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Prediction of tourism zombie companies using artificial intelligence algorithms and accounting data

Agustín J. Sánchez-Medina [1], Félix Blázquez-Santana [1], Mónica Pellejero [1] and Daniel L. Cerviño-Cortínez [2, 1*]

[1] University of Las Palmas de Gran Canaria, Campus de Tafira, 35017, Las Palmas de Gran Canaria, Spain.
[2] Universidad del Atlántico Medio, Carretera de Quilmes, 37, 35017 Tafira Baja, Las Palmas de Gran Canaria, Spain.
Email: Daniel.cervino@pdi.atlanticomedio.es

*Corresponding author

Abstract
This paper addresses the problem of the prediction of zombie companies. Despite their relevance, financial issues represent an area scarcely considered in relation to the tourism industry: the topic has so far remained totally unexplored. Zombie firms cause great damage to the sector in which they compete. However, there is no consensus regarding what actions should be applied to them due to the negative consequences of maintaining or liquidating them. In view of this, the key issue is to prevent them from entering the zombie state. It would therefore be useful to have a methodology for predicting years in advance when a company will become a zombie firm. For this purpose, this article has used different artificial intelligence algorithms applied to easily obtained accountant data. Utilizing a dataset of 356 Spanish small and medium-sized enterprises in the tourism sector, 78.4% of predictions have been correct.

Keywords: zombie firms, tourism SMEs, artificial intelligence, machine learning, prediction.

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1. Introduction

The importance of the tourism sector as a decisive factor in the growth of the global economy is an axiom that in the 21st century is completely beyond doubt. This industry generates millions of jobs and contributes to the social development of the planet (Andajani *et al.*, 2018; Khan *et al.*, 2020; Mohammed, 2022). The evident relevance of the tourism sector is supported by the organizations that compose it, being the small and medium-sized enterprises (SMEs), the backbone of the tourism industry (Mohammed, 2022).

According to the Organisation for Economic Co-operation and Development (OECD, 2021), SMEs play a crucial role in the economy of every nation, with tourism SMEs representing up to 90% of commercial activity in emerging countries.

In Spain, tourism activity has reached 155,946 million euros, representing 11.6% of the country's GDP and contributing to 9.3% of total employment. These figures determine the importance of the sector in the company's economy as a whole, in which the significant contribution of Spanish SMEs stands out (Instituto Nacional de Estadística [INE], 2022). Globally, tourism represents 10.6% of jobs and reduces poverty by employing vulnerable groups (Mohammed, 2022).

Despite their importance, tourism SMEs face important challenges that compromise their continuity, one of which is their financial vulnerability (Mohammed, 2022). In addition, their small size makes them particularly fragile in times of crisis because they often lack the resources and management skills to implement effective sustainable practices. This represents a significant challenge to their long-term development (Adikaram & Surangi, 2024). These characteristics highlight the need for continued support and specific strategies to strengthen the resilience and sustainability of SMEs in the tourism sector (Mohammed, 2022).

However, according to Thomas *et al.* (2011), these have been very little studied. A review of the literature has shown that the statement by Thomas *et al.* (2011) from just over a decade ago is still valid, with relatively few papers referring to tourism SMEs. These works have focused mainly on analyzing the importance of governmental support in the expansion of such companies (e.g., Adikaram & Surangi, 2024; Awang & Mustapha, 2020; Omar *et al.*, 2020; Supriyadi *et al.*, 2018); their relevance to territorial development (e.g., Hallak *et al.*, 2013; McCamley & Gilmore, 2017; Mohammed, 2022; Tambunan, 2009), or their need for new marketing and e-commerce models to drive their growth (e.g., Moral *et al.*, 2014; Pickernell *et al.*, 2013). Nevertheless, despite the vulnerability of SMEs, especially in times of crisis (Blažková & Dvouletý, 2022; Goto & Wilbur, 2019; Pardal *et al.*, 2021), no papers have been found that focus on the financial problems of the SMEs in the tourism industry, or that deal with the problem of the prediction of zombie firms.

The companies considered zombie firms are insolvent businesses with little hope of recovery (Hoshi, 2006), to which the literature attributes a set of more specific characteristics such as (i) low rentability and productivity, as well as high indebtedness (Carreira *et al.*, 2022; El Ghoul *et al.*, 2021; Urionabarrenetxea *et al.*, 2018), (ii) a lack of efficiency (Anh *et al.*, 2021; Blažková & Dvouletý, 2022; Kane, 1987), and (iii) in extreme cases, negative net equity (Blažková & Dvouletý, 2022; San-Jose *et al.*, 2021; Urionabarrenetxea *et al.*, 2016). They have no apparent possibilities of continuing their activity and should, under normal conditions, have exited a competitive market. Nevertheless, they can maintain their activity with the help of creditors (Hoshi, 2006), subsidized loans from banks (Anh *et al.*, 2021), and/or financial support from governments (Dai *et al.*, 2019).

If the main reasons for the emergence of zombie companies are considered, there is a certain consensus on their definition wherein the circumstances described in the previous section must converge. However, some studies highlight government intervention and subsidized bank loans as the main causes (e.g. Chang *et al*., 2021; Dai *et al*., 2019; Zhang & Huang, 2022), while other authors emphasize the companies' operational inefficiency and low productivity (e.g. Blažková & Dvouletý, 2022; McGowan *et al*., 2018).

Despite the negative effects, McGowan *et al*. (2018) note that there has been a considerable increase in the resources invested in this type of company since 2005. However, the literature has highlighted the danger posed by zombie firms because of the damage they cause to healthy ones, provoking significant issues for a country's economy (e.g., Ahearne & Shinada, 2005; Shen & Chen, 2017; Wang & Zhu, 2020). More specifically, they negatively affect investment and job creation (Caballero *et al*., 2008; Hoshi, 2006; Tan *et al*., 2016), as well as productivity by remaining inefficient companies that block the entry of new potentially more productive participants (Carreira *et al*., 2022; McGowan *et al*., 2018). In the same way, they eliminate growth opportunities by concentrating a higher proportion of lending to distressed borrowers (Storz *et al*., 2017), and reduce incentives to innovate (Geng *et al*., 2021). For their part, Caballero *et al*. (2008) state that the volume of zombie firms in a country affects the level of competitiveness of its companies, even distorting the normal patterns of the creation and destruction of firms.

Despite all the problems generated by zombie firms, there is no consensus agreement on the appropriate policy to apply to them. On the one hand, some authors consider it necessary to eliminate these firms to direct resources to more productive companies (e.g., Anh *et al*., 2021; Tan *et al*., 2016). On the other hand, some scholars disagree with their elimination, noting that government aid to zombie companies prevents the damage spreading to other healthy firms (Asanuma, 2015) or that many zombie SMEs can survive. For this reason, they believe it is necessary to carry out a preliminary evaluation to avoid eliminating those that can recover (Goto & Wilbur, 2019).

This lack of consensus on how to act on zombie companies could be due to the diversity of the economic and sectoral contexts in which these companies have been analysed. Thus, in some regions or countries with less developed financial markets or those affected by economic crises, government intervention is considered necessary to promote the resilience of vulnerable companies. In these cases, such intervention may be perceived as a crucial tool for maintaining economic stability (Dawley *et al*., 2010). In more advanced economies, the elimination of zombie companies may be seen as a necessary strategy to promote efficiency and innovation (McGowan *et al*., 2018). These contextual differences highlight the need to tailor policies to the specific circumstances of each country and sector, suggesting that a single solution may not be appropriate for all scenarios (Caballero *et al*., 2008).

However, a clear agreement does seem to exist regarding the damage they cause to the sector and the economy in general. It is therefore necessary, as highlighted by Blažková and Dvouletý (2022), to recognize in advance the appearance of zombie companies to implement the most appropriate policies in each specific case.

Despite the importance of identifying this type of company in advance and avoiding the negative aspects derived from them, prediction of zombie companies in the tourism sector, especially in SMEs, has not so far been studied in the academic literature. After reviewing the literature, it was observed that research on zombie companies has predominantly focused on large corporations (e.g. Acharya *et al*., 2019; Caballero *et al*., 2008; Fukuda & Nakamura, 2011; Kane, 1987; McGowan *et al*., 2018). However, this is not the case in the tourism sector, where the lack of studies, and specifically in tourism SMEs, creates a critical gap. These companies represent a substantial part of the economy in many regions, and their inability to recover can devastate employment and economic stability (Mohammed, 2022; OECD, 2021). Therefore, following the suggestions of Blažková and Dvouletý (2022), and to reduce the important gap existing in the academic literature on the early prediction of those SMEs that may become zombies in the tourism sector, the main objective of this research is to provide a methodology for an information system that allows for the early detection of this type of company. Thus, the aforementioned methodology based on artificial intelligence algorithms (e.g., logistic regression (LOGIT), random forest (RFC), and artificial neural networks (ANN)) has achieved a 78.4 correct prediction rate three years in advance. In addition, it should be noted that this has been achieved using only easily obtainable accountant data as the model input. The sample used was made up of a total of 356 Spanish SMEs belonging to the tourism sector during the period 2016-2019.

It should be highlighted that after reviewing the papers published in journals listed in the Web of Science and Scopus databases, no work related to the prediction of a company's entry into a zombie state has been identified. Therefore, this paper is the first to provide knowledge in this field. In addition, it contributes to increasing the scarce number of works focused on the financial problems of tourism SMEs.

2. Literature review

2.1 Zombie companies and their implications

The first author to use the term zombie to refer to a company was Kane (1987), when he discussed North American banks that in the 1980s continued to exist despite presenting serious financial problems. Since then, the term has been used by different scholars to identify those companies that continue to be active mainly thanks to the support of government and credit institutions, in spite of their insolvency and lack of efficiency (e.g., Anh *et al*., 2021; Dai *et al*., 2019).

Subsequently, the prolonged economic recession in Japan suffered in the late 1990s was the trigger for the development of an interesting line of research focused on this type of company. During that decade, there was a stagnant situation in the Japanese economy that caused significant credit delinquencies. Despite this, many banks continued to grant credits at lower interest rates than the market average (Caballero *et al*., 2008) or partially forgive debts to highly indebted and inefficient companies (Ahearne & Shinada, 2005; Fukuda & Nakamura, 2011).

On the other hand, in Europe, as a result of the great global financial crisis of 2008, governments promoted rescue programs by supporting companies in difficulty through loans at subsidized interest rates. These measures were intended to support employment and the economy in general (Papava, 2010), driving the emergence of zombie firms, which have come to represent 10% of all companies in the European Union (San-Jose *et al*., 2021). In light of this, some researchers focused on zombies firm, considering that their existence was one of the causes of the long-term stagnation of the economy of some European countries (e.g., Acharya *et al*., 2019; Broz & Ridzak, 2017; Goto & Wilbur, 2019). It should be noted that, as happened in Japan, SMEs were the most likely firms to become zombies (Blažková & Dvouletý, 2022; Carreira *et al*., 2022; Pardal *et al*., 2021).

In addition, a significant number of papers have analyzed the effect of zombie firms in China. In this country, unlike Japan and Europe, the issue affects large companies (Wu *et al*., 2021) with large state-owned business being the most likely to be zombies (Shiraishi & Yano, 2021). However, as with other economies, government intervention and subsidized bank lending are still the main causes of their emergence (Chang *et al*., 2021; Dai *et al*., 2019; Lu *et al*., 2022; Tan *et al*., 2016). Nevertheless, continued government support has been insufficient for the recovery of these companies (Dai *et al*., 2019). This is because they have caused serious and widespread damage to China's economy due to the waste of human, material, and financial resources (Chang *et al*., 2021).

Although they are scarce, there are studies that address the problem of zombie companies focused on a specific sector. Examples are the works of Hoshi and Kashyap (2010), Kane (1987), and Zhang and Huang (2022), which focus on the financial sector and use different criteria for identifying zombie companies. Kane (1987) uses economic insolvency; Hoshi and Kashyap (2010) aim at reliance on subsidized loans; and Zhang and Huang (2022) target subsidize loans with debts exceeding 50% of total assets. In the manufacturing sector, the identification criterion based on loans at subsidized interest rates is also used (e.g. Caballero *et al*., 2008; Shen & Chen, 2017), in addition to recurrent negative profitability and high debt (Fukuda & Nakamura, 2011; Imai *et al*., 2016).

As far as the tourism sector is concerned, no studies were found that specifically address the problem of zombie companies, although SMEs in this sector are crucial (Thomas *et al*., 2011). It is necessary to consider this situation due to the financial vulnerability of tourism SMEs (Mohammed, 2022), and because they operate in a competitive environment (Hallak *et al*., 2013). This issue is of particular concern given the importance of tourism in many regions and countries, where it may even be the main economic activity, as is the case in Spain, the country where the work was performed.

Despite the aforementioned serious drawbacks of zombie firms in the economy, there is no consensus regarding the suitability of their elimination. This is mainly because (i) many of these companies can recover (Goto & Wilbur, 2019), (ii) the elimination of government subsidies could lead to the contamination of healthy companies (Asanuma, 2015), and (iii) their elimination would affect employment (Foglia, 2022; Hoshi, 2006; Zoller-Rydzek & Keller, 2020), which could aggravate the economic situation of certain territories.

Considering the significant problems generated by zombie companies, it is especially important to be able to identify their emergence in advance to establish the most appropriate policies to mitigate their effects (Blažková & Dvouletý, 2022). With this early information, stakeholders can adopt various strategies depending on their interests or the economic effect that these companies have on the competitive environment in which they operate. More specifically, governments can reorient their subsidy policies more efficiently.

2.2 Identification and prediction of zombie firms

Based on the literature review, it has been observed that there is no consensus criterion for identifying zombie firms. For this reason, a large number of works have used as their methodological basis the criteria established by Caballero *et al*. (2008) and Fukuda and Nakamura (2011) (e.g. Chang *et al*., 2021; Dai *et al*., 2019; Du & Li, 2019; Liu *et al*., 2019; Shen & Chen, 2017; Tan *et al*., 2016; Wang & Zhu, 2020; Zhang *et al*., 2020). These criteria have been adapted in studies to suit the characteristics of the research. This lack of consensus on the identification criteria could be due to the different types of data available or the need to adapt the methodology to different economic or sectoral contexts.

Caballero *et al*. (2008) consider that a company in difficulty is a zombie if its subsistence depends on bank lending with interest rates well below market rates. More specifically, a firm is a zombie if the interest payments (R) are less than a hypothetical lower bound expected to be paid by higher quality or risk-free borrowers (R^*), calculating R^* as shown in the following equation 1:

$R_{i,t}^{*} = rs_{t-1}BS_{i,t-1} + \left(\frac{1}{5} * \sum_{j=1}^{5} rl_{t-j}\right) * BL_{i,t-1} + rcb_{\min\, over\, las\, 5\, years,t} * Bonds_{i,t-1}$ (1)

Where $R_{i,t}^{*}$ is the minimum interest payment required from company i in the year t, while $BS_{i,t-1}$, $BL_{i,t-1}$, and $Bonds_{i,t-1}$ are the short and long-term bank lending and outstanding bonds (including convertible and collateralized bonds), respectively, of company i in the period t-1. On the other side, rs_{t-1}, rl_{t-j} and $rcb_{\min\, over\, las\, 5\, years,t}$ correspond to the average short-term preferential interest rate in the year t-1, the average long-term preferential interest rate over the five-year period up to and including t, and the minimum observed coupon rate of any convertible corporate bond issued in the last five years prior to t, respectively.

Subsequently, Fukuda and Nakamura (2011) consider the identification criterion of Caballero *et al.* (2008) to be a simple one that generates type I and/or type II errors. This is because it recognizes healthy firms as zombie companies, and/or companies that should be considered zombies as non-zombies. On the one hand, they able to negotiate more advantageous interest rates. On the other, they are willing to pay market interest rates to avoid or delay bankruptcy. To avoid these problems, Fukuda and Nakamura (2011) added to this a profitability criterion and another related to evergreen lending. According to the first criterion, those firms whose earnings before interest and taxes (EBIT) exceed the risk-free interest payments are not considered zombies. Under the second, those companies whose EBIT is lower than R* in period t, when the total external debt is more than half of their total assets in period t-1, and whose lending has increased in period t, are categorized as zombies in period t.

It should be noted that most publications have focused on large listed companies, using the criteria of Caballero *et al.* (2008), and Fukuda and Nakamura (2011) together to identify zombie firms (e.g., Chang *et al.*, 2021; Chen, 2022; Liu *et al.*, 2019; Wang & Zhu, 2020). This set of works focusing on large listed firms and using these criteria together has incorporated other conditions for a company to be classified as a zombie. Thus, Dai *et al.* (2019), and Shen and Chen (2017) consider that companies are zombies if their leverage exceeds 50%, their annual profits are negative, and their current annual liabilities exceed those of the previous year. To these requirements, Geng *et al.* (2021) add that annual losses must be incurred for three consecutive years. Q. He *et al.* (2020) state that the return on assets of these companies must be less than 50% of the sector to which they belong. In addition, Du and Li (2019) incorporate into these criteria the condition that the company's profit must be less than zero after subtracting the subsidies obtained from the government and banks.

Regarding the identification of zombie SMEs, the number of works produced has been much lower than in the case of large firms. Of particular note is the study of Imai (2016), whose identification criteria have been among the most widely used in the literature (e.g., Du & Li, 2019; Goto & Wilbur, 2019; Wu *et al.*, 2021). Although this author relies on the criteria of Caballero *et al.* (2008), and Fukuda and Nakamura (2011), he notes different problems in their direct application. On the one hand, he warns that Caballero *et al.* (2008)'s criterion identifies high-performing companies that obtain financing at low-interest rates as zombie firms. On the other, when applying Fukuda and Nakamura (2011)'s criterion to healthy firms that have experienced temporary declines in profits, they could be mistakenly considered zombie firms. For these reasons, the criterion issued by Imai (2016) proposes the fulfillment of conditions included in equations 2 and 3 for a company to be identified as a zombie:

$$\begin{cases} \sum_{m=0}^{T=3} \left(EBIT_{i,t-m} - R_{i,t-m}^{*}\right) < 0 \quad (2) \\ RD_{i,t} > RD_{i,t-1} \; OR \; R_{i,t} > R_{i,t}^{*} \quad (3) \end{cases}$$

Where $EBIT_{i,t-m}$ is the earnings before interest and taxes of the company i at time t; $R_{i,t}$ is the effective interest rate paid by company i at time t; $R^*_{i,t}$ is the minimum interest payment required from company i at time t; $RD_{i,t}$ is the total interest-bearing debt of the company i at time t; finally, T is the number of consecutive periods with which a zombie firm could be stably identified, which according to Imai (2016) should be three periods.

In relation to SMEs, studies have been published using the interest coverage ratio (EBIT/financial expenses) to identify zombie companies (e.g., Carreira *et al*., 2022; Nieto-Carrillo *et al*., 2022). According to this criterion, a firm is considered a zombie if its return on assets is lower than the interest rates for three consecutive years, it is at least five years old and its leverage is higher than the median of the companies in its industry (e.g., McGowan *et al*., 2018).

Due to Imai (2016)'s criterion being the most widely used in the literature, a variation of this was chosen, although there are difficulties in obtaining data to determine the ability of companies to comply with interest payments (Urionabarrenetxea *et al*., 2018). This problem has been solved as in other works (e.g., McGowan *et al*., 2018), by using interest rates calculated through the average of the monthly rates instead of using preferential interest rates as applied in other research where such information is available (e.g., Dai *et al*., 2019; Tan *et al*., 2016). Specifically, Imai's criterion has been modified in the calculation of R and R*, as shown in equations 4 and 5, respectively:

$$R_{i,t} = \frac{FE_{i,t}}{RD_{i,t-1}} \quad (4)$$

$$R^*_{i,t} = rs_{t-1} * RDS_{i,t-1} + \left(\frac{1}{5} * \sum_{j=1}^{5} rl_{t-j}\right) * RDL_{i,t-1} \quad (5)$$

Where $FE_{i,t}$ are the financial expenses of company i in period t; $RD_{i,t-1}$ is the total interest-bearing debt of company i in period t-1; $RDS_{i,t-1}$ and $RDL_{i,t-1}$ represent the short-term and long-term interest-bearing debt of company i in period t-1, respectively. In addition, rs_{t-1} and rl_{t-j} are the short-term annual interest rate for period t-1 and the long-term annual interest rate for period t-j, respectively.

After reviewing the literature, it is worth noting that there are research articles that analyze those factors that are most relevant for the emergence of zombie firms (e.g., Blažková & Dvouletý, 2022; Chang *et al*., 2021; Tan *et al*., 2016). However, there are only essays that attempt to predict the zombie status of firms (see Table 1). These essays have a number of shortcomings: (a) not showing the criterion for identifying a zombie firm (e.g., Parosa & Sadany, 2018); (b) not using techniques to verify the validity and robustness of the results such as k-fold based stratified cross-validation (e.g., Martiis *et al*., 2021; Parosa & Sadany, 2018), or applying a small number of k as is 2 (e.g., Bargagli-Stoffi *et al*., 2020), or splitting the dataset into training and testing (e.g., Martiis *et al*., 2021); (c) not presenting employ metrics that facilitate comparison with other similar work (e.g., Martiis *et al*., 2021). Although essays such as those by Bargagli-Stoffi *et al*. (2020)), and Parosa and Sadany (2018) offer results with very high predictive ability, they are not comparable to those of this research paper. This is because it is not presented how many years in advance the zombie state of the companies is predicted. In addition, the essays presented in Table 1 do not employ only accounting variables.

Table 1. *Research related to the prediction of zombie firms*

Authors and year	Sample size	Algorithm	Country	Time period	Typology of variables	Most promising outcome
Parosa and Sadany (2018)	479,279 observations	Logistic regression, neural network	24 European countries	2000-2018	Accounting and macroeconomic data	AUC-ROC=0.976
Bargagli Stoffi *et al.* (2020)	304.906 companies	Logistic regression, classification and regression tree (CART), random forests, super learner, bayesian additive regression tree with missing incorporated in attributes (BART-MIA)	Italy	2008-2017	Accounting and non-accounting data	AUC-ROC=0.967
Martiis *et al.* (2021)	210.000 observations	Logistic regression and classification and regression trees (CART)	32 European countries and United States	2007-2016	Accounting and market data	Not defined

3. Methodology

In this research, a similar methodology to that applied in similar works was followed (e.g., Dudjak & Martinović, 2021; Kozlovskaia & Zaytsev, 2017; Veganzones & Séverin, 2018), see Figure 1.

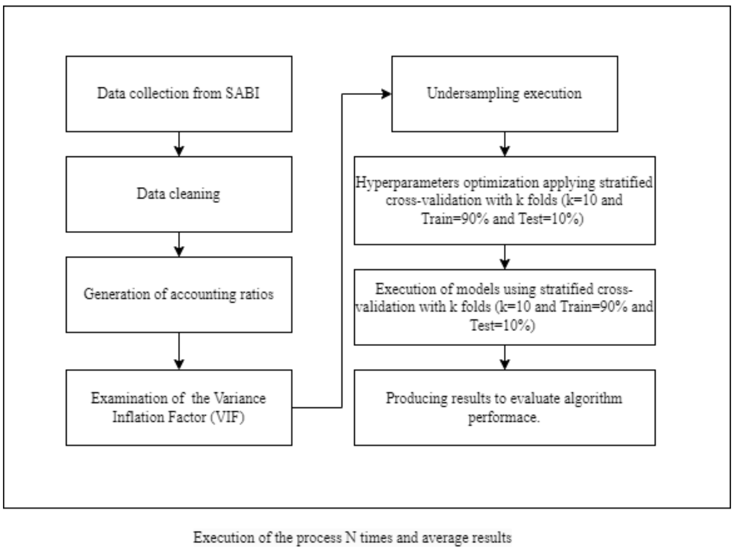


Figure 1. *Methodological process flow diagram*

3.1 Data collection and variable selection

A sample composed of Spanish tourism SMEs that, according to the identification criteria outlined in Section 2.2, were considered zombies in 2019 was obtained. This sample contains accounting information for the period 2016-2019 on companies in the Iberian Balance Analysis System (SABI) database (Bureau Van Dijk, 2023). Accounting information from the years 2017-2019 was used to determine if a firm is a zombie one, and from the year 2016 for the generation of ratios. In addition, a series of filters were applied to it: first of all, companies considered SMEs according to the European Union Regulation (EU, No 651/2014, 2014) were selected. Second, firms that are active and have accounting data for the period 2016-2019 were chosen. Third, those whose main activity is tourism (i.e., accommodation and food and beverage services) were identified. In addition, to obtain monthly interest rates, those published by the Spanish national central bank were used (Banco de España, 2023).

After applying the identification criteria explained in Section 2.2., 356 SMEs were selected, of which 329 (92.42%) were non-zombie firms and 27 (7.58%) were considered zombies.

The set of variables used in this research to predict the emergence of zombie firms is drawn from academic works focused on the identification of zombie firms (e.g., Blažková & Dvouletý, 2022; Hoshi, 2006; McGowan *et al.*, 2018). Such variables are characterized by being easily obtainable in the annual accounts of companies. This fact is key for the reproducibility of the model proposed. Initially, different categories of financial ratios were selected, such as, for example, solvency, indebtedness, profitability, etc. However, after performing a multicollinearity analysis, some were eliminated by measuring their variance inflation factor (see Appendix A), where the frontier value employed was 4, as applied in other studies (e.g., Fossen & Sorgner, 2022; Huang & Crotts, 2019; Kim *et al.*, 2015). The resulting variables after applying this filter can be observed in Table 2 (a descriptive analysis of these variables can be found in Appendix B). Finally, it should be noted that the dependent variable used was created as a binary taking the value 0 if the company is considered non-zombie and 1 otherwise.

In this study, several accounting variables were used to predict the emergence of zombie firms in tourism SMEs. These have been widely used in the academic literature analysing the financial health of companies and, more specifically, in the literature analysing the identification of zombie companies (see Table 2). The variables considered include debt ratio, return on assets (ROA), return on operating assets, return on equity (ROE), return on sales, ratios of subsidies, coverage of financial expenses, and debt service capacity. In a competitive and dynamic industry such as the tourism sector, high indebtedness may indicate a higher probability of insolvency, while low ROA, return on operating assets, and ROE values indicate inefficient assets, operating assets, and equity management. In addition, low debt service capacity and coverage of financial expenses reflect difficulties managing financial obligations, such as during periods of low tourism demand. Finally, a high dependence on subsidies reveals the financial vulnerability of these companies and their inability to be self-sustainable.

3.2 Classification algorithms

To detect in advance that a company will become a zombie, a set of classification algorithms was applied considering their use in other studies on predicting the zombie state in companies: logistic regression (LOGIT) (e.g. Bargagli-Stoffi *et al.*, 2020; Martiis *et al.*, 2021; Parosa & Sadany, 2018); artificial neural networks (ANN) (e.g. Parosa & Sadany, 2018); and random forest (RFC) (e.g. Parosa & Sadany, 2018). It should be noted that algorithms such as LOGIT (Dumitrescu *et al.*, 2022) and RFC (Uddin *et al.*, 2022) allow a high level of interpretability compared to methods such as ANN with a limited level of interpretability (Uddin *et al.*, 2022). For their part, ANN and RFC provide high predictive capability

Table 2. *Variables used in this research*

Variables	Descriptions	Calculation method	Prior research
		ACCOUNTING VARIABLES	
Debt ratio	Evaluates a company's ability to measure its financial risk	$\frac{Total\ interest\ bearing\ debt}{Total\ assets}$	Hoshi (2006)
Return on assets	Measures a company's efficiency in the use of its assets to generate profits	$\frac{EBIT}{Total\ assets}$	Aysun *et al.* (2018); Dai *et al.* (2019); Fukuda (2020); Goto & Wilbur (2019); Guo *et al.* (2022); Han *et al.* (2019, 2020); Imai (2016); Shiraishi & Yano (2021); Storz *et al.* (2017); Wang & Zhu (2021); Zhang *et al.* (2020)
Return on operating assets	Checks the efficiency of operating assets in relation to operating profit	$\frac{Adjusted\ operating\ income}{Functional\ assets}$	Fang *et al.* (2020); Hoshi (2006); Liu *et al.* (2019)
Return on equity	Measures the return on equity invested in the company	$\frac{Income\ for\ the\ period}{Equity}$	Fukuda (2020); Q. He *et al.* (2020)
Return on sales	Indicates the company's efficiency in converting sales into profits	$\frac{EBIT}{Net\ revenues}$	Blažková & Dvouletý (2022); Wu *et al.* (2021)
Ratio of subsidies I	Assesses the company's dependence on external subsidies and aids	$\frac{Subsidies}{Net\ revenues}$	Zhang *et al.* (2020)
Ratio of subsidies II		$\frac{Subisidies}{Total\ assets}$	Zhang *et al.* (2020)
Ratio of subsidies III		$\frac{Subsidies}{Profit\ (loss)\ from\ the\ period}$	Zhang *et al.* (2020)
Coverage of financial expenses	Measures the company's ability to cover its financial expenses with its operating profits	$\frac{EBIT}{\lvert Financial\ expenses\rvert}$	Acharya *et al.* (2019); Carreira *et al.* (2022); McGowan *et al.* (2018); Nieto-Carrillo *et al.* (2022)
Debt service capacity	Evaluates the company's ability to fulfill its debt obligations based on its earnings before interest, taxes, depreciation and amortization (EBITDA)	$\frac{EBITDA}{Total\ interest\ bearing\ debt}$	Storz *et al.* (2017)

(Dumitrescu *et al.*, 2022) and can handle high dimensional data (Mishra *et al.*, 2024; Pravallika *et al.*, 2022). Regarding the limitations of the proposed methods, LOGIT and RFC show high sensitivity to noise in algorithms (Abellán *et al.*, 2018; Li *et al.*, 2023); ANN presents high difficulty defining the set of hyperparameters (C. He *et al.*, 2020) and a high tendency to overfit (Gouda & Marzouk, 2021); and in the same way, a high tendency to overfit occurs with RFC (Abellán *et al.*, 2018).

To obtain the optimal hyperparameters for each algorithm, a grid search and stratified cross-validation based on the k-fold technique were utilized (see Appendix C). On the one hand, the grid search technique tests all possible combinations of hyperparameters in the algorithms from a list to obtain the ones that generate the best results. Hyperparameters were obtained by considering the values of metrics such as f1-score and the area under the receiver operating characteristics curve. On the other hand, to check the robustness of the results, stratified cross-validation based on the k-fold technique was used. The objective was to divide the dataset into k partitions, where one partition is used for the test subset and the rest for the training subset. It should be noted that this process is repeated k times, and that, when stratified, each subset has the same proportion of classes of observations—i.e. depending on whether it is zombie or not. In the case of this work, a value of k=10 was used; the training subsets were 90% of the total sample, the remaining 10% for testing. To generate the classification models, the stratified cross-validation based on the k-fold technique with optimal hyperparameters was used again with the same value for k. Due to an imbalance in the number of observations in each class studied (27 zombie firms compared to 329 non-zombie firms), and following the procedure used in other studies (e.g. Pozzolo *et al.*, 2015; Robinson *et al.*, 2020; Yu *et al.*, 2013), a random undersampling technique repeating the process 100 times was applied.

3.2.1 Logistic regression

The LOGIT is an algorithm based on the concept of regression, where a group of independent variables is used to predict a dichotomous dependent variable through the linear relationship between them. The formula that defines the classifier is found in equation 6:

$$logit(p_i) = \ln\left(\frac{p_i}{1-p_i}\right) = \sum_{i=1}^{N} \beta_i X_i + \beta o \quad (6)$$

where p_i is the probability that the company is a zombie, X_i is each of the independent variables, βi are the calculated coefficients, and N is the sample size.

3.2.2 Artificial neural networks

ANN are computational networks that aim to simulate the decision-making process of biological nerve cells in the central nervous system (Graupe, 2013). In this case, a type of ANN has been applied whose neurons are fully connected. This algorithm is composed of a series of layers: the input, hidden, and output types (see Figure 2). The first is defined by a set of neurons equal to the number of variables used for prediction. Subsequently, one or more hidden layers with several neurons are selected. Finally, the output layer with one or more neurons depends on the type of classification problem. In this work, after performing different tests, the structure that generated the best results was the one that had 10 neurons in the input layer, one hidden layer with 64 neurons, and one neuron in the output layer. The latter was composed of a single neuron because it was a binary classification problem.

3.2.3 Random forest

The RFC is an algorithm based on a set of decision trees, where from a random vector generated independently, a sample of data is chosen randomly for the same distribution (Breiman, 2001). With the combination of the predictions obtained from all these decision trees, the final prediction is made according to different criteria, e.g. the selection of most voted by majority or on average (Breiman, 2001).

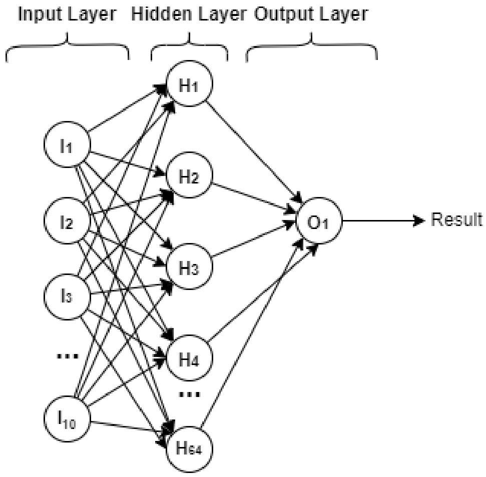
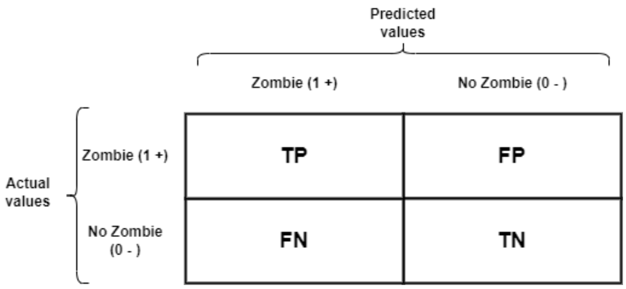


Figure 2. *Structure of artificial neural networks*

3.3 Evaluation of the generated models

For the correct evaluation of the generated models, a set of metrics that arise from the confusion matrix (see Figure 3) was applied. These were accuracy, the f1-score, precision, recall, and specificity (see equations 7, 8, 9, 10, and 11). In addition, the area under the curve receiver operating characteristics (AUC-ROC) was considered as a metric.



Note: TP (True Positive), FP (False Positive), TN (True Negative), and FN (False Negative)

Figure 3. *Confusion matrix*

- Accuracy: $\frac{TP+TN}{TP+FN+TN+FP}$ (7)
- F1-score: $\frac{2xprecisionxrecall}{precision+recall}$ (8)
- Precision: $\frac{TP}{TP+FP}$ (9)
- Recall: $\frac{TP}{TP+FN}$ (10)
- Specificity: $\frac{TN}{TN+FP}$ (11)
- AUC-ROC (Area Under the Curve – Receiver Operating Characteristics). It focuses on the calculation of the area under the curve described by the recall on the X-axis and by the 1 – specificity on the Y-axis. It measures the probability of belonging to the positive or zombie class.

4. Results

As can be seen in Table 3, the algorithm that achieves the best prediction results about which company will become zombie 3 years in advance is the RFC, followed by ANN and LOGIT. This is because all the values of the metrics evaluated are superior. In terms of accuracy, the result obtained by the RFC was 75.3%, followed by the ANN (67.0%) and LOGIT (66.6%). The same applies to the f1-score metric, with values of 76.1% for the RFC, then 66.3% for the ANN, and 65.8% for the LOGIT. In terms of the f1-score, there are the precision and recall metrics, where for the first one, the RFC obtains the best result (72.1%), followed by the ANN (65.7%) and LOGIT (65.3%), and for the second, the RFC achieves the best result (82.0%), with 71.0% for the ANN and 70.0% for the LOGIT. On the other hand, the algorithm that achieves the best results for the specificity is the RFC with 68.8%, then the LOGIT (63.9%) and ANN (63.6%). Because of the above, we note that the RFC model is the one that generates the fewest false positives and false negatives. Finally, the algorithm that performs best in terms of AUC-ROC is the RFC (78.4%), followed by the ANN (70.2%) and LOGIT (69.4%) (see Figure 4).

Table 3. *Results*

Algorithm	Accuracy	F1-score	Precision	Recall	Specificity	AUC-ROC
LOGIT	**0.666**	**0.658**	**0.653**	**0.700**	**0.639**	**0.694**
	(0.059)	(0.069)	(0.047)	(0.077)	(0.071)	(0.081)
ANN	**0.670**	**0.663**	**0.657**	**0.710**	**0.636**	**0.702**
	(0.051)	(0.062)	(0.043)	(0.068)	(0.072)	(0.076)
RFC	**0.753***	**0.761***	**0.721***	**0.820***	**0.688***	**0.784***
	(0.051)	(0.053)	(0.051)	(0.052)	(0.067)	(0.062)

Note. The result in bold is the average result of the generated models in each iteration for each fold of the cross-validation, and the one in parentheses is the standard deviation. The asterisk indicates the best value of each metric.

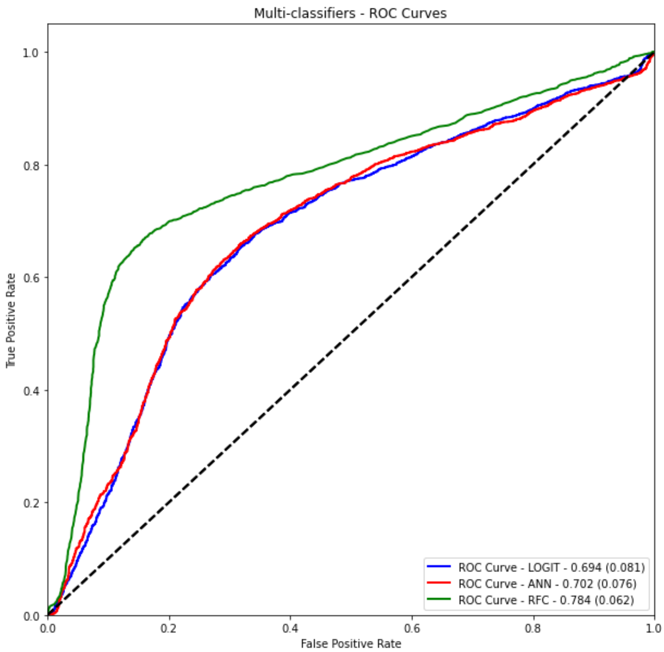


Figure 4. *ROC curve of classifiers*

On the other hand, Table 4 shows the variables with the highest permutation importance for predicting the zombie state in the algorithm that yielded the best results, which is the RFC. Thus, the most important variables for predicting the zombie state are debt service capacity, return on assets, return on operating assets, and debt ratio. This is in line with Schivardi *et al.* (2022), who state that variables related to return on assets and default risk measures are fundamental for determining this situation. Moreover, these variables have been significant for the detection of zombie firms in other works, e.g., debt service capacity in Storz *et al.* (2017), return on assets in Dai *et al.* (2019), and Goto and Wilbur (2019), return on operating assets in Fang *et al.* (2020), and Liu *et al.* (2019), and debt ratio in Hoshi (2006).

Table 4. *Permutation importance values of the features for random forest*

Variable	Permutation importance of the features
Debt service capacity	**0.043** (0.111)
Return on assets	**0.04** (0.048)
Return on operating assets	**0.018** (0.06)
Debt ratio	**0.012** (0.051)
Return on sales	**0.0** (0.024)
Ratio of subsidies I	**0.0** (0.0)
Ratio of subsidies II	**0.0** (0.0)
Ratio of subsidies III	**0.0** (0.0)
Coverage of financial expenses	**-0.024** (0.051)
Return on equity	**-0.004** (0.012)

Note. The result in bold is the average result of the generated models in each iteration for each fold of the cross-validation, and the one in parentheses is the standard deviation.

5. Conclusions, implications, limitations, and future research

The existence of zombie firms generates multiple drawbacks within the environment or sector in which they operate. Their negative effects on investment and job creation (Caballero *et al.*, 2008; Hoshi, 2006; Tan *et al.*, 2016), growth opportunities (Storz *et al.*, 2017), and incentives for innovation (Geng *et al.*, 2021) is noted. In addition, they cause significant financial constraints for other companies (Wang & Zhu, 2020).

Considering all the negative effects caused by zombie firms, it would be extremely useful to be able to detect a company that is going to enter this state in advance (Blažková & Dvouletý, 2022). For this purpose, a methodology has been developed based on easily obtained accounting information for the three years before the zombie state occurs. It applies artificial intelligence algorithms (e.g., ANN, RFC, and LOGIT) to a set of 356 Spanish SMEs in the tourism sector, where 329 were non-zombie and 27 were zombies. This methodology can predict with a 78.4% accuracy rate the companies that are going to become zombies.

As for the theoretical implications of the paper, the most important is that it proposes a new way of assessing the risk of tourism SMEs becoming zombie companies. Moreover, this is accomplished through a small set of financial variables. Another of the theoretical contributions consists of testing the usefulness of using only financial data to make the aforementioned prediction. Thus, although the exclusive use of this type of data for the prediction of certain financial situations (e.g., entry into bankruptcy) has been questioned in other studies (Laitinen, 2011), this work confirms its usefulness.
As far as the practical implications are concerned, the first is derived from the theoretical ones. The proposed model can be used in a relatively simple way because it utilizes only accounting data as inputs

for the predictions. The complexity of obtaining non-financial information from companies should not be overlooked. In addition, the recording of much of this information is not usually standardized, which complicates its processing. This is because each company may record such information in a different way. However, the main contribution of this work is the proposal of a methodology capable of predicting, three years in advance and through artificial intelligence tools, those tourism companies that are going to enter a zombie state.

The methodology for early detection of companies at risk of becoming zombies would provide a valuable tool for public policymakers to make efficient public policy decisions. To apply this methodology, public administrations must have the necessary resources for its implementation and maintenance, which would guarantee the accuracy of the predictions. This tool could help to prevent tourism SMEs from entering a zombie state, as it allows early identification of those most at risk. As a result, prevention, awareness, and training campaigns on this issue could be much more targeted. In the same vein, it would make it possible to manage aid and subsidies better according to the policies concerning zombie companies. This optimization in the management of resources and sector sanitation would free up funds that could be used to promote a more dynamic tourism sector oriented towards innovation and improvement of the quality of services.

The proposed methodology would also allow destination management organizations (DMOs) to provide SMEs in the sector with an assessment of their financial situation with a three-year perspective and simulate the impact of changes in the model's variables, which would help them to assess their risk, guide their financial policies, and take preventive measures.

In summary, the findings of this study could help public administrations and tourism SMEs to identify and mitigate risks effectively, thus contributing to a healthier, more competitive, and efficient economy. This is because application of the methodology would make it possible to reduce the number of zombie companies that depend on external aid. This reduction would improve market competitiveness (Blažková & Dvouletý, 2022), making the sector healthier and enabling companies to generate employment more efficiently (Banerjee & Hofmann, 2022), as well as increasing their capacity to innovate (Yu *et al.*, 2023).

A review of the literature did not reveal any preventive measures to avoid the emergence of zombie companies: such measures are always taken once the problem exists. An example of this is that in Japan, interest rate increases have been proposed to eliminate these companies following a 30% increase in their number over the previous year (Yamaguchi & Kyodo News, 2024).

For its part, in Europe, aid has been established for companies with a high risk of insolvency, although not specifically for zombies. Thus, they have been granted loans (Demirgüç-Kunt *et al.*, 2023) and other government aid (Romei, 2023). However, this aid has not been as efficient as intended, since the increase in interest rates has led to an increase in corporate indebtedness and, as a result, to the highest levels of bankruptcy in recent years (Arnold & Jopson, 2023). All of the above highlights the need to anticipate the emergence of zombie companies, given that it is still a problem.

One of the main limitations of this paper is the focus on the use of accounting data from Spanish tourism SMEs only. Therefore, It would be of interest to test the performance of the algorithms in companies from other countries, sectors, and sizes to improve their robustness.

As a future line of research, we suggest the application of other algorithms, as well as the simultaneous use of accounting and non-accounting variables to improve the predictive capacity. In addition, this work could be enriched with the development of studies on the prediction of the recovery of zombie firms.

Data availability
The datasets generated and/or analyzed during the present study are not publicly available because it comes from the SABI database, but can be requested from the corresponding author upon reasonable request.

Appendices

Appendix A. Variance inflation factor

Feature	Variance inflation factor
Return on assets	3.152
Return on operating assets	2.906
Ratio of subsidies II	1.815
Ratio of subsidies I	1.750
Return on sales	1.696
Coverage of financial expenses	1.320
Debt service capacity	1.240
Debt ratio	1.066
Return on equity	1.063
Ratio of subsidies III	1.061

Appendix B. Descriptive analysis of selected variables

Variables	Mean	Standard deviation	Minimum	First quartile	Median	Third quartile	Maximum
Return on assets	0.099	0.211	-1.380	0.027	0.083	0.148	2.656
Return on operating assets	0.162	0.369	-1.390	0.031	0.106	0.198	3.756
Ratio of subsidies II	0.022	0.065	0.000	0.0001	0.005	0.021	0.806
Ratio of subsidies I	0.020	0.082	0.000	0.00005	0.003	0.010	0.903
Return on sales	0.045	0.126	-0.973	0.014	0.043	0.094	0.370
Coverage of financial expenses	134.361	1094.815	-5942.048	6.260	17.972	38.716	12981.860
Debt service capacity	10.855	103.332	-9.262	0.183	0.439	0.995	1572.758
Debt ratio	0.378	0.342	0.0001	0.171	0.330	0.546	4.852
Return on equity	0.214	8.395	-108.346	0.049	0.168	0.312	101.248
Ratio of subsidies III	0.914	5.434	-26.148	0.000	0.033	0.238	63.896

Appendix C. Hyperparameters tuning

Algorithm	Hyperparameters	Optimal hyperparameters
Logistic regression	Solver = [‘newton-cg’, ‘lbfgs’, ‘liblinear’, ‘sag’, ‘saga’] Penalty = [‘l1’,’l2’,’elasticnet’,’none’] Max_iter = [100,200,300,400,600,800,1000] C = [100, 10, 1.0, 0.1, 0.01]	Solver = ‘saga’ Penalty= ‘elasticnet’ Max_iter=3000 C = 1.0
Random forest	n_estimators= [100,200,300,400,500,600,1000] max_depth= [10,20,30,40,50,60] min_samples_split= [2,3,4,5,6] max_features=[’auto’,’sqrt’,’log2’] max_samples= [0.2,0.4,0.6,0.8] criterion=[‘gini’,’entropy’]	n_estimators=600 max_depth=40 min_samples_split=2 max_features=’auto’ max_samples=0.4 criterion=’gini’
Artificial neural networks	Max_iter= [400,500,600,700,900,2000,3000,4000,5000] Hidden_layer_sizes= Activation = [‘identity’,’ logistic’,’tanh’,’relu’] Solver = [‘lbfgs’,’sgd’, ‘adam’] Hidden_layer_sizes = =[32,],[64],[128],[32,32],[32,64],[64,32],[32,64,128],[32,32,32],[64,64,64],[128,128,128]	Max_iter = 3000 Activation=’relu’ Solver=’sgd’ Hidden_layer_sizes= [64,]

Note. Stratified cross-validation based on k-folds (where k=10, train=90%, and test=10%) and relying on metrics such as f1-score and area under the curve ROC was used for hyperparameters optimization.

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