-score model, they assessed the financial health of the travel conglomerate Thomas Cook over a decade, underscoring the reliability of financial ratios as indicators of fiscal stability.

Wieprow and Gawlik [84] utilized multiple discriminant analysis (MDA) and logit models [37] to evaluate the bankruptcy risk of Polish tourism firms during the pandemic. Their research confirmed the predictive accuracy of these models for the Polish tourism sector. These studies collectively underscore the relevance of financial ratios and management practices in evaluating the viability of tourism businesses, marking a vital direction for future research to ensure the sector's sustainability amidst challenges.

In 2022, Matejić et al. delved into the impact of the COVID-19 crisis on the bankruptcy risks of 100 Serbian hotel companies. Employing five advanced structural time series models, including aspects of Altman's EM Z-score model, they observed an increasing trend in bankruptcy risk from 2020, which is anticipated to continue until 2023. The following year, Nagendrakumar et al. [78] examined the financial difficulties confronting the travel and tourism industry in various countries, both developed and developing, including the US, Australia, Singapore, South Africa, Malaysia, and Sri Lanka. Through the use of Altman's Z-score model, they identified a substantial number of companies in financial distress.

The discourse on business failure encompasses various perspectives, each attributing financial distress to different causes. Marco [70] and Guilhot [42] adopted an economic viewpoint, shedding light on the overarching economic factors leading to business failure. Concurrently, Laitinen [64] and Van Caillie and Dighaye [45] investigated how firms' strategic decisions impact financial outcomes, emphasizing the significance of such choices for a company's financial well-being. From an administrative and managerial angle, Argenti [9], Daigne [28], and Cormier et al. [24] discussed how management and administrative processes contribute to financial failures, identifying these issues as primary causes of bankruptcy.

Our research takes a financial perspective, underlining the crucial role of predictive models in bankruptcy forecasting. These models rely on financial statistics as their primary predictive tool, offering a rapid assessment of a company's financial health. Du Jardin [29] has notably compiled an exhaustive list of 50 financial metrics, meticulously derived from accurate balance sheet data. These metrics fall into four main categories: cash flow, solvency, profitability, and structure, with most studies utilizing annual data from the year preceding bankruptcy.

The primary aim of our study is to identify the most crucial financial metrics for the Belgian tourism industry. Table 1 showcases a wide range of studies within the Belgian context related to failure modeling. We investigate how each category of financial ratios might influence the future bankruptcy probability of Belgian tourism enterprises. The financial ratios used in the table are organized based on Du Jardin's [29] initial set of variables. By employing this research approach, our study enriches existing literature, offering more nuanced, context-specific insights into the financial factors influencing the success and longevity of tourism businesses.

The development of bankruptcy prediction models, especially in the tourism sector, has become a significant focus of academic research in the aftermath of the COVID-19 pandemic. Notably, researchers García and Miguélez [34] devised a model specifically for the tourism industry, targeting entities such as hotels, restaurants, and travel agencies. Their study, which analyzed data from 406 Spanish companies using advanced artificial neural network techniques, demonstrated that their comprehensive model outperformed other specialized models in predicting business failures.

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Wieprow and Gawlik [84] assessed the bankruptcy risk of Polish tourism firms during the pandemic using multiple discriminant analysis (MDA) and logit models. Their findings affirmed the predictive accuracy of these models for the Polish tourism industry. Collectively, these studies emphasize the significance of financial ratios and

Table 1 General study for assessing bankruptcy in touristic firms

Study	Authors	Country	Data	Estimation method	Structure and financial ratios used	Error rate (%)
A logistic regression analysis for predicting bankruptcy in the hospitality industry	Kim and Gu [56]	U.S	32 firms between 1999 and 2004	Logistic Regression	– **Profitability**: ROA; Gross profit margin; Net profit margin; Gross return on assets – **Solvency**: total liabilities/ total assets; Times interest earned ratio – **Liquidity**: Current ratio; Quick ratio; Operating cash flows/current liabilities; Debt ratio – **Turnover**: Total assets turnover; Fixed assets turnover – **Structure**: Long-term debt/total capitalization	Logit = 9
Prediction of hotel bankruptcy using support vector machine, artificial neural network, logistic regression, and multivariate discriminant analysis	Kim [58]	Korea	–	Support vector machine, artificial neural network, logistic regression, and multivariate discriminant analysis	– **Profitability**: Ordinary Income to Owner's Equity (ROE) – **Solvency**: Debt-Equity Ratio – **Liquidity**: Quick Ratio – **Turnover**: Account Receivable Turnover – **Growth**: Growth in Assets	MDA = 27.4 Logit = 20 ANN = 12.1 SVN = 4

(continued)

Table 1 (continued)

Study	Authors	Country	Data	Estimation method	Structure and financial ratios used	Error rate (%)
Hospitality Bankruptcy in United States of America: A Multiple Discriminant Analysis-Logit Model Comparison	Barreda and al. [10]	U.S	30 touristic firm (restaurants and hotels) between 1992 and 2010	Logistic regression, MDA	– **Profitability**: ROA – **Solvency**: Debt/equity – **Liquidity**: Working capital/Total assets – **Turnover**: Sales/Total assets	Logit = 23.3

(continued)

Table 1 (continued)

Study	Authors	Country	Data	Estimation method	Structure and financial ratios used	Error rate (%)
Predicting hospitality financial distress with ensemble models: the case of US hotels, restaurants, and amusement and recreation	Kim [61]	U.S	5812 eating Places, 7011 hotels and motels, 7990, between 1988 and 2010	multivariate discriminant analysis (MDA) logistic regression models	– **Profitability**: Net Profit margin; Operating income margin; ROCE (Return on common equity); ROE; Operating income to shareholders' equity ratio – **Solvency**: Debt-to-equity ratio; Fixed assets to long-term capital ratio; Operating CF/TD – **Liquidity**: Current ratio; Quick ratio; Account receivable turnover; Operating CF/CL – **Activity:** Total asset turnover; Inventory turnover in days; Fixed asset turnover – **Growth**: Growth in revenue; Growth in assets; Growth in operating income; Growth in net income; Growth in owners' equity	Restaurant model = 2.18 Hotel model = 4.43 Amusement model = 9.03

(continued)

Table 1 (continued)

Study	Authors	Country	Data	Estimation method	Structure and financial ratios used	Error rate (%)
Influence of firm characteristics and the environment on hotel survival across MSMES segments during the 2007–2015 period	Vivel-Búa et al. [50]	Spain	11 558 hotels, between 2007 and 2015	Hazard model	– **Profitability**: ROA – **Solvency**: Debt/equity; Total Liabilities/Total Assets – **Liquidity**: Working capital/total assets) * 100 – **Cash Flow**: Cash Flow/ Total Sales – **Turnover**: Sales/Total assets	–
Survival of the fittest: tourism exposure and firm survival	Caires et al. [20]	Portugal	2006 and 2017	hazard model	– **Profitability:** ROA; – **Solvency**: Debt-obtained funds/total assets – **Liquidity**: Working capital/total assets) * 100 – **Structure:** fixed assets/ total assets (**tangibility**)	–

management practices in evaluating the viability of tourism businesses, marking a crucial area for future research to ensure the sector's sustainability amidst challenges.

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The discourse on business failure spans various perspectives, each attributing financial distress to different causes. Marco [70] and Guilhot [42] approached the issue from an economic standpoint, shedding light on general economic factors leading to business failure. Concurrently, Laitinen [64] and Van Caillie and Dighaye [45] examined how firms' strategic decisions influence financial outcomes, emphasizing the significance of such decisions for a company's financial health. From a different perspective, Argenti [9], Daigne [28], and Cormier et al. [24] discussed the administrative and managerial aspects of bankruptcy, arguing that issues within management and administrative processes are major contributors to financial failure.

Our study adopts a financial perspective, underscoring the pivotal role of predictive models in forecasting bankruptcy. These models leverage financial statistics as primary predictive tools, offering a quick glimpse into a company's financial condition. Du Jardin [29] compiled an exhaustive list of 50 financial metrics derived from precise balance sheet data, encompassing cash flow, solvency, profitability, and structural ratios. Typically, the examination of these ratios involves annual data from the year preceding bankruptcy.

The main aim of our study is to identify the most crucial financial measures for the Belgian tourism industry. Our research method enriches existing literature by providing more detailed and context-specific insights into the financial factors influencing the success and longevity of tourism businesses, structured based on Du Jardin's [29] initial set of variables.

Hypothesis 1: A higher return on assets (ROA) decreases the likelihood of bankruptcy within one year.

Examining solvency is essential for evaluating the likelihood of bankruptcy. The debt ratio is a financial metric that quantifies the extent to which a company's total assets are funded by debt. It is determined by dividing total liabilities by total assets. A high debt ratio suggests a greater dependence on debt for funding business activities, which in turn increases the likelihood of bankruptcy, especially in times of downturn in the tourism industry. Conversely, a low debt ratio might indicate a more prudent and risk-averse strategy. Within the volatile tourism landscape, a high debt ratio may signal financial instability and a heightened likelihood of bankruptcy among tourism SMEs. Hence, we propose the following hypothesis:

Hypothesis 2: A higher debt ratio increases the likelihood of bankruptcy within one year.

Analyzing asset structure, specifically asset tangibility, pertains to the ratio of physical assets to intangible assets. Tangible assets, such as equipment, buildings, and inventories, serve dual purposes: they represent the company's asset composition and investment approach, while also influencing its liquidity and capacity to quickly convert assets into cash. In the sensitive tourism sector, a lack of tangible assets may indicate higher risk during periods of financial limitation. Therefore, we propose the following hypothesis:

Hypothesis 3: Higher asset tangibility reduces the likelihood of bankruptcy within one year.

Liquidity analysis is particularly important in assessing the financial health of companies, especially in the tourism industry, as it helps gauge their ability to meet short-term obligations. According to Altman [6], liquidity ratios like the working capital ratio showed greater statistical significance when compared to other liquidity ratios (such as the current ratio and quick ratio). The working capital ratio measures a firm's net liquidity and is defined as the difference between current assets and current liabilities relative to total assets Toudas et al. [72]. Accordingly, we propose the following hypothesis:

Hypothesis 4: A higher working capital ratio decreases the likelihood of bankruptcy within one year.

3 Materials and Methods

3.1 Sample and Data

In 2021, Belgium's tourism sector demonstrated resilience following the pandemic, with significant recovery across regions like Flanders, Wallonia, and Brussels. These areas contributed 4.3%, 5.3%, and 4.1%, respectively, to the Gross Value Added (GVA) in 2016. Despite a sharp decline in foreign visitors to 1.8 million in 2020, there was a notable recovery to 2.3 million tourists in 2021. The rate of domestic tourist stays in hotels significantly increased from 42 to 63%, leading to a total of 11.0 million tourists visiting Belgium, predominantly from France, the Netherlands, and Germany. The sector is anticipated to fully recover by 2025, according to the OECD [79].

This study delves into predicting bankruptcy likelihood in small and medium-sized enterprises (SMEs) within the Belgian tourism sector. SMEs are generally defined based on factors such as employee count, total revenue, and capital. According to the European Commission [32], as explained by Lambrecht and Pirnay [60] and Schepers et al. [53], SMEs are categorized as companies with fewer than 250 employees, annual sales below €50 million, and a balance sheet total under €43 million.

Focusing on hotels (151 businesses), restaurants (670 businesses), and travel brokers (260 businesses), as detailed by Kim [61], this study aims to offer a comprehensive assessment of financial health in these sectors. This selection was made to ensure access to detailed financial data and to cover a significant portion of the tourism industry in Belgium, thereby providing a thorough overview of bankruptcy risk for SMEs in this sector.

Utilizing a dataset of 1070 active Belgian tourism enterprises from 2018 to 2022, sourced from the Bureau Van Dijk database, this research includes accounting characteristics and bankruptcy details of these firms. To enhance the model's robustness and reliability, a stratified sampling technique was employed, dividing the sample into a training group of 749 firms (70% of the total) and a control group of 321 businesses (30%). This division allows for the effective training and evaluation of the model's accuracy in predicting bankruptcy.

3.2 Measures

3.2.1 Dependent Variable

This paper examines "firm bankruptcy" as a binary variable by reviewing various academic literature, including papers from Belgium and throughout the globe. This technique highlights the significance of logistic regression models in examining the financial health of Belgian enterprises, as shown by research conducted by Brédart [15], Brédart et al. [16], Cultrera et al. [27], and Cultrera and Brédart [26]. The research studies use dummy variables to differentiate between bankrupt and non-bankrupt enterprises, improving the accuracy and interpretability of the model.

3.2.2 Independent Variable

Academic research on firm performance identifies the Return on Assets (ROA) ratio as vital to profitability assessment. ROA compares net income to total assets to determine a company's asset base profitability [19]. Its ability to anticipate a firm's internal operational efficiency and profitability makes it popular in bankruptcy prediction studies. Cultrera et al. [27] found a negative link between ROA and financial troubles, indicating that high ROA values indicate good management and lower bankruptcy risk. The debt ratio shows the amount of a company's assets backed by debt, which helps assess leverage and financial risk [44]. The debt ratio in prediction models is important since a company's bankruptcy risk grows when its debt exceeds its assets. This debt ratio shows a company's financial leverage. Brédart et al. [16] endorse the debt ratio as a valid predictor of financial instability, highlighting its importance in predictive analytics.

Tangibility compares fixed assets to total assets to reveal a company's asset mix and financial strength. Tangible assets are a company's physical and financial support system that may be transformed into cash in emergencies, impacting bankruptcy risk. Kim [58] suggested that the tangibility ratio affects financial stability and predicts company bankruptcy. Working capital shows a company's liquidity by displaying its ability to settle short-term loans with current assets [56]. Working capital indicates a company's capacity to run its operations and pay its bills. Shetty et al. [43] found that working capital ratios indicate insolvency. Insufficient working capital ratios were linked to more bankruptcies, proving the ratio's analytical relevance.

According to the literature, return on equity, leverage, tangibility and working capital are key predictors of SME failure, particularly in the tourism sector. They help determine financial health by focusing on profitability, leverage, structure, and liquidity. Existing research documents the robust quantitative effects of various actions, helping stakeholders navigate the complex environment of financial stability. Table 2 shows the measures of each ratio, calculated, in our case, from the most recent balance sheet data, prior to the insolvency of the now inactive companies. For organizations that are operational today, the values of the variables used are aligned with those applicable to the year 2022.

3.3 Estimation Method

Several studies on tourism and Belgian research have proven that the logistic regression model can effectively analyze the link between financial variables and firm survival. Belgium-based studies by Brédart [15], Brédart et al. [16], Cultrera et al. [27], and Cultrera and Brédart [26] utilized logistic regression to detect patterns of financial distress. Similarly, Kim [58], Barreda et al. [10], and Kim [61] emphasize how the model's widespread application in industries like tourism enhances its role in predictive analytics. Predicting bankruptcy involves successfully combining an internal binary variable with a linear sum of external financial data. This method is essential for studying corporate degradation indicators from fresh perspectives.

According to Liao [67], the logistic regression model, often known as logit, demonstrates the connection between a binary dependent variable (1 for an active company, 0 for an inactive firm) and several explanatory variables ($X_1, X_2, \ldots, X_n$), such as financial ratios [83]. The dependent variable follows a Bernoulli distribution, where "$P_i = P(Y_i = 1)$" represents the likelihood of bankruptcy, and "$1 - P_i$" signifies the likelihood of non-bankruptcy [26]. The estimated model requires the endogenous variable, indicating a linear expression of the exogenous variables.

$$Y_i = \beta X_i + \varepsilon_i \tag{1}$$

where ε is the error term and β the vector of coefficients

According to Ohlson [83], P is positively related to Y the formula of the logit model can be written as follows [56, 80]:

Table 2 Variables definition and measurement

	Variable	Proxy	Abbreviation	Measurement	Expected impact	Source
Dependent variable	Firm bankruptcy		FB	Dummy indicator (1 if the firm is bankrupt firm, and 0 otherwise)		Ohlson [83], Cultrera and Brédart [26], Ogachi et al. [80]
Independent variable	Profitability	Return on asset	ROA	Net income/ total assets	−	Barreda et al. [10], Kim and Gu [56], Caires et al. [20]
	Solvency	Debt ratio	DEBT	Total debt/ total assets	+	Kim and Gu [56], Vivel-Búa et al. [50]
	Structure	Tangibility	TANG	Fixed assets/ total assets	−	Pisula [59], Caires et al. [20]
	Liquidity	Working capital	WC	(Current assets − currents liabilities)/ total assets	−	Ogach et al [80] Rahman et al. [47], Vo et al [], Metaxas and Romanopoulos [77], Rodeiro-Pazos et al. [70]
Control variable	Age	Firm's age	AGE	Creation year − last active year	−	Cultrera and Brédart [26], Caires et al. [20]
	Size	Firm size	SIZE	Ln (total assets)	−	[62], Caires et al. [20], Gémar et al. [35]
	Industry	Firm's industry	SEC	Sec1 = hotel; Sec2 = restaurant; Sec3 = travel agency	+	Caires et al. [20], Wieprow and Gawlik [84], Barreda et al. [10]

The codes «5510—Hôtels et hébergement similaire», «5610—Restaurants et services de restauration mobile», «7911—Activités des agences de voyage» were created using NACE codes

$$Y = \log\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_k X_{ik} + \varepsilon_i \qquad (2)$$

where:

- Y_i is the **dependent variable** for firm *i* (1 for bankrupt, 0 for non-bankrupt).
- $P(Y_i = 1)$: Probability of bankruptcy for firm i.
- Logit $(P(Y = 1))$ is the natural logarithm of bankruptcy for firm i
- $X_{i1}, X_{i2}, \ldots, X_{ik}$ are the exogenous variables for firm *i*.
- $\beta_0, \beta_1, \ldots, \beta_k$ are the coefficients to be estimated.
- ε is the error term.

According to Cultrera and Brédart [26], The probability of bankrupt (a posteriori) of firm i is given by:

$$\mathrm{P(Y_i = 1) = P_i}$$

Similarly, the probability of survival (a posteriori) for firm i is:

$$\mathrm{P(Y_i = 0) = 1{-}P_i}$$

In this paper, the first logistic regression equation can be written as:

$$Logit\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 ROA_{i,1} + \beta_2 Debt_{i,2} + \beta_3 TANG_{i,3} + \beta_4 WC_{i,4} + \beta_5 Size_{i,5} + \beta_6 AGE_{i,6} + \varepsilon_i \tag{3}$$

The β coefficients will be estimated using the method of maximum likelihood.

Hence, the predicted likelihood of a company facing financial bankruptcy, denoted as P_i, is stated as follows:

$$P_i = \frac{1}{1 + e^{-\left(\beta_0 + \beta_1\, ROA_{i,1} + \beta_2 DEBT_{i,2} + \beta_3\, TANG_{i,3} + \beta_4 WC_{i,4} + \beta_5 AGE_{i,5} + \beta_6\, SIZE_{i,6} + \varepsilon i\right)}} \tag{4}$$

4 Findings

4.1 Descriptive Statistics

Table 3 categorizes the analyzed data into two groups: Bankrupt companies and Active enterprises, revealing significant differences in their financial profiles. Non-bankrupt organizations exhibit an average Return on Assets (ROA) of 4.369, in contrast to bankrupt firms, which have an average ROA of − 0.532. This disparity underscores that active firms are generally more profitable than their bankrupt counterparts, highlighting that companies facing bankruptcy typically suffer from poorer performance and greater volatility.

Moreover, the analysis indicates a nuanced trend in debt levels between the two groups. Active businesses maintain a moderate average debt ratio of 0.751, slightly lower than the 0.762 average for insolvent companies. This pattern suggests a tendency toward increased borrowing among businesses that eventually fail.

In terms of asset tangibility, non-bankrupt enterprises boast a significantly higher average of 0.363, with a standard deviation of 0.286, compared to a mere 0.160 for unsuccessful firms. Financial analyses reveal that thriving tourism companies are

Table 3 Descriptive statistic on bankrupt and non-bankrupt touristic firms

Bankrupt firms						Non-bankrupt firm					
Variable	Obs.	Mean	Std. dev.	Min	Max	Variable	Obs.	Mean	Std. dev.	Min	Max
ROA	535	− 0.532	16.07	− 47.81	46.50	ROA	535	4.369	15.188	− 47.86	46.72
DEBT	535	0.762	1.176	0	9.011	DEBT	535	0.751	0.7817	0.011	8.391
TANG	535	0.160	0.261	0	0.983	TANG	535	0.363	0.286	0	0.983
WC	535	− 0.60	1.12	9.88	13.81	WC	535	0.0296	0.759	− 6.52	5.267
AGE	535	2.48	0.830	0	4.430	AGE	535	2.902	0.728	1.38	4.80
Size	535	2.82	0.413	1.79	3.76	Size	535	3.089	0.778	1.791	4.938

characterized by higher levels of tangible assets, likely contributing to their stability and resilience.

The study also examines the working capital ratio, finding that operational businesses have a positive average of 0.0296, whereas failing organizations show a markedly negative average of − 0.60. This indicates that bankrupt firms typically face more immediate financial obligations than they can meet with their current assets, potentially forcing them to liquidate assets to address liquidity issues.

Additionally, active enterprises display greater leverage in terms of size and age, with mean values of 2.902 and 3.089, respectively, compared to bankrupt firms, which have mean values of 2.48 and 2.82. This descriptive analysis suggests that active firms are generally larger and older, indicating attributes of higher maturity compared to those that have gone bankrupt.

Overall, the financial data analysis delineates clear differences between bankrupt and active companies, with active enterprises demonstrating superior profitability, asset tangibility, and financial stability. This comprehensive evaluation highlights the critical financial indicators distinguishing successful from failing businesses within the context examined.

4.2 Correlation and VIF Results

Table 4 presents the results of the Pearson correlation analysis, confirming that there are no concerns of collinearity within the data, as all coefficients fall below 0.8. The correlation matrix reveals a significant negative association (below the 1% threshold) between firm bankruptcy (FB) and several variables: return on assets (ROA), tangibility of assets (TANG), working capital (WC), age (AGE), and company size (SIZE). Specifically, the strong negative correlation of − 0.155 between FB and ROA underscores the vital role profitability plays in an organization's long-term viability. Furthermore, a negative correlation of − 0.3475 between FB and TANG

Table 4 Pearson correlations

Variables	FB	(1)	(2)	(3)	(4)	(5)	(6)
FB	1.000						
(1) ROA	– 0.1550***	1.000					
(2) DEBT	0.0053	– 0.0985***	1.000				
(3) TANG	– 0.3475**	– 0.0430	0.1542***	1.000			
(4) WC	– 0.2053***	0.0772**	– 0.3340***	– 0.0722**	1.000		
(5) AGE	– 0.2588***	0.0711**	– 0.0835***	0.0524*	0.1928***	1.000	
(6) SIZE	– 0.2088***	0.0435	– 0.0100	0.0521*	0.0473	0.0297	1.000

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

suggests that tourism firms with a considerable amount of tangible assets are likely to be more stable and financially robust.

The statistical analysis also demonstrates a significant negative correlation between FB and WC, with a coefficient of – 0.2053. This finding indicates that Belgian tourism businesses facing financial difficulties often grapple with liquidity problems, struggling to meet financial obligations, especially during crises. Additionally, the debt ratio (DEBT) has a non-significant correlation of 0.0053, implying that high levels of debt do not have a strong association with bankruptcy in this sample.

Furthermore, a negative correlation of – 0.258 between AGE and FB highlights how experience, reputation, and established business relationships significantly contribute to a company's success. Lastly, the correlation of – 0.2088 between company size and FB indicates that firm size is a critical factor, with a significant impact at the 1% level in our dataset.

4.3 Logistic Regression Model Results

The analysis of our bankruptcy prediction model, which includes 1070 data points, shows an R-squared value of 0.2545, indicating a modest portion of variance explained by the model. A significant LR chi-square statistic (377.50) with a p-value (0.000) suggests the model's predictive superiority over a null model. The model's constant term is significant at 1.997, implying positive log odds when all variables are zero.

The Return on Assets (ROA) is significantly negative (– 0.0229), highlighting its importance in predicting bankruptcy in the volatile tourism sector. The leverage ratio showed a negative but statistically insignificant coefficient (− 0.06098; p = 0.474), suggesting minimal impact on prediction. Conversely, the tangibility ratio (− 3.081) significantly predicts higher firm resilience in tourism.

Working capital's strong negative correlation (− 0.4036) with bankruptcy underscores the inverse relationship between liquidity and bankruptcy risk. Organizational longevity and size, with coefficients of − 0.4884 and − 0.8011 respectively ($p < 0.01$), indicate that experience and scale significantly benefit firm performance, especially in Belgium (Table 5).

The chi-squared test plays a crucial role in assessing the precise calibration of our model during adjustment. The results of two goodness-of-fit tests, Pearson's chi-squared test (p = 0.555) and the Hosmer–Lemeshow test (p = 0.710), show that both tests yield p-values greater than 0.05. This indicates that the model fits the data well, with no need for further adjustments. Consequently, there is no reason to reject the null hypothesis, which posits the absence of significant discrepancies between the observed and predicted values.

Evaluating a predictive model's effectiveness in forecasting corporate insolvency focuses on its accuracy in identifying at-risk companies using historical and current financial data. The model demonstrated an accuracy rate of 81.87%, correctly identifying 876 out of 1070 instances. This performance slightly surpasses that of a control group, which achieved an 81.71% accuracy rate, and closely matches the validation cohort's 81.93%, showcasing the model's robust discriminatory capabilities.

The findings affirm the model's strong potential to predict corporate bankruptcies a year in advance, particularly within the Belgian tourism sector. This predictive capacity provides stakeholders with critical insights, enabling them to devise effective financial strategies and implement risk mitigation measures (Table 6).

Table 5 Logistic regression results

	Coefficient	Standard error
ROA	− 0.02291***	(0.004)
DEBT	− 0.06098	(0.085)
TANG	− 3.081***	(0.301)
WC	− 0.4036***	(0.071)
AGE	− 0.4884***	(0.100)
SIZE	− 0.8011***	(0.131)
Industry effect	Yes	
Constant	1.997**	(0.933)
Observations	1070	
R squared	0.2545	
LR chi2	377.50(8)	
Prob > chi2	0.000	
Log likelihood	− 552.91648	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6 Classification and prediction results

Observations	Status	% of good predictions	% of incorrect predictions
1070	Bankrupt	83.74	16.26
	Non-bankrupt	80.00	20.00
	Global	81.87	18.13

In addition, The Area Under the Curve (AUC) is a statistical measure that provides a summary of performance across all classification criteria. Our model shows an AUC = 0.9171 in our curve, suggests that the model is very capable of reliably differentiating between the positive (bankrupt) and negative (non-bankrupt) classes. The AUC quantifies the model's ability to predict more true positives while minimizing false positives. The large Area Under the Curve (AUC) suggests that the logistic regression model is effective in forecasting bankruptcy, making it a valuable tool for financial risk evaluation.

5 Discussions

The tourism sector is marked by considerable fluctuations and rapid changes, primarily due to its susceptibility to evolving economic environments. This characteristic exposes businesses within the sector to heightened risks of financial distress, particularly when management practices, especially those related to financial stewardship, are lacking. The essence of this study is to shed light on the bankruptcy risks currently affecting small and medium-sized enterprises (SMEs) in Belgium's tourism sector, with a focus on the increasing prevalence of these risks.

Our investigation encompasses an analysis of 1070 tourism-related enterprises, including hotels, restaurants, and travel agencies, during the period from 2018 to 2022. Of these, 535 firms were observed to have filed for bankruptcy. We employed logistic regression, a method praised for its contributions to finance and management scholarship [81], to determine the likelihood of business failure. The model uses four key financial ratios, profitability (ROA), leverage (DEBT), asset structure (TANG), and liquidity (WC), alongside control variables such as company age, size, and sector-specific activities to account for the heterogeneity among the sampled firms.

The logistic model findings confirm the anticipated early effects documented in the literature. Goodness-of-fit tests, including the Hosmer–Lemeshow test ($chi2 = 3.75$; $p = 0.71$), show a strong agreement between observed and projected frequencies, demonstrating the model's suitability for Belgian tourism SMEs. The model's overall performance, with an accuracy of 81.87%, supports its validity. Our results confirm that return on assets (ROA) is a significant indicator of sustainability for Belgian tourism companies, with a negative coefficient ($\beta = -0.026$; $p < 0.01$) in relation to failure. This aligns with Barreda et al. [10] findings, identifying ROA as a crucial factor affecting company survival in the tourism industry. Studies suggest that increased profitability enhances long-term viability [2, 7, 40, 50, 69].

The model indicates that the debt ratio (DEBT) is inversely correlated with bankruptcy, but its lack of statistical significance ($\beta = -0.06098$; $p = 0.474$) suggests it is not a reliable predictor. This is supported by the correlation matrix, which shows a positive link between debt levels and bankruptcy (0.0053), in line with financial theory suggesting that high debt increases the risk of financial difficulties and bankruptcy. Similar results were found by Barreda et al. [10], indicating that collapsed hotel enterprises from 1992 to 2010 had lower liquidity, higher debt ratios, and poorer returns on equity, signaling low solvency [3].

The model demonstrates that tangibility (TANG) has a statistically significant explanatory value of − 3.081, suggesting that companies with more tangible assets are less susceptible to bankruptcy in the volatile tourism sector. Caires et al. [20] conducted a similar study, showing that tangible assets are a significant factor in predicting bankruptcy across various tourism sectors, including transport, restaurants, bars, travel agencies, and hotels.

These findings are consistent with agency theory, the behavioral theory of the firm, and strategy theory. As [21] showed, the way assets are invested and ownership is structured impacts a firm's debt capacity. Companies with more physical assets can borrow more and invest more. However, in contrast to resource-based theory, which emphasizes intangible resources, Kamasak [54] found that intangible resources and capabilities are more important to firm performance than tangible resources.

In terms of liquidity, the working capital (WC) variable is significant at the 1% threshold, with a negative coefficient ($\beta = -0.4036$; $p < 0.01$), confirming hypothesis 4: greater liquidity positively affects a company's survival probability in times of crisis. Proper working capital management significantly impacts a company's ability to pay bills, operate efficiently, and maintain financial health. Mohanty and Mehrotra [74] similarly argued that cash is critical for business continuity, as companies with sufficient liquid assets are better able to meet short-term obligations and avoid costly external borrowing, thus reducing financial distress.

Our research demonstrates that company characteristics play a crucial role in predicting bankruptcy. The survival of Belgian tourism firms is significantly influenced by their size ($\beta = -0.8011$) and age ($\beta = -0.8011$), with larger and older firms more likely to survive [26]. The expertise and connections developed over time, alongside personnel and asset size, are valuable assets. This study underscores the importance of sound financial management and strategic planning, which are essential not only for business survival but also for fostering innovation and long-term growth in a sector integral to cultural and economic heritage. Table 7 provides a summary of the study outcomes.

Table 7 Summary of study's results

Hypothesis			Expected Sign	Decision
H1	ROA	→ Firm bankruptcy	–	Supported
H2	DEBT	→ Firm bankruptcy	+	Rejected
H3	TANG	→ Firm bankruptcy	–	Supported
H4	WC	→ Firm bankruptcy	–	Supported
H5	Age	→ Firm bankruptcy	–	Supported
H6	SIZE	→ Firm bankruptcy	–	Supported

6 Conclusions

This study aims to enhance the understanding of bankruptcy prediction within small and medium-sized enterprises (SMEs) in the Belgian tourism sector through the application of logistic regression analysis. A critical review of the existing literature reveals widespread coverage of bankruptcy prediction across various geographic and business contexts. However, there is a notable gap in Belgian academic research concerning the application of advanced statistical methods for bankruptcy prediction specifically within the tourism industry, a gap not observed in countries like Spain and Portugal, where the economic significance of tourism is extensively explored.

Our analysis identifies several key predictive indicators of bankruptcy, most of which are significant at the $p < 0.01$ level, except for the debt ratio. Asset tangibility stands out as a potent predictor, with a coefficient of − 3.081. Firm-specific characteristics such as size and age also play critical roles, highlighting the importance of working capital (coefficient: − 0.4036) and profitability (coefficient: − 0.0229) in forecasting bankruptcy. This study aligns with the works of Pompe and Bilderbeek [71] and Hamza and Baghdadi [48]. Our findings reaffirm the significant predictive power of return on equity and working capital, as concluded by Cultrera and Brédart [26].

By focusing on the underrepresented cohort of SMEs in the Belgian tourism sector, this research fills a critical gap in the existing literature and presents a tailored annual forecasting model. This model holds significant value for both academic contributions and practical applications, offering business managers and banking institutions a tool for informed financing decisions.

This article enhances empirical discussions in Belgium by emphasizing various factors within the tourism industry and calling for more thorough sector-specific research, particularly in catering and hospitality. Future studies could improve this analysis by incorporating additional financial ratios and qualitative factors, such as leadership qualities and governance changes, especially during crises, to gain a deeper understanding of insolvency indicators in the tourism sector.

The adoption of the logistic regression (logit) model in this study is supported by its theoretical robustness and widespread application in scholarly works, such as those of Barreda et al. [10] and Kim [61]. These references underscore the model's suitability for capturing binary outcomes, such as firm bankruptcy, making it an appropriate choice for this research.

Our logistic regression analysis on a dataset of 1070 tourism entities produced a well-calibrated model, as demonstrated by a Pearson test score of 0.555 and a Hosmer–Lemeshow test score of 0.710. The model exhibited strong classification performance, with an accuracy rate of 81.87%. All variables, except for the debt ratio, were statistically significant ($p < 0.01$). The most influential predictor was asset tangibility, with a coefficient of − 3.081. Company size and age had coefficients of − 0.8011 and − 0.4884, respectively, while working capital (− 0.4036) and profitability (− 0.0229) were also significant predictors.

In a world where sustainability is becoming a key priority across industries [12, 63], our study makes a meaningful contribution to the tourism sector by examining how sound financial management and bankruptcy prediction models can support long-term business resilience. In line with the works of Pompe and Bilderbeek [71] and Hamza and Baghdadi [48], our research highlights the importance of profitability and liquidity ratios not only in assessing financial health but also in promoting sustainable business practices. By demonstrating that key financial indicators such as return on equity and working capital [26] are essential for predicting SME survival, we present a model that serves as a strategic tool for fostering economic sustainability and resilience within the tourism sector.

In an industry as vulnerable as tourism, particularly in the Belgian context, the ability to foresee and mitigate financial distress plays a crucial role in ensuring long-term sustainability. Our model, with its superior forecasting accuracy, empowers stakeholders, particularly SMEs, to adopt more sustainable financial practices. By doing so, it strengthens their capacity to withstand economic fluctuations while preserving cultural and heritage assets intrinsic to the tourism industry's value proposition.

This research introduces a novel annual bankruptcy prediction model tailored specifically for Belgian tourism SMEs, a group underexplored in the literature. This focus on financial forecasting addresses a core challenge for the sustainability of tourism enterprises, equipping businesses with the foresight to navigate financial risks. Diversifying methodologies is necessary to capture the complexities of sustainability in tourism. Future research should expand on this by integrating alternative financial ratios and qualitative factors, such as leadership and governance strategies, which are vital for understanding resilience beyond financial metrics [26].

By advocating for sector-specific models, particularly in the hotel and restaurant industries, this study challenges the notion of universal theories of business survival. We emphasize the necessity of tailoring research to reflect the unique financial and operational challenges faced by tourism businesses. Moreover, sustainable financial management is not merely about avoiding bankruptcy, it is about fostering growth that aligns with long-term societal and environmental objectives.

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