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Efficient bankruptcy prediction and its role for a more resilient Alpine tourism

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ABSTRACT

This paper examines the impact of selected variables on the value creation of tourism enterprises in Western Austria (Salzburg, Tyrol, and Vorarlberg) with the objective of developing an insolvency prediction model for Alpine tourism businesses. This study specifically highlights practical applications for business owners, policymakers, and financial institutions, providing strategies to mitigate bankruptcy risks in the tourism sector. The objective of this study is to address existing gaps in the literature regarding the early detection of insolvency in the tourism sector, particularly in German-speaking regions. To this end, a hybrid analytical method is employed, combining quantitative statistical approaches with sector-specific contextual analysis. A dataset comprising tourism firms was divided into two groups, namely solvent and insolvent, with a view to identifying significant explanatory variables influencing insolvency risks. The primary findings indicate that enterprise size, company age, and debt levels (as indicated by the equity ratio) are significant risk factors for insolvency. Furthermore, the results suggest that small and medium-sized enterprises (SMEs) are particularly vulnerable to financial crises. Finally, the findings demonstrate that macroeconomic structures and sectoral effects significantly impact insolvency probabilities. These findings emphasise the necessity for the development of early warning systems that are tailored to the specific requirements of SMEs in Alpine tourism.This research is particularly pertinent in light of the rising insolvency rates in the tourism industry and the lack of comprehensive official statistics, which impede effective crisis management. By addressing these challenges, the study contributes to the development of targeted risk management and intervention strategies to enhance the resilience of tourism enterprises in the region.

Introduction

The challenges faced by tourism businesses have significantly evolved over recent years. Strategies and business models are constantly changing and must be re-evaluated more frequently. This also requires adaptation to a continuously changing environment and its conditions (e.g. global competition including globalisation, e-commerce, outsourcing, new technologies, etc.) to ensure long-term and sustainable survival (Brisson-Banks, 2010; Stanleigh, 2008). This issue appears to be more pronounced in small and medium-sized enterprises, as their managers are often more focused on day-to-day operations, leaving them with less time to address strategic agendas (Brunninge et al., 2007).

Despite the growing importance of tourism to regional economies, research on bankruptcy prediction in the tourism sector, particularly in Alpine regions like Western Austria, remains limited. Existing studies largely focus on large enterprises or specific

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sectors, with few addressing the unique challenges and risk factors faced by small and medium-sized enterprises (SMEs) in the tourism industry. This gap in the literature highlights the need for an integrated approach to insolvency prediction tailored to the characteristics of the tourism sector.

This increases the risk of crises or insolvency. This is also reflected in the causes of insolvency within companies. Fifty-one per cent of insolvencies are caused by internal errors or sources of loss (e.g. lack of commercial foresight, calculation errors, difficulties in sales, insufficient monitoring of the company's environment, etc.). A further 11% are attributed to negligence (e.g. insufficient knowledge of practices and the industry, inexperience, etc.) (KSV1870, 2016). Therefore, it can be concluded that the majority of corporate insolvencies are due to internal factors, primarily management errors (Altman & Hotchkiss, 2006; Collet, Pandit & Saarikko, 2014; Purves et al., 2016).

The case of Tyrol highlights the importance of tourism to the region. Without tourism, Tyrol's gross value added would be 23.9% lower, and employment would be 24.5% lower (Stadler et al., 2016). Therefore, it is imperative to maintain the financial health of tourism businesses and prevent corporate insolvencies in the interest of all stakeholders.

This study contributes to filling this research gap by focusing on the specific needs and challenges of SMEs in the tourism sector. By developing an insolvency prediction model tailored to the unique characteristics of Alpine tourism businesses, this study advances both bankruptcy prediction models and tourism resilience literature.

The development of company closures in Austria is illustrated in Figure 1. Insolvencies were generally examined and specifically for the accommodation and food service sector. It can be observed that there was an increase in company closures in 2009, 2012 and 2011 compared to 2008, which can be attributed to the effects of the global financial crisis. In subsequent years, consolidation is apparent (with a declining insolvency rate).

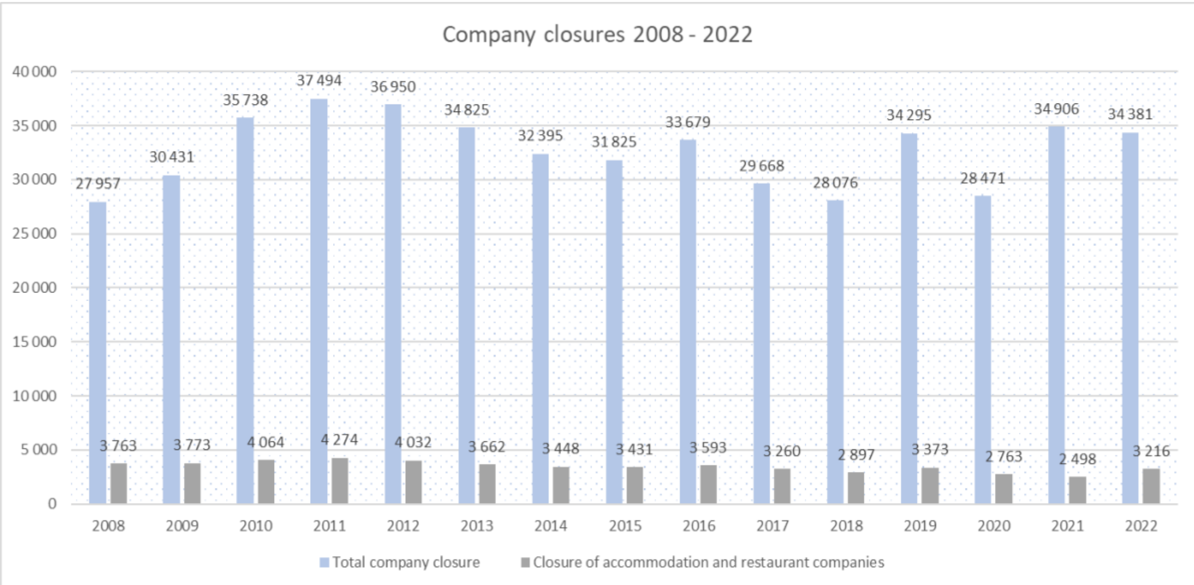

Figure 1: Development of company closures in Austria between 2008–2022; Illustration: authors; **Source**: Statistik Austria (n.d., 2023, 2024)

The proposed study aims to provide valid, representative, and practical answers to the following research questions:

i. What factors or variables distinguish successful from unsuccessful tourism businesses in Western Austria?
ii. What role does profitability play within the industry?
iii. How does the location of the business influence success, which regions are particularly attractive, and what other location factors contribute to sustainable survival?
iv. Which macroeconomic factors can be identified as the key drivers of crises, reorganisation, and insolvency?
v. What variables are crucial for ensuring the long-term viability of a business and preventing crises and insolvency?

These questions will be addressed for Western Austria, with further analysis for each included federal state (Salzburg, Tyrol, and Vorarlberg). This will also help answer the broader question of the commonalities and differences between these federal states.

Literature Review

Most literature does not limit itself to bankruptcy prediction but addresses the broader concept of business failure. Researchers often define this term variably, depending on their study's objectives, allowing considerable flexibility (Dimitras et al., 1996; Gu & Gao, 2000). Youn and Gu (2010) argue that failure involves a breakdown of basic operations due to inadequate capabilities. Tavlin et al.

(1989) further describe this as a condition where a company cannot cover its expenses with revenues. However, a firm's economic activity decline does not always stem from failure, leading to diverse interpretations. To clarify how a business may cease operations, Tavlin et al. categorise financial failures into 'economic failure', 'technical insolvency', and 'bankruptcy'.

The distinction between economic failure, technical insolvency, and bankruptcy is important when considering financial distress theories. Theories of financial distress often draw on these concepts, linking them to models of bankruptcy prediction. Economic failure and technical insolvency can often precede bankruptcy, which is the final stage of a prolonged financial deterioration process. Therefore, understanding the progression from one state to another is crucial for developing accurate bankruptcy prediction models. For instance, the Z-score model by Altman (1968) primarily targets bankruptcy, but it is equally valuable in detecting early signs of technical insolvency, as financial ratios reveal liquidity and solvency weaknesses that may lead to bankruptcy if left unaddressed.

Economic failure denotes a situation where a firm's costs exceed its revenues, often due to capital costs outpacing returns. Technical insolvency arises when liquid assets are insufficient to cover existing debts, yet the firm may still possess a positive net worth. A company can potentially resolve this by converting assets into cash to settle debts over time. Conversely, bankruptcy occurs when liabilities exceed asset valuations, resulting in an inability to meet obligations. This process does not happen suddenly; rather, it encompasses various stages of financial failure, which can be protracted in larger firms, while small and medium enterprises (SMEs) may experience a more rapid progression (Lukason & Hoffman, 2014).

Since this study focuses on bankruptcy prediction in alpine tourism businesses in West Austria, a detailed examination of country-specific regulations is pertinent. Austrian bankruptcy matters are governed by insolvency statutes, particularly articles 66 and 67, which state that initiating insolvency proceedings is contingent upon the debtor's illiquidity, typically evident when payments are suspended (Jusline, 2019a, 2019b). Even partial satisfaction of creditors does not necessarily imply solvency.

In summary, researchers often use various definitions for business failure, including 'bankruptcy', 'default', and 'financial distress' (Gu & Gao, 2000). The ambiguity surrounding these terms leads this study to focus on the definition of bankruptcy under Austrian law. Thus, a clear distinction is made: Austrian alpine tourism companies subject to published insolvency proceedings are considered bankrupt, differentiating them from firms facing financial distress without qualifying for bankruptcy. For this study, 'bankrupt' and 'insolvent' are used interchangeably, representing identical conditions for the firms involved.

Theoretical framework in bankruptcy prediction

Bankruptcy prediction models are inextricably linked to broader financial distress theories. According to the Resource-Based View (RBV) (Barney, 1991), organisations that possess unique and valuable resources are able to achieve sustained competitive advantages, thereby reducing the risk of bankruptcy. Assuming that smaller companies have more often fewer such resources, they, therefore, have a higher probability of insolvency (Parsa et al., 2015).

The Pecking Order Theory (Myers & Majluf, 1984) offers valuable insight into financing behaviors that impact bankruptcy and contextualizes why debt-heavy capital structures exacerbate financial fragility. According to this theory, firms prioritize internal financing, followed by debt, and equity as a last resort. High debt ratios increase insolvency likelihood (Gu & Gao, 2000).

The Institutional Theory, as propounded by North (1990), underscores the salient role that regulatory and macroeconomic environments play in the survival of firms. Hence, an advanced (tourism) infrastructure and government initiatives could potentially lead to reduced bankruptcy rates.

Methods in bankruptcy prediction

This chapter highlights the key techniques for predicting bankruptcy. Based on findings from Du Jardin (2009) and Situm (2016), three primary methods have emerged as effective for constructing prediction models: linear multiple discriminant analysis (MDA), logistic regression, and neural networks. Other methods often fail to provide reliable long-term forecasts, making these three particularly noteworthy.

Linear multiple discriminant analysis

MDA was introduced by Altman (1968) in his 'Z-score model' for bankruptcy prediction. While a few researchers utilise the quadratic version, most prefer the linear approach, which aims to forecast a qualitative dependent variable by categorising observations into mutually exclusive groups, such as bankrupt or solvent firms. Altman (1968, p. 591) describes MDA as "a statistical technique used to classify an observation into one of several a priori groupings dependent upon the observation's individual characteristics."

The definition of distinct groups is crucial for the MDA model, as it uses various independent variables to derive a linear combination that best discriminates between the categories. The resulting discriminant score allows researchers to classify firms into bankrupt or solvent cohorts (Altman, 1968). The Z-score is calculated as follows:

$$\mathbf{Zi = V1X1 + V2X2 + ... + VnXn}$$

Equation 1. MDA function

Where Z = discriminant – or Z-Score

X_j = value of the independent variable (with j = 1, …, n)

V_n = discriminant coefficient (with j = 1, …, n)

The score can range from -∞ to +∞, but classification requires a cut-off point. Altman determined that a score below 2.675 indicates potential bankruptcy within one year, while a score above this threshold suggests solvency. Typically, a high Z-score correlates with a strong financial position (Dimitras et al., 1996).

The accuracy of MDA models is often assessed through type I and II errors, where type I errors represent false positives (misclassifying bankrupt firms as solvent), and type II errors refer to false negatives (classifying solvent firms as bankrupt) (Youn & Gu, 2010). MDA has specific requirements: the groups must be mutually exclusive, independent variables should follow a multivariate normal distribution, and variance-covariance matrices for both groups should be similar.

However, many researchers neglect these assumptions, leading to flawed MDA results (Eisenbeis, 1977). Issues arise when multivariate normality is violated, affecting significance tests and error rate calculations. To mitigate this, techniques like winsorising may eliminate outliers, but these adjustments can distort variable relationships and compromise the model's integrity.

Furthermore, the MDA's strict linear classification can be problematic for variables that do not exhibit such correlation with bankruptcy. The ordinal nature of discriminant scores complicates interpretations, as they do not provide probabilities for bankruptcy occurrence. Additionally, the coefficients do not reveal the relative contributions of the variables, and multicollinearity issues can hinder accurate assessments (Altman, 1968; Eisenbeis, 1977; Taffler, 1982).

In summary, while MDA is a valuable tool for bankruptcy prediction, it requires careful application and consideration of its limitations to ensure reliable results.

Logistic regression

Logistic regression (LR), also known as logit analysis (LA), has emerged as the most popular conditional probability method for bankruptcy prediction, first introduced by Ohlson (1980). While alternatives such as probit analysis and linear probability modelling exist, they are less frequently applied in the literature (Balcaen & Ooghe, 2006; Dimitras et al., 1996). LA employs independent variables to determine the likelihood of a binary outcome, such as insolvency, using a non-linear maximum likelihood estimation that assumes a logistic distribution (Hosmer & Lemeshow, 2000).

Considering the exemplary case aiming to detect the probability of a firm going bankrupt, which rests upon several variables designated in a previous procedure. Then, the vector x'

= (x1, x2, …., xn) entails all independent factors defined before. Further, as already mentioned, LA is based on conditional probability, that is the reason why the likelihood of a firm to become insolvent can be illustrated by $P(Y=1|x) = \pi(x)$, referring to the logistic regression model $\pi(x)$. The calculation of π however, requires the prior classification of the logit of the multiple logistic regression model which is constituted by the following equation (Balcaen and Ooghe 2006; Hosmer and Lemeshow 2000):

$$\mathbf{g(x) = \beta 0 + \beta 1X1 + \beta 2X2 + \ldots + \beta nXn}$$

Equation 2. Logit of the logistic regression model

where β_0 = intercept

β_j = coefficient of the attribute j (with j = 1, …, n) X_j = value of the attribute j (with j = 1, …, n).

The logistic regression model $\pi(x)$ is clarified by applying g(x) (Dimitras et al. 1996):

$$\boldsymbol{\pi}(\mathbf{x}) = \frac{?}{? + \mathbf{e} - \mathbf{g}^{(\mathbf{x})}}$$

Equation 3. Logistic regression model

where e = base of the natural logarithm.

This gives rise to the probability of bankruptcy for a random firm (Balcaen and Ooghe 2006; Dimitras et al. 1996; Hosmer and Lemeshow 2000):

$$\mathbf{P(Y=1|x) = \boldsymbol{\pi}(x) =} \frac{?}{? + \mathbf{e} - \mathbf{g}^{(\mathbf{x})}}$$

Equation 4. Probability function of LA

This probability ranges from 0 to 1, indicating the likelihood of insolvency. A high logit score suggests a higher likelihood of bankruptcy, while a low score indicates solvency. Classification requires a defined cut-off point, which determines the appropriate class for each company based on the ‘resemblance principle’ (Balcaen & Ooghe, 2006).

Logistic regression differs from MDA in that it does not require assumptions regarding the distributions of independent variables and can handle disproportionate samples (Hair, 2010; Ohlson, 1980). However, it necessitates a clearly defined dichotomous dependent variable and a specified cut-off point to manage type I and II error costs (Hsieh, 1993; Ohlson, 1980).

One of the strengths of LA is its interpretability; coefficients reveal the individual contributions of variables to the estimated bankruptcy probability. Additionally, LA easily accommodates dummy variables for qualitative factors (Mensah, 1984; Ohlson, 1980). However, it is sensitive to multicollinearity, outliers, and missing values, which can be mitigated through careful dataset preparation (Balcaen & Ooghe, 2006; Doumpos & Zopounidis, 1999).

Figure 1 illustrates the logistic regression curve, highlighting the relationship between a dependent variable (bankruptcy likelihood) and an independent variable. The curve approaches but never exceeds the limits of 0 (total solvency) and 1 (total bankruptcy), demonstrating the superiority of LA in handling such probabilities compared to linear models (Hair, 2010).

Bankruptcy prediction in general

This section reviews the most influential bankruptcy prediction models, beginning with Beaver (1966) and concluding with Shumway (2001). It also discusses broader studies focusing on specific industries, such as manufacturing and retailing, as Dimitras et al. (1996) highlighted. These models form the foundation of bankruptcy prediction literature, offering insights into various methodologies and approaches used to assess a firm's likelihood of insolvency.

In 1966, Beaver pioneered bankruptcy prediction by applying univariate analysis to assess the financial statements of 79 failed and 79 non-failed enterprises from 1954 to 1964, examining data from one year prior to default. The firms represented 38 distinct industries, focusing on companies neither too small nor too large, with asset sizes between \$0.6 million and \$45.0 million.

Rather than creating new variables, Beaver aimed to validate existing coefficients. He established three criteria for selecting financial ratios, ultimately qualifying 30 factors based on prior literature and their relevance to a “cash-flow concept.” He selected six ratios from these, including cash flow to total debt and net income to total assets, representing the lowest error probabilities over five years.

Beaver conducted a dichotomous classification test to predict bankruptcy likelihood and calculated “likelihood ratios” to assess insolvency probabilities. His analysis indicated that ‘cash flow to total debt’ was the most effective predictor, followed by ‘net income to total assets’.

The model achieved an overall accuracy of 87% in identifying bankrupt firms, with a type I error rate of 21.5% and a type II error rate of 5%. Over a five-year horizon, type I errors increased significantly (up to 42%). Beaver's work highlighted that well-chosen financial ratios could forecast bankruptcy up to five years in advance and stressed the importance of a systematic selection process for these ratios.

Altman (1968)

Altman (1968) critiqued Beaver's univariate approach, introducing his Z-Score model based on Multivariate Discriminant Analysis (MDA). His study examined 33 bankrupt and 33 non-bankrupt firms in the manufacturing sector from 1946 to 1965, ensuring that firms were neither too large nor too small. Altman selected five financial ratios as predictors of bankruptcy, culminating in the equation:

$$\mathbf{Z = 0.012\,X1 + 0.014\,X2 + 0.033\,X3 + 0.006\,X4 + 0.999\,X5}$$

Equation 5. Model of Altman (1968)

Where X1 = ‘working capital to total assets’, the liquidity ratio was applied in virtue of its high statistical significance in univariate analysis

X2 = ‘retained earnings to total assets’, the leverage ratio was used to indicate the age of the firm by referring to cumulative profits which normally are low for young firms

X3 = ‘earnings before interest and taxes (EBIT) to total assets’, the profitability ratio was employed with the objective to merely cover primary operations

X4 = ‘market-value of equity to book value of total debts’, a leverage ratio indicating leeway for the respective company’s assets

X5 = ‘sales to total assets’ (‘total asset turnover’), the profitability ratio revealed the management’s abilities to act within a strong external environment

Z = overall Index.

Ohlson (1980)

Ohlson (1980) devised his own accounting-based concept by employing logistic regression model to predict bankruptcy. With his model he responded to predominant limitations existing in Altman's (1968) MDA method. His study focused on 105 bankrupt and 2,058 non-bankrupt firms from 1970 to 1976, emphasising on size, profitability, leverage and liquidity of the enterprises from which he created a logit function model:

$$\mathbf{Y = -1.3 - 0.4\ X1 + 6.0\ X2 - 1.4\ X3 + 0.1\ X4 - 2.4\ X5 - 1.8\ X6 + 0.3\ X7 - 1.7\ X8 - 0.5\ X9}$$

Equation 6. Model of Ohlson (1980)

where:	X1	= 'log (total assets to gross national product price-level index)'	- size ratio
	X2	= 'total liabilities to total assets'	- leverage ratio
	X3	= 'working capital to total assets'	- liquidity ratio
	X4	= 'current liabilities to current assets'	- liquidity ratio
	X5	= '1, if 'total liabilities exceed total assets', otherwise 0	- leverage ratio
	X6	= 'net income (NI) to total assets'	- profitability ratio
	X7	= 'funds provided by operations to total liabilities'	- liquidity ratio
	X8	= 1, if 'NI negative for at least two years', otherwise 0	- liquidity ratio
	X9	= 'change in net income'	- profitability ratio
	Y	= overall index	

Ohlson's model predicted bankruptcy with an accuracy of 96%, even maintaining around 93% accuracy three years before default. However, it faced criticism for treating all parameters as fixed and lacking behavioural definitions.

In the following chapters various bankruptcy prediction models developed by Taffler (1983), Zmijewski (1984), Lau (1987), and Shumway (2001) are provided.

Taffler (1983)

In 1983, Taffler developed an insolvency prediction model using Multiple Discriminant Analysis, similar to Altman's (1968). Taffler's approach is characterised through its ratio-scarcity by simultaneously high accuracy. All chosen variables entail distinct aspects of an enterprise giving rise to ideal diversification in the space of the model. He studied 46 bankrupt companies listed on the London Stock Exchange (1969-1976) and matched them with 46 solvent firms using a two-stage sampling process to avoid bias. The initial variable selection was based on 80 ratios from previous research. Taffler then used stepwise discriminant analysis to create a Z-Score model that best distinguished between bankrupt and solvent firms.

$$\mathbf{Z = 3.20 + 12.18\ X1 + 2.50\ X2 - 10.68\ X3 + 0.029\ X4}$$

Equation 7. Model of Taffler (1983)

where:	X1= 'profit before tax to current liabilities' (53%)	- profitability ratio
	X2= current assets to total liabilities' (13%)	- liquidity ratio
	X3= 'current liabilities to total assets' (18%)	- leverage ratio
	X4= 'no-credit interval1' (16%)	- liquidity ratio
	Z= overall Index	

The Mosteller-Wallace method shows that the 'profit before tax to current liabilities' ratio contributes over 50% of the model's power, equalling the combined effect of the other three factors. Taffler's model achieved 98% accuracy, with a type I error of 4.3% and no type II error, and the hold-out sample confirmed the same precision, using a cut-off point of -1.95. Firms above this score are unlikely to fail within a year, while those below are at higher risk.

Zmijewski (1984)

In 1984, Zmijewski developed a widely used bankruptcy prediction model using probit regression. His sample included 40 bankrupt and 800 solvent firms, focusing on companies listed on the AMEX and NYSE (1972-1978). He excluded public administration, finance, and service firms due to their unique balance sheets.

Zmijewski highlighted two key biases weakening the quality of existing bankruptcy prediction studies: 'choice-based sample' and 'sample selection' bias. While his study confirmed these biases, they did not significantly affect classification accuracy. His model used three key ratios—profitability, leverage, and liquidity—based on their success in prior studies.

The variable selection process for the probit model underlay the factors' prior achievements in earlier studies whereby three major ratios quantifying profitability, leverage and liquidity were figured out (Zmijewski, 1984):

$$X = -4.3 - 4.5\,X1 + 5.7\,X2 + 0.004\,X3$$

Equation 8. Model of Zmijewski (1984)

where:	X1 = 'net income to total assets'	- profitability ratio
	X2 = 'total liabilities to total assets'	- leverage ratio
	X3= 'current assets to current liabilities'	- liquidity ratio
	X = overall index	

Like the logit model, Zmijewski's (1984) probit model calculates a value between zero and one, classifying firms with probabilities above 0.5 as bankrupt and those below as solvent. While the model achieved an accuracy of 97.1% for the research sample and 97.4% for the validation sample, it failed to predict any bankruptcies, possibly due to an inappropriate cut-off point.

Unlike Altman (1968), Zmijewski used 'net income to total assets' instead of 'EBIT to total assets' to measure profitability, capturing financial profits or losses, which makes the probit model slightly redundant. Critics like Shumway (2001) argued that the high correlation between Zmijewski's variables (p = 0.40) suggested multicollinearity, weakening the model's validity. Platt and Platt (2002) further criticised Zmijewski for not fully addressing choice-based sample bias, limiting the robustness of his findings.

Lau (1987)

In 1987, Lau applied as one of the first researcher multinomial logit analysis to bankruptcy prediction, marking a key shift from a binary dependent variable (insolvent or solvent) to a five-tier classification of financial distress. These categories included: "financial stability," "dividend omission or reduction," "technical default," "protection under Chapter X or XI," and "bankruptcy and liquidation" (Lau, 1987). Lau's study examined 350 companies, with varying numbers in each category, using data from 1976-1980. Her model focused on financial flexibility, emphasising a firm's ability to maintain solvency. Variables were grouped into three categories: "financial flexibility," "trend variables," and "current financial state indicators," forming the basis for the logit model.

$$Zj = bj1X1 + bj2X2 + ... + bj10X10$$

Equation 9. Model of Lau (1987)

where**:**	X1	= 'loan restrictive terms'	- group (1)
	X2	= 'industry normalized debt-to-equity ratio'	- group (1)
	X3	= 'working-capital flow to total debt ratio'	- group (1)
	X4	= 'trend of common stock prices'	- group (1)
	X5	= 'industry normalized operating expenses to sales ratio'	- group (1)
	X6	= 'distribution of common stock dividends'	- group (1)
	X7	= 'liquidation of operating assets'	- group (1)

X8	= ‘trend of capital expenditure’	- group (2)
X9	= ‘trend of working-capital flow’	- group (2)
X10	= ‘omission or reduction of dividend payments’	- group (3)
J	= each one of the five states from 0 to 4	
Z	= overall index	

Lau’s (1987) model used dichotomous variables and accounting ratios to predict five states of financial distress over three periods (1-3 years in advance), resulting in 15 logit equations. The model achieved 96% accuracy for one year and 90% for three years in the estimation sample and 80% and 85% accuracy in the hold-out sample. Lau’s five-tier approach was a significant advancement in bankruptcy prediction, but it faced criticism, particularly regarding limitations in multinomial logit analysis, such as issues with independently and identically distributed (IDD) errors.

Shumway (2001)

In 2001, Shumway introduced a discrete-time hazard model for bankruptcy prediction based on the Cox model used in medicine. Its dynamic nature, incorporating panel data, sets it apart from traditional logistic models (Cox and Snell 1968; Wu et al. 2010). This model, often called the panel-logit model, utilises extensive information across multiple periods (Balcaen and Ooghe 2006).

Shumway analysed 300 bankrupt firms from the Compustat database for NYSE and AMEX companies from 1962 to 1992, excluding those in the financial sector. The variable selection was based on Altman’s (1968) and Zmijewski’s (1984) models, along with key market-driven factors, highlighting the distinction of his approach from static models.

$$\mathbf{Y = -13.303 - 1.982\, X1 + 3.593\, X2 - 0.467\, X3 - 1.809\, X4 + 5.791\, X5}$$

Equation 10. Model of Shumway (2001)

where:	X1 = ‘net income to total assets’	- profitability ratio
	X2 = ‘total liabilities to total assets’	- leverage ratio
	X3 = ‘relative size’	- size ratio
	X4 = ‘excess return’	- market ratio
	X5 = ‘sigma’	- market ratio
	Y = overall index	

Shumway's model includes factors related to a company's market environment. ‘Excess return’ is defined as the firm’s return in year t - 1 minus the CRSP NYSE/AMEX index return for the same period (Shumway, 2001). Annual returns are calculated as the sum of monthly revenues, while ‘sigma’ indicates the idiosyncratic standard deviation of the firm's stock returns, reflecting variability in earnings relative to the market. Higher sigma values may signal increased insolvency risk. The signs of the factors indicate their relationship to bankruptcy, with negative signs suggesting lower insolvency risk. Shumway (2001) found that this combination of market-driven variables and accounting ratios resulted in an accuracy of 96.5%. Beaver et al. (2005) highlighted the hazard model’s improved prediction performance due to reduced multicollinearity compared to static models. Unlike the logit model, the hazard model captures gradual changes in firm failure probability over time, enhancing its predictive power.

Each model has advanced bankruptcy prediction methodologies, showcasing various statistical techniques and the importance of selecting relevant financial ratios to enhance accuracy and address biases. The shift from binary classifications in Lau's model to more nuanced approaches and Shumway's dynamic method represents significant progress in the field.

Betts and Belhoul (1987) analyzed 106 companies using 29 financial ratios, achieving around 90% accuracy one year before insolvency with critical ratios like EBIT to total assets. Aziz and Lawson (1989) developed hybrid models based on cash-flow and accounting ratios, reaching 96% accuracy with key ratios such as working capital to total assets. Dimitras et al. (1996): reviewed 158 studies and highlighted MDA and LA as common methods, emphasizing the relevance of solvency and profitability ratios. Chava and Jarrow (2004) compared models by Altman, Zmijewski, and Shumway, favouring Shumway's model for its market variable integration, achieving 86% accuracy. Wu (2010) focused on 175 insolvent firms, achieving 92% accuracy using machine learning techniques and significant variables like return on assets. Hernandez Tinoco and Wilson (2013) studied British firms, finding macroeconomic and accounting ratios predicted insolvency with 85% accuracy. Du Jardin (2015) analysed French firms, achieving about 80% accuracy with liquidity and profitability ratios. Situm (2016): Developed models for Austrian companies, achieving nearly

92% accuracy by focusing on inflation-adjusted accounting ratios. Liang et al. (2016) investigated manufacturing and service firms, confirming critical profitability and solvency ratios with 82% to 83% accuracy. Jones (2017): Analyzed 1,115 U.S. public firm insolvencies, achieving 96% accuracy using gradient boosting methods. Ben Jabeur (2017) achieved 93% to 94.5% prediction accuracies with logistic regression and partial least squares regression for 800 French companies. These studies highlight the evolving nature of bankruptcy prediction models, integrating accounting ratios, cash flow measures, and market variables to improve predictive accuracy.

Bankruptcy prediction in tourism

Research on bankruptcy prediction in the tourism industry is limited but essential for sustainable management and identifying low-risk investments. Most existing literature focuses on the hospitality sector, such as hotels and restaurants, making it difficult to apply findings to specific areas like alpine tourism (Barreda et al., 2017; Gu & Gao, 2000; Youn & Gu, 2010).

Gu and Gao (2000) analyzed 27 hospitality business defaults from 1987 to 1996, using 14 financial ratios from the year before bankruptcy. They identified five critical coefficients, including total liabilities to total assets and EBIT to current liabilities, achieving approximately 93% overall accuracy with an 82% jackknife precision rate. Notably, while the debt ratio correlated positively with insolvency, long-term liabilities negatively impacted bankruptcy risk.

In 2002, Gu assessed bankruptcy likelihood for U.S. restaurants, identifying two main factors: EBIT to total liabilities and total liabilities to total assets, achieving a model precision of around 92%. Kim and Gu (2006) explored U.S. restaurant bankruptcy probabilities, finding seven significant financial ratios and achieving a new logit model accuracy of 94%.

In their 2010 study, Kim and Gu assessed hospitality firm insolvencies, finding that operating cash flows to total liabilities was the most crucial variable, with model accuracy at 84% for one year and 91% for two years ahead. Youn and Gu (2010) identified key variables in predicting U.S. restaurant bankruptcies, achieving accuracies of 88% and 76% for one and two years in advance, respectively.

Kim (2011) studied 33 Korean tourist hotels, finding that Neural Network (NN) and support vector machine (SVM) models outperformed traditional methods, highlighting liquidity and debt ratios. Park and Hancer (2012) compared NN and linear analysis across 48 firms, achieving up to 98% accuracy for the NN model.

Li et al. (2017) examined 35 Chinese hospitality firms, achieving accuracy levels from 75% to 98%, depending on the prediction horizon. Barreda et al. (2017) compared predictive powers of linear analysis and MDA, achieving around 77% accuracy for both models.

Parsa et al. (2005) confirmed that high competition increases bankruptcy risk, especially for smaller establishments, while their 2015 study reinforced the importance of location and demographic factors in predicting bankruptcy for 496 U.S. restaurants.

Wieprow and Gawlik (2021) analysed the threat of insolvency of nine Polish tourism companies listed on the national stock exchange before and after the covid-19 event by applying multiple discriminant analyses and logit models. The authors compared financial half-year data from 2019 and 2020 using various profitability, solvency and leverage ratios across four bankruptcy prediction models. Their findings indicate an increased bankruptcy risk for all companies, as reflected in a general deterioration of the Z-scores across the sample.

Candera (2024) conducted a comparative analysis of widely used bankruptcy prediction models on twenty Indonesian companies primarily operating in the hotel, restaurant and tourism sectors during the covid-19 pandemic. The study found significant differences among prediction models, particularly betweenAltman’s (1968) Z-score and Zmijewski’s (1984) X-score model, corroborating findings by Sandra et al. (2023) stating that these models yield distinct results as well as to those of Ohlson’s (1984). This variation suggests the cruciality of a good model choice under crisis conditions.

Bankruptcy prediction for SMEs

In alpine tourism, many businesses are SMEs, which significantly drive innovation and economic growth (Berg, 2010). Since 2005, SMEs are defined in Europe as having a maximum of ten employees and revenues under €2 million for micro firms, up to 50 employees and €10 million for small firms, and five times those amounts for medium businesses (El Kalak & Hudson, 2016). Research has primarily focused on larger companies, often neglecting smaller entities (Pompe & Bilderbeek, 2005). Prior to 2000, limited studies yielded inconclusive results due to small sample sizes (Huyhebaert et al., 2000; Keasey & Watson, 1987; Laitinen, 1991).

Pompe and Bilderbeek (2005) examined 1,369 SMEs, identifying four key predictive variables for bankruptcy: cash flow to total debt, net results to financial charges, profit after taxes to total assets, and profit after taxes to turnover. Their models achieved 79% accuracy for neural networks and 78% for MDA, with cash flow proving the strongest predictor, aligning with Beaver's findings (1966).

Altman and Sabato (2007) analysed American SMEs with revenues under $65 million, finding similar predictors. Their model's accuracy reached approximately 75% and improved to 87% with logarithmic transformations. They confirmed the Z-score model's decreasing relevance in recent years (Lin 2015). Altman et al. (2017) assessed 34 countries, finding that their model still predicted outcomes with around 90% accuracy.

In British SMEs, Altman et al. (2010) developed two models, achieving 74-78% accuracy by considering a mix of new accounting variables. Yazdanfar (2011) focused on Swedish firms, finding a model with 97% predictive power one year before bankruptcy.

Lin et al. (2012) investigated British SMEs, achieving up to 88% accuracy with seven ratios. El Kalak and Hudson (2016) analysed U.S. SMEs, identifying six main factors related to insolvency and achieving accuracy rates between 60-80%.

Cultrera and Brédart (2016) assessed over 7,000 Belgian SMEs, identifying four significant predictors with an 80% accuracy rate. Calabrese et al. (2016) reviewed 50,000 Italian SMEs, finding five critical ratios and achieving 75-84% accuracy.

Gupta et al. (2018) focused on American SMEs, with a hazard model yielding four crucial ratios and a ROC value above 0.8. Andrikopoulos and Khorasgani (2018) examined over 10,000 failed British firms, finding significant ratios aligned with previous studies, and noted that incorporating market data improved predictive accuracy.

Bankruptcy prediction for family businesses

Berg (2010) highlighted the overlap between SMEs and family businesses in alpine tourism, noting that family firms prioritise socioemotional wealth and family continuity alongside financial gains (Dressler & Tauer, 2015; Berrone et al., 2012). Gedajlovic et al. (2012) found that shared ownership and leadership in family businesses enhance social capital and reduce agency costs (Gottardo & Moisello, 2017), leading to different bankruptcy predictors compared to other structures.

He and Kamath (2005) analysed 200 small family enterprises from 1990 to 1998, using an adjusted Logistic Analysis (LA) model. They identified five key insolvency indicators, achieving accuracy rates of around 90% for Ohlson's model and 92% for Shumway's. Wilson et al. (2013) found that enterprise age negatively correlated with bankruptcy likelihood, while size positively related to default risk, with predictors including total debt to total assets and cash to total assets.

Blanco et al. (2015) examined over 20,000 UK micro-entities from 1999 to 2008, achieving 77% accuracy with Logistic Regression and about 82% with a multilayer perceptron approach. Kristanti et al. (2016) identified current ratio and leverage as significant predictors in Indonesian family firms, although the current ratio's relationship to default likelihood was unexpectedly positive.

Gottardo and Moisello (2017) confirmed that family firms are generally less susceptible to bankruptcy, while Fernández-Gámez et al. (2018) developed models achieving approximately 99% accuracy one year before bankruptcy, with Naïve Bayes being the most effective at nearly 95% accuracy.

Empirical review and hypothesis development

The following sections present the key findings of the study. In Chapter 3.1, the results of the univariate analysis are outlined. This enables the identification of risk drivers and provides initial answers to the research questions. In the multivariate analysis (see Chapter 3.2), several models for early crisis and insolvency detection were calculated using logistic regression. These results form the basis for a final assessment.

Research and methodology

This study uses a pragmatic quantative approach to examine the bankruptcy risk among Alpine tourism SMEs in Western Austria, focusing on the Tyrol, Salzburg, and Vorarlberg regions. According to Patton (2015), methodological appropriateness is central in pragmatic research, and methods are selected, evaluated and described according to the research problem. Toursims SMEs are crucial for the local economy, making their resilience vital for sustainable regional development. The research is organised into three main phases:

I. Phase 1 – Literature Review and Determination of Research Variables:

A comprehensive analysis of existing literature was conducted to a) gain an understanding of current research, and b) identify factors and variables from previous studies that are relevant to the topic.

II. Phase 2 – Data Integration:

Financial statement data of Austrian tourism businesses (classified under "I" according to the ÖNACE 2008 code) in Western Austria (Salzburg, Tyrol, and Vorarlberg) for the period 2003–2016 were extracted and prepared from an existing database.

III. Phase 3 – Evaluation including Statistical Analyses:

The data were analysed and summarised using descriptive statistics.

In the first phase, a comprehensive literature review was conducted to identify financial and non-financial indicators relevant to predicting bankruptcy in the tourism industry. Prior research highlights the significance of financial ratios, operational metrics, and macroeconomic variables in forecasting corporate insolvency (Altman, 1968; Dimitras et al., 1996; Situm, 2016). Key risk indicators were chosen based on their relevance to small and medium-sized tourism enterprises in Austria, taking into account factors like firm size, age, equity ratios, and challenges specific to Alpine tourism.

The second phase involves data integration, with data gathered from the established Austrian financial database Creditreform, covering tourism-related companies within the designated regions for the years 2003 to 2016. The dataset includes balance sheet and income statement data of 2,075 solvent and 190 insolvent West Austrian companies all of which have already filed for bankruptcy, providing a representative sample for analysing regional bankruptcy risks. Additional macroeconomic data, such as consumer price indices, were integrated to contextualise the economic environment affecting these businesses. Variables were added to capture unique aspects of location, industry specifities,, and economic indicators, and a summary of these variables along with their calculation methods is presented in Table 2.

Despite the robust data sample, there are potential limitations related to representativeness, particularly in the exclusion of qualitative resilience factors such as managerial experience, market adaptability, or crisis management practices. These non-quantifiable factors play a significant role in the sustainability and survival of businesses, especially SMEs in a highly competitive and changing environment like tourism. Incorporating these factors could provide a more holistic understanding of bankruptcy risk. Additionally, the dataset only includes quantitative financial variables, which may overlook important qualitative aspects of business resilience.

In the third phase, statistical analysis was performed using both univariate and multivariate methods. Descriptive statistics initially profiled companies at risk and identified possible risk factors. Logistic regression models were then used for multivariate analysis, assessing combined risk factors influencing insolvency. This approach aligns with the work of Chen et al. (2021) and Jencova et al. (2024), who used logistic regression within the electrotechnical industry, demonstrating the model's adaptability and precision in forecasting financial distress across diverse sectors. These findings underscore logistic regression's effectiveness in forecasting binary outcomes, such as bankruptcy, across industries.

However, the models used for multivariate analysis also face calibration challenges. The adjustment of variables in the logistic regression models may lead to overfitting, especially when dealing with limited data points for insolvent firms. Ensuring that the models are adequately calibrated to account for different regional and sectoral variations is important for enhancing predictive accuracy. Further sensitivity analyses could be valuable to assess the robustness of the results in various scenarios.

In the regression analysis, multivariate models assessed the significance of variables one year (t-1) and two years (t-2) before recorded insolvency events. By adjusting variables in these models, the study seeks to identify critical risk factors and understand the interplay of individual drivers affecting the likelihood of crisis and insolvency. This methodology aims to deliver a thorough analysis of insolvency risks for Alpine tourism SMEs, providing insights that can inform early-warning mechanisms and strategic recommendations to enhance financial resilience in the industry. This phased approach helps to develop a comprehensive understanding of both internal and external factors, offering valuable insights for stakeholders focused on regional tourism and business sustainability.

Table 1: Summary of literature review

Author (Date)	Subject	Variables	Methods	Findings
Altman (1968)	Bankruptcy Prediction Using MDA	Working capital to total assets, retained earnings to total assets, EBIT to total assets, market value of equity to book value of total debts, sales to total assets	Multiple Discriminant Analysis (MDA)	Developed the Z-score model, using a linear combination of financial ratios to predict bankruptcy. Set a score threshold to distinguish between bankrupt and solvent firms, achieving high predictive accuracy but limited by multicollinearity and linear classification constraints.
Ohlson (1980)	Bankruptcy Prediction Using Logistic Regression	Total assets to GNP price-level index, liabilities to assets, working capital to assets, net income, funds from operations, negative net income, etc.	Logistic Regression (Logit Analysis)	Introduced logistic regression to predict bankruptcy, allowing for probability-based predictions without assumptions on variable distribution. Achieved 96% accuracy with strengths in handling disproportionate samples and interpretability of

				individual variable contributions.
Taffler (1983)	Bankruptcy Prediction Using MDA	Profit before tax to current liabilities, current assets to total liabilities, current liabilities to total assets, no-credit interval	Multiple Discriminant Analysis (MDA)	Developed a Z-score model similar to Altman's with a focus on UK firms, achieving 98% accuracy with low error rates. Highlighted the profit-to-liability ratio as the most significant predictor.
Lau (1987)	Multinomial Logit for Financial Distress Classification	Financial flexibility, trend variables, current financial state indicators	Multinomial Logit Analysis	Classified firms into five levels of financial distress with high accuracy over one to three years. Expanded beyond binary classification, providing a nuanced view of financial health.
Shumway (2001)	Hazard Model for Bankruptcy Prediction	Net income to assets, liabilities to assets, relative size, excess return, sigma	Discrete-time Hazard Model (Panel-Logit)	Improved on traditional models by introducing a time-dynamic hazard model, achieving 96.5% accuracy. Incorporated market-based variables for better prediction, addressing multicollinearity issues and enhancing gradual prediction over time.

Source: Authors

The risk drivers in the tourism industry for companies in Western Austria can be summarised as follows:

i. Company size (SIZE): The larger the company, the lower the probability of a crisis or insolvency.
ii. Age of the company (AGE): The older the company, the lower the probability of a crisis or insolvency.
iii. Working capital ratio (WC/TA): The higher the working capital in relation to total assets, the higher the likelihood of a crisis or insolvency.
iv. Retained earnings (RE/TA): The more retained earnings a company has, the lower the probability of insolvency.
v. Equity ratio (TE/TA): The higher the equity ratio, the lower the probability of insolvency.
vi. Debt ratio (TD/TA): The higher the company's debt, the higher the probability of insolvency.
vii. Consumer Price Index (CPI): A higher CPI is associated with a lower probability of insolvency.
viii. Annual change in apprentice numbers (QA): A decline in the number of apprentices in the industry correlates with a lower probability of insolvency.
ix. Insolvency rate of the industry (IR): A higher annual insolvency rate in the industry corresponds to a lower probability of insolvency.
x. Urbanisation level 1 (URB 1): Companies located in city centres and metropolitan areas face a higher probability of crisis or insolvency.
xi. Urbanisation level 2 (URB 2): Companies located in cities and suburban areas face a higher probability of crisis or insolvency.
xii. Urbanisation level 3 (URB 3): Companies in rural areas are less likely to experience crises or insolvency.
xiii. Federal state of Tyrol (Tyrol): Companies located in Tyrol have a lower probability of crisis or insolvency.
xiv. Federal state of Vorarlberg (Vbg.): Companies located in Vorarlberg have a higher probability of crisis or insolvency.
xv. Univariate Risk Drivers in the Tourism Industry in Western Austria
xvi. Larger and older (established) companies have a higher likelihood of sustaining success in the market.
xvii. Weak or insufficient working capital management is a cause of potential liquidity shortages within a company.
xviii. Companies in the industry tend to have high debt levels and, consequently, low equity ratios, which increases the likelihood of crises and insolvency.
xix. Centres, cities, and suburban areas are generally unfavourable locations for businesses.
xx. The location in Tyrol is generally advantageous for the successful development of companies, while tourism businesses in Vorarlberg face greater challenges in maintaining success.

Results of the multivariate analysis

In the logistic regression conducted one year and two years before insolvency, multiple models were tested by adding and removing various variables. A multivariate approach was chosen to identify the interplay of individual risk drivers on the likelihood of a crisis or insolvency.

Table 3: Selected Relevant Results of Regression Analyses for One Year and Two Years Prior to Insolvency

Vector	**Variable**	**Abbreviation**	**Calculation**
Size	Company Size	SIZE	Ln(Total Assets)
Age	Age of the Company	AGE	Ln(Age of the Company in Years)
Activity/Efficiency	Working Capital to Total Assets	WC/TA	Working Capital / Total Assets
Capital Structure	Debt Ratio	TD/TA	Total Debt / Total Assets
Location	Federal State of Tyrol	Tyrol	Dummy Variable (1 = Tyrol; 0 = otherwise)
	Federal State of Vorarlberg	Vorarlberg	Dummy Variable (1 = Vorarlberg; 0 = otherwise)
	Urbanisation Degree 1	URB 1	Dummy Variable (1 = City and Centres; 0 = otherwise)
	Urbanisation Degree 3	URB 2	Dummy Variable (1 = Rural; 0 = otherwise)
Year	Observation Year	2005 to 2014	Dummy Variable (1 = YEAR; 0 = otherwise)
Industry	Annual Change in Apprentice Numbers	QA	(Number of Apprentices - Number of Apprentices-1) / Number of Apprentices-1
	Industry Bankruptcy Rate	IR	Number of Bankruptcies / 1000 Companies
Macroeconomics	Consumer Price Index	CPI	Consumer Price Index / 100

Source: Authors

The results show that certain risk drivers are relevant early warning indicators in both periods before the actual onset of the crisis. From a Resource-Based View (RBV) perspective, the resilience exhibited by larger firms is attributed to their capacity to leverage resources, including fiscal reserves, established networks, and Brand Equity, to mitigate crises (Barney, 1991). Pecking Order Theory (Myers & Majluf, 1984) provides further elucidation on the observed debt-related risks. The reliance on external debt leads to increased financial pressure. Recognised best practice recommendations, namely the restructuring of debt and the improvement of internal financing, are in accordance with this Theory's hierarchy of funding preferences (Gupta et al., 2018). Institutional Theory (North, 1990) provides a contextual framework for examining regional disparities, with Tyrol's lower bankruptcy rates potentially indicating institutional advantages. Proactive policy support, such as subsidised apprenticeships, and destination management strategies, which enhance firm stability (Hallmann et al., 2014; Government Program for Tyrol 2018-2023), may play a role in this context.

Analogous to various studies (Shumway, 2001; Parsa et al. 2015; Agrarwell & Taffler, 2008) company size has been identified as a significant factor, and it was observed that crisis companies tend to shrink in size over time (Situm, 2015). This is a clear indicator that assets are being reduced, which in turn increases insolvency costs (Herzog et al., 2008,). This finding is closely related to the Resource-Based View (RBV) in business studies and demonstrates that companies with greater capacities and resources have a higher survival probability (Chava & Jarrow, 2004; Ohlson, 1980; Hol, 2007). Larger companies are also better equipped to withstand losses during crises compared to smaller businesses, as they possess assets that can be liquidated in emergencies to fund operations (Dawley et al., 2003,; Moulton & Thomas, 1993). Smaller companies, therefore, need to focus more on liquidity constraints and higher profitability to prevent bankruptcy (Kliestik et al. (2021). Company age also remains a significant factor, indicating that established companies in the market have a significantly higher probability of survival, which is consistent with findings in the existing literature (Hill et al. 2014; Bates, 1990; Chava & Jarrow, 2004; Cressy, 2006; Gu, 2002; Parsa et al., 2011; Parsa et al., 2005).

Higher equity ratios or lower debt levels significantly increase the likelihood that a company will avoid a crisis or insolvency (Gu, 2002; Gu & Gao, 2000; Kim & Gu, 2006; Park & Hancer, 2012). It was found that larger companies tend to have higher equity ratios than smaller firms, although this was not statistically significant. The location (federal state) of the company does not play a significant role in the likelihood of insolvency. More detailed data on the company's location (district, region, etc.) could not be further analysed in this study, presenting an interesting avenue for future research. Urbanisation data did not show significance in the multivariate analysis, though a smaller qualitative regional study with 18 interviews highlighted high significance regarding the remoteness of regions in the context of employer branding (Plaikner et al., 2019).

In the framework of the logistic regression analysis conducted one year (t-1) and two years (t-2) prior to insolvency, multiple models were tested by adding and removing various variables. Table 3 presents two selected models for the respective timeframes. This multivariate approach aims to identify the interplay of individual risk drivers on the probability of a crisis and insolvency.

Based on the results of the study, a variety of recommendations can be derived for tourism businesses in Western Austria:

Smaller companies face significant challenges in successfully and sustainably remaining in the market over the long term. They should therefore aim to expand their capacities and resources to be better prepared during times of crisis. Thus, remaining small cannot be a long-term strategic option. In this context, entrepreneurs should also seek to broaden their networks, as these can contribute both to an increase in resources and to business success, while also reducing the likelihood of a crisis (Andersson, Forsgren, & Holm, 2002; Hite & Hesterly, 2001).

Companies with tradition and longer-standing histories can leverage this aspect to establish themselves sustainably in the market. This presents a significant opportunity, particularly for family businesses, as the "family" itself often represents an undervalued brand that is insufficiently utilised in branding (Zanon et al., 2019; Krappe et al., 2011). This can create a differentiating characteristic because the "family" constitutes a non-replicable resource (Beugelsdijk et al., 2013), which is thus relevant for family firms (Beck, 2016). By establishing a strong brand, it may be possible to create a long-term orientation and strengthen connections with various stakeholders (Basile, 2013; Krappe et al., 2011; Peters & Frehse, 2011).

Businesses in the tourism sector should thoroughly examine their capital structure. Practical experience shows that many companies possess inadequate financing structures—this applies to both short- and long-term credit financing. These cases necessitate considerations regarding the restructuring of the capital and financing structure (Situm, 2016). Furthermore, considerations should also be made on how to optimise working capital. In this context, areas such as procurement and inventory management, debtor and creditor management, and the analysis of other expenses or costs need to be addressed (Situm, 2016).

In inventory management, for example, electronic or digital systems can be implemented to optimise inventory and storage, thereby reducing related costs (Arnold & Furmans, 2009; Ross et al., 2013). Smaller companies may face disadvantages compared to larger ones, as they often lack the financial means to make necessary investments. Additionally, companies in crisis tend not to have professional debtor management (Heesen et al., 2018), negatively affecting operational activities' cash flow.

A strong employer brand is crucial for tourism businesses to develop a sustainable foundation for success (Peters et al., 2019; Plaikner et al., 2023). A company with a well-constructed employer brand attracts suitable employees. These individuals will engage long-term with the organization and consistently strive to deliver the best output. Ultimately, this creates value, enhances reputation in the job market, and leads to economic success (Moroko & Uncles, 2008). Opportunities for career advancement and training/development are also significant factors for motivated and talented employees. Therefore, tourism companies need to develop concepts that facilitate career progression. Additionally, these concepts should implement work-life balance approaches and incentive systems that aim to increase the attractiveness of working in tourism (Baum, 2008).

The study identified several variables that significantly influence the likelihood of crises and insolvencies among tourism businesses in Western Austria. From a resource-based perspective, companies can take proactive measures to mitigate risks. However, it remains uncertain whether business owners can implement these measures effectively. A critical issue in business management is that over 70% of micro-enterprises and 53% of small businesses report no control. This gap explains why many tourism businesses face crises as outlined in Chapter 2. They lack early warning systems that could be used for proactive management, preventing such situations.

The reasons behind this could be a lack of experience or knowledge regarding controlling (Andric & Kammerlander, 2017; Deimel, 2008; Sierke et al., 2017), a failure to recognise the importance or benefits of controlling for management (Deimel et al., 2017; Duller et al., 2014), or a lack of resources to establish an internal controlling system or hire external consultants (Berens et al., 2005; Deimel, 2008; Hiebl et al., 2013; Rautenstrauch & Müller, 2005). The number of insolvencies in a region can be interpreted as an indicator of the economy's robustness (McKee, 2000). Higher insolvencies suggest greater market inefficiencies (Altman, 1968). Therefore, it is recommended that crises and insolvencies be detected earlier, allowing time for countermeasures (Exler & Situm, 2014; Exler & Situm, 2013).

Achieving this requires raising awareness among business owners through targeted actions. One approach could be offering free workshops (e.g., through the Chamber of Commerce) to introduce the topic. "Best-practice" examples from successful entrepreneurs who use controlling could be presented at regional roundtable discussions, showcasing its usefulness from a business perspective. This could also establish a network where experts and entrepreneurs can exchange ideas for education and training and to share innovative solutions. This could be realised as part of a larger, government-funded project, directly supporting the objectives of the Tyrolean government's program to "enhance value creation and quality in local tourism with a focus on sustainable benefits for the local population" (Government Program for Tyrol 2018-2023).

Although not explicitly mentioned earlier, profitability is relevant, as it intersects with all other variables in the study. Moreover, the success of a tourism destination is not solely dependent on its input factors or resources. According to competence-based theory, resource allocation is only partially relevant. Success is more tied to the competitive advantages of the tourism providers in a destination (Pechlaner et al., 2011).

Given that tourism is an integral part of Tyrol's economy and society (Government Programme for Tyrol 2018-2023), these findings should be used to optimise early crisis detection systems. In this context, an open and responsible dialogue with the local population and key tourism stakeholders is essential to prepare small and medium-sized tourism businesses for the future. Destinations must be aware of their attractiveness and credibility towards visitors to remain competitive against a broad array of alternative destinations. Therefore, it is crucial to continuously improve information quality, enabling more efficient planning and decision-making processes (Crouch & Ritchie, 1999).

Furthermore, within the destination management process, factors such as excellent transport links to the destination, the offering of personalised products and services, and the enhancement of service quality are crucial (Hallmann et al., 2014).

Conclusion

Recommendations for Tourism Businesses in Western Austria

i. Smaller businesses should aim to expand their capacities and resources to be better prepared for potential crises. To achieve this, they could incorporate bankruptcy risk assessment tools into their financial planning processes, such as the Z-score model or logistic regression models, to identify early warning signals and assess their financial health regularly.
ii. Entrepreneurs should focus on expanding their regional and national networks to strategically utilise these resources. Leveraging network data and integrating predictive bankruptcy risk tools into their strategic planning could allow SMEs to identify regional financial risks, which might otherwise go unnoticed, and implement targeted interventions.
iii. Older companies can capitalise on their traditions, with an emphasis on promoting the "family" aspect.
iv. The concept of "family" should be leveraged to strengthen the company's brand, creating a distinct differentiating and identifying feature.
v. It is advisable to assess whether the current financing and capital structure fits the company, and if necessary, to undertake restructuring.
vi. Tourism businesses require professional working capital management to maintain liquidity and short-term funding lines.
vii. Measures should be implemented to introduce efficient processes and reduce various costs. Regular use of financial distress prediction models can help identify areas where costs can be reduced without negatively impacting service quality, ensuring a balance between financial health and competitiveness.
viii. A strong employer brand is essential for attracting skilled employees. By integrating bankruptcy risk assessment tools into HR planning, businesses can anticipate financial difficulties and avoid layoffs or other financial challenges that might damage the company's reputation as an employer.
ix. Strategies should be developed to enhance the appeal of working in the tourism industry.
x. Stragtegic government financial support programs could consider bankrupty indicators in future selection processes.

This study is limited to the Alpine environment and urbanization levels in Salzburg, Tyrol, and Vorarlberg, restricting generalizability to other regions. Additional limitations include data representativeness, model calibration, and the exclusion of qualitative business resilience factors.

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