BBR
BRAZILIAN BUSINESS REVIEW

ARTICLE

Insolvency in Brazilian Football Clubs: Proposition of Models Based on Neural Networks

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ABSTRACT

The literature underlines that football clubs face financial problems, which can lead to insolvency. Existing models seek to predict insolvency for organizations in different sectors, but only recently have they been developed for European clubs. Thus, this study proposes insolvency prediction models for Brazilian football clubs. Based on the ranking elaborated by the Brazilian Football Confederation, we analyzed 35 football clubs that published their complete financial statements from 2011 to 2018. Financial and sports indicators were considered in the development of our neural network-based models. Results indicated that the variables immediate liquidity, net working capital, asset turnover, and sports performance in the Brazilian Championship were significant for predicting insolvency in at least one of the developed models. This study contributes to the literature on football clubs' insolvency by proposing accurate predictive models based on financial and sporting indicators.

KEYWORDS

Insolvency, Brazilian Football Clubs, Neural Networks

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Received: 06/10/2020.
Revised: 11/05/2020.
Accepted: 02/22/2021.
Published Online: 11/05/2021.
DOI: http://dx.doi.org/10.15728/bbr.2021.18.6.2

1. INTRODUCTION

Insolvency in football clubs usually derives from overspending to achieve better positions in the championships in which they compete (Beech, Horsman, & Magraw, 2010; Szymanski, 2017). According to Szymanski (2015), the insolvency of a football club is established as assets become insufficient to cover obligations. Szymanski (2017) adds that a club may become insolvent and recover subsequently. Therefore, the sought after maximization of sporting performance can generate losses and deteriorate the organization's equity if economic goals are not simultaneously considered.

Within the literature related to insolvency in football clubs, the existence of a financial crisis was addressed by Lago et al. (2006), causes for such a phenomenon were discussed theoretically by Beech et al. (2010) and models formulated for companies were applied by Barajas and Rodriguez (2014). Recently, Alaminos and Fernández (2019) have devised insolvency prediction models specifically for football clubs. This literature, however, is focused on the European reality. Barajas and Rodriguez (2014) recommended the elaboration of models including variables in addition to those proposed by Altman (1968). Alaminos and Fernández (2019) also suggested the development of models for South American football clubs, therefore, emerging as a gap in the existing literature.

Addressing the prediction of insolvency in football clubs is justified. As Szymanski (2017) points out, it is a chronic problem in the sector. In Brazil, this statement seems to be particularly pertinent, considering that, according to Dantas, Machado and Macedo (2015), approximately half of the Brazilian clubs analyzed presented negative equity from 2010 to 2012.

Considering the amount owed by clubs to the Federal Government, tax benefits such as discounts and installment plans have been implemented for the reversal of part of these debts. The principles and practices of fiscal responsibility applied to football clubs is regulated by Law No. 13.155/2015, which created the Brazilian Football Management Modernization and Fiscal Responsibility Program (PROFUT) and the Public Authority of Football Governance (APFUT). In case a club adheres to the installment plan, some requirements are established, such as the publication of standardized statements on its website. This refinancing program for debts with the government was instituted considering a scenario where several clubs had high debts with public entities. As an example, in 2019, the 20 participant clubs in the national championship's first division owed a combined total of R$1.8 billion to the Union (Petrocilo, 2019).

Therefore, there is a need for a better balance between revenues and expenses to avoid new indebtedness (Dias & Monteiro, 2020). It is noteworthy that there is a need for efficient laws and regulations to stimulate better practices in the sector, which is difficult to achieve, but these actions are not sufficient (Evans, Walters, & Tacon, 2019). The European scenario has some examples that can be adapted to the Brazilian reality, allowing Brazil to collect taxes related to the development of the sector instead of regularly pardoning debts.

In this context, our goal is to propose insolvency prediction models for Brazilian football clubs. The models are developed from neural networks, using financial and sports indicators as input variables. Results demonstrate that the inclusion of these indicators present predictive power for insolvency with comparable accuracy to that of Alaminos and Fernández (2019). The most important variables are immediate liquidity, net working capital, asset turnover, and the sports performance indicator, in the Brazilian Championship, for at least one model.

We intend to contribute to the literature on the analysis of football clubs' insolvency, considering that this is an important factor to the sports sector and to the economy in general, and the literature's demand for predictive models (Alaminos & Fernández, 2019). Additionally, since insolvency is a stage prior to the bankruptcy of an organization, it is important to understand the factors that are related to the insolvency of clubs for preventative purposes.

Furthermore, it is highlighted that the financial regulation imposed on European clubs (Financial Fair Play), with a possible future applicability in Brazil (Pereira, 2019), focuses on the insolvency of clubs and on losses they cause, with sporting and financial punishments for those who do not meet the requirements (Alaminos & Fernández, 2019; Plumley, Wilson, & Ramchandani, 2017). Finally, we highlight the relevance of football clubs as a social and cultural phenomenon for society and how their insolvency negatively affects creditors, governments, and other stakeholders (Alaminos & Fernández, 2019; Beech et al., 2010; Freestone & Manoli, 2017).

2. INSOLVENCY IN FOOTBALL CLUBS

It is necessary to distinguish between insolvency and bankruptcy with are similar terms both frequently used in the literature. The former can be conceptualized as the inability to meet financial obligations as they fall due. Bankruptcy, on the other hand, is determined when the legal process to terminate the organization's activities has been undertaken and concluded (Beech et al., 2010; Silva, Wienhage, Souza, Bezerra, & Lyra, 2012). In this study, insolvency is analyzed considering as a criterion the presence of negative equity on the balance sheet, i.e., whether total liabilities exceed total assets (Altman & Hotchkiss, 2006; Coelho, Edwards, Scherer, & Colauto, 2017).

Beech et al. (2010) flag possible causes that lead football clubs to insolvency. One of these refers to the competitive structure, as teams compete in championships in which it is possible to be relegated to a lower division in the following year. In addition, minor differences in sporting results can affect the teams' income and their planning (Alm & Storm, 2019). Thus, clubs invest their financial resources, even above their limits, hoping to convert them into positive sporting results. However, by failing to obtain them, financial imbalance can occur and compromise their sporting results (Beech et al., 2010; Szymanski, 2017). Finally, clubs' indebtedness may increase, leading them to insolvency (Scelles, Szymanski, & Dermit-Richard, 2018).

In international literature, studies have conducted analyses on the financial difficulties presented by European clubs. Barajas and Rodriguez (2014), for example, examined insolvency in Spanish football clubs of first and second divisions, to classify them into solvent and insolvent. To achieve this goal, the indicator proposed by Altman (1968) was employed. As results, the indicator classified most of the Spanish clubs as insolvent, besides the presence of negative equity for 80% of them. Therefore, it is notable that the study presented evidence of insolvency for most Spanish clubs at that time.

Alaminos and Fernández (2019) deepened the discussion regarding insolvency in European football clubs by elaborating models for insolvency prediction based on neural networks and logistic regression. To develop the model, the authors used corporate governance variables and indicators to measure the clubs' economic, financial, and sporting performance. As for results, the authors identified that low liquidity, high leverage, and low sports performance were the main predictors of insolvency. It is noteworthy that this study was the only one found in the analyzed literature that proposes to predict the insolvency of football clubs through models.

3. METHODOLOGY

3.1. Population, sample, and time period

The population comprises the 50 largest football clubs in Brazil, according to the ranking released by the Brazilian Football Confederation in 2019. Such ranking has been used in previous studies as a selection criterion, such as Dantas et al. (2015). Information from clubs referring to the eight-year period (2011-2018) was analyzed. The sample is composed by clubs that published their financial statements on their own websites, websites of football federations, or websites of large circulation newspapers in at last four years, which represents the disclosure of statements in at least half of the period. Table 1 shows the 35 clubs in the final sample and their positions in the ranking mentioned above. Regarding the number of observations, 255 were in total.

Table 1
Sample

Rank	Club	Rank	Club	Rank	Club
1	Palmeiras	13	Fluminense	25	Atlético Goianiense
2	Cruzeiro	14	Vasco da Gama	26	Paraná
3	Grêmio	15	Bahia	27	Paysandu
4	Santos	16	Sport	28	Santa Cruz
5	Corinthians	17	Vitória	29	Criciúma
6	Flamengo	18	Ponte Preta	31	Juventude
7	Atlético Mineiro	19	América Mineiro	34	Vila Nova
8	Athletico Paranaense	20	Coritiba	36	Náutico
9	Internacional	21	Avaí	39	Joinville
10	Chapecoense	22	Figueirense	41	Brasil de Pelotas
11	Botafogo	23	Ceará	44	Guarani
12	São Paulo	24	Goiás		

Source: Authors' own elaboration

3.2. Financial and sports indicators

The economic and financial indicators, input variables in the neural network-based model, serve as supports for analyzing the financial statements of these clubs and assisting in measuring their performance. The indicators were calculated based on the information collected from the selected clubs' financial statements. The selected financial statements were the balance sheet and the income statement, along with explanatory notes. The financial data of the clubs were updated by the Accumulated Consumer Price Index (IPC-A) until December 2019, to minimize the inflationary effect of the period.

To calibrate the neural network-based model according to the business model and structure of the financial statements of a football club, adjustments were required. Therefore, the indicator that measures the representativeness of intangible assets in relation to total assets was included. The inclusion of this indicator can be considered an innovation on the study of Alaminos and Fernández (2019), which developed an insolvency prediction model for European football disregarding indicators that considered the intangible assets of these entities.

Including financial indicators, we intend to analyze the liquidity, indebtedness, return on investment, and profitability of football clubs. It is assumed that insolvent clubs present indicators at different levels from those presented by solvent clubs. We emphasize that indicators that directly or indirectly use the net equity were not included, as it is related to the insolvency criterion adopted in this study. Table 2 presents the selected indicators.

Table 2
Financial Indicators

N.	Indicator	Operationalization	Theoretical Background
I1	Immediate Liquidity	$\frac{\textit{Cash and Equivalents}}{\textit{Current Liabilities}}$	(Ecer & Boyukaslan, 2014)
I2	Current Ratio	$\frac{\textit{Current Assets}}{\textit{Current Liabilities}}$	(Alaminos & Fernández, 2019)
I3	Net Working Capital	$\frac{\textit{Current Assets} - \textit{Current Liabilities}}{\textit{Total Assets}}$	(Alaminos & Fernández, 2019)
I4	General Liquidity	$\frac{\textit{Current Assets} + \textit{Long Term Assets}}{\textit{Current Liabilities} + \textit{Long Term Liabilities}}$	(Kanitz, 1976)*
I5	Asset Composition	$\frac{\textit{Current Assets}}{\textit{Total Assets}}$	(Gutiérrez-Fernández, Talavero-Álvarez, & Coca-Pérez, 2017)
I6	Fixed to Total Assets	$\frac{\textit{Fixed Assets}}{\textit{Total Assets}}$	(Alaminos & Fernández, 2019)**
I7	Intangible to Total Assets	$\frac{\textit{Intangible Assets}}{\textit{Total Assets}}$	(Guo, Kubick & Masli, 2018)*
I8	Total Debt	$\frac{\textit{Short and Long Term Loans}}{\textit{Total Assets}}$	(Alaminos & Fernández, 2019)
I9	Debt Composition	$\frac{\textit{Current Liabilities}}{\textit{Current Liabilities} + \textit{Long Term Liabilities}}$	(Martins, Diniz, & Miranda, 2017)*
I10	Net Debt	$\frac{\textit{Net Debt}}{\textit{Total Revenue}}$	(Szymanski, 2017)
I11	Asset Turnover	$\frac{\textit{Total Revenue}}{\textit{Total Assets}}$	(Alaminos & Fernández, 2019; Ecer & Boyukaslan, 2014)
I12	Return on Assets	$\frac{\textit{Net Income}}{\textit{Total Assets}}$	(Ecer & Boyukaslan, 2014)
I13	Net Margin	$\frac{\textit{Net Income}}{\textit{Total Revenue}}$	(Plumley, Wilson, & Ramchandani, 2017; R. Wilson, Plumley, & Ramchandani, 2013)
I14	EBIT to Total Revenue	$\frac{\textit{EBIT}}{\textit{Total Revenue}}$	(Alaminos & Fernández, 2019)

Note: * Except for these studies, the others applied these indicators to Brazilian or European football clubs ** In this study, the denominator used originally was the equity of football clubs. Due to the criteria for insolvency in this study to involve equity, this is replaced by total assets. All indicators that used values taken from the balance sheet were calculated from the final date balance sheet. Source: Authors' own elaboration

To ensure that the model becomes more robust and aligned with the reality of Brazilian football clubs, sporting indicators that represent their respective sporting performances were included. These indicators were selected from the literature that analyzes the sports performance in Brazilian and European football clubs.

Some metrics were used to evaluate the performance achieved in the national championship. As examples, we can mention the club's final position in the Brazilian Championship, the percentage of earned points in this championship, and the number of earned points. In order to measure the sports performance of the teams in the Brazilian Championship, the indicator formulated in Szymanski and Smith's study (1997) and employed in other studies since then (Alaminos & Fernández, 2019; Szymanski, 2017) was used. The proposed sport variables are evidenced in Table 3.

Table 3
Sportive Indicators

N.	Indicator	Operationalization	Theoretical Background
E1	Szymanski and Smith (1997) Indicator	The indicator formulated in the study by Szymanski and Smith (1997) is used.	(Alaminos & Fernández, 2019; Szymanski, 2017; Szymanski & Smith, 1997)
E2	Brazilian Championship Position	Position in the Brazilian Championship. The position of the 20 clubs that played in the first division varies between 1 and 20, of the 20 clubs that played in the second division varies between 21 and 40, of the 20 clubs that played in the second division varies between 41 and 60 and of the 20 clubs that played in the third division, and fourth division ranges from 61 to 128.	(Scelles et al., 2018)
E3	Earned points percentual	Represents the percentage of points won by the club in the Brazilian Championship. The victory of a match represents 3 points, the tie 1 point and the defeat have no score. The indicator is calculated from the points earned divided by the possible number of points earned.	(Plumley, Wilson, & Ramchandani, 2017)
E4	Division	Dummy variable to reflect the effects of disputing lower divisions.	(Alaminos & Fernández, 2019; Dantas et al., 2015)
E5	Fans' Attendance	Average paying attendance for the Brazilian Championship.	(Alaminos & Fernández, 2019)
E6	Size	Dummy for the 12 major teams in the country (Atlético-MG, Botafogo, Corinthians, Cruzeiro, Flamengo, Fluminense, Grêmio, Internacional, Palmeiras, Santos, São Paulo and Vasco). (1 for the aforementioned and 0 for the others).	(Dantas et al., 2015)
E7	Relegation	Dummy for relegated clubs (1 for relegation and 0 for the others).	(Dantas et al., 2015; Ruta, Lorenzon, & Sironi, 2019)
E8	Promotion	Dummy for promoted clubs (1 for promoted clubs 0 for the others)	(Ruta et al., 2019)
E9	Total Games	Total number of games played in the season.	(Plumley, Wilson, & Shibli, 2017)

Note: The data regarding the sports performance of the clubs were taken from the websites (Ogol, 2019), (Gool, 2019) e GloboEsporte.com (2019). Source: Authors' own elaboration.

3.3. Neural Network-Based Model Design

Neural networks can be defined as a type of machine learning algorithm that artificially represents the processing of a human brain. They are characterized by learning from errors that occur during training (Taylor & Koning, 2017). The feedforward configuration is used in this study, being that in which connections are made only in the direction from the input layer to the output layer (Al-shayea, El-refae, & El-itter, 2010). Figure 1 illustrates the representation of a feedforward neural network.

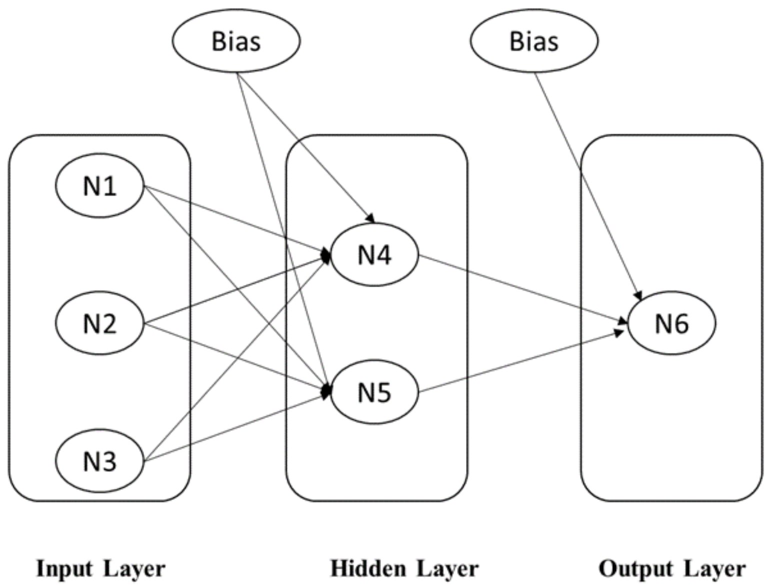

Figure 1. Neural Network Model
Source: Elaborated by the authors

Financial indicators are entered in the input layer of the proposed neural network along with the sports indicators, according to Table 2 and Table 3, respectively. The included indicators were normalized according to Formula 1, a process indicated to reduce network training time and improve network learning (Bishop, 1996; Heaton, 2012). The normalization of variables in the same range is crucial to avoid problems presented by different scales.

$$\frac{Xn - minimum(Xn)}{maximum(Xn) - minimum(Xn)} \tag{1}$$

In Formula 1, Xn represents the value of the input variable, while the minimum and maximum represent the minimum and maximum values of this variable in the sample. The process is performed separately for each input variable. We operationalize the response variable of the neural network model in this study as follows: Solvent club = 0 and Insolvent club = 1.

An insolvent club is the one that presents negative equity, and this is assigned a value of 1. Clubs that present positive net worth are assigned a value of 0. For the output variable, i.e., the one that measures insolvency, it presents a continuous interval between 0 and 1. When this generated value is higher than 0.5, the club is considered insolvent while lower values qualify solvent clubs (Alaminos & Fernández, 2019). The type I error occurs when insolvent balance sheets are classified as solvent by the models. Type II error occurs when the models classify solvent balance sheets as insolvent (Agarwal & Taffler, 2007; Bellovary, Giacomino, & Akers, 2007).

In order to avoid redundancy among the indicators, a correlation matrix was prepared based on Spearman's method. The value used by Gajowniczek, Orłowski, and Ząbkowski (2019) is taken as a parameter, in which indicators with a correlation higher than 0.7 or lower than -0.7 should be excluded. For the treatment of outliers winsorization at 5% is used. As pointed out by Azme Khamis (2001), the presence of outliers that are at a distance of at least 2 times the variance affects the networks' learning.

Three prediction models were elaborated in this study. Thus, the prediction of insolvency for Brazilian clubs is predicted for the periods t-1 year, t-2 years, and t-3 years, where t is the year of the test sample. For model t-1 the training sample consists of the information from the period 2011 to 2017. Model t-2 has, as a training sample, the information between the years 2011 to 2016, while model t-3 consists of using the observations from 2011 to 2015.

To measure the network's success level, two confusion matrices are prepared in conjunction with Receiver Operating Characteristic (ROC) and Area Under the Curve (AUC) analysis for the training and testing phases of the proposed neural network. To measure the importance of the indicators used as input variables in a neural network, Olden's (2002) algorithm is used.

The use of neural networks to develop the model in the present research is justified because it presents the results with greater accuracy in predicting organizations' bankruptcy and insolvency, when compared to other methods such as logistic regression and discriminant analysis, for example (Alaka et al., 2018; Alaminos & Fernández, 2019; Bellovary et al., 2007; R. L. Wilson & Sharda, 1994).

The software R, through the packages neuralnet, ROCR, Hmisc, psych, and NeuralNetTools was used to elaborate the models through neural networks.

A limitation of this research is the criterion adopted for the solvency of the clubs. The literature uses this criterion to analyze the solvency of organizations (Altman & Hotchkiss, 2006; Coelho et al., 2017), but other criteria, such as negative generation of operating cash flow (Balcaen & Ooghe, 2006), could be adopted and could change the perception regarding this scenario.

4. RESULTS

4.1. Descriptive Statistics

From the analyzed statements, 129 of the 255 showed a positive net worth, and therefore were classified as solvent. The remaining balance sheets (126) presented negative equity, classified as insolvent. Such results are similar to those found in Barajas and Rodriguez (2014) and Dantas et al. (2015), in which nearly half of the Spanish clubs in the first two divisions in 2011 and nearly half of the largest Brazilian clubs in the period from 2010 to 2012 presented negative equity, respectively. Additionally, the number of clubs with negative equity throughout the analyzed period increased, as 21 clubs presented negative equity in 2018, which represents 60% of the examined clubs. Table 4 presents the results of the sports variables selected to compose the insolvency classification model.

Table 4
Sportive Indicators Descriptive Statistics

Panel A – Continuous Variables Descriptive Statistics				
Solvent	**E1**	**E2**	**E3**	**E5**
Minimum	-1,01	1,00	0,13	1614,00
First Quartile	1,17	7,00	0,39	5310,00
Median	1,83	15,00	0,46	11467,00
Mean	1,96	18,48	0,46	13193,33
Third Quartile	2,76	25,00	0,54	18220,00
Maximum	4,85	74,00	0,70	47140,00
Standard Deviation	1,16	14,74	0,12	9475,89
Insolvent	**E1**	**E2**	**E3**	**E5**
Minimum	0,14	1,00	0,12	1799,00
First Quartile	1,17	10,00	0,39	7028,25
Median	1,67	18,00	0,44	10854,50
Mean	1,81	19,70	0,45	11961,21
Third Quartile	2,31	27,75	0,52	15016,75
Maximum	4,85	60,00	0,71	34150,00
Standard Deviation	0,97	12,33	0,11	6966,29
General	**E1**	**E2**	**E3**	**E5**
Minimum	-1,01	1,00	0,12	1614,00
First Quartile	1,17	8,50	0,39	6017,00
Median	1,75	17,00	0,46	11225,00
Mean	1,89	19,16	0,45	12654,47
Third Quartile	2,48	26,50	0,53	17202,50
Maximum	4,85	74,00	0,71	47140,00
Standard Deviation	1,07	13,59	0,12	8337,46

Panel B – Dummy Variables Descriptive Statistics						
	Size (E6)	Relegation (E7)	Promotion (E8)	Brazilian Championship Titles	Brazilian Cups Titles	Libertadores Cup participations
Solvent	45	18	14	5	2	18
Insolvent	51	21	21	3	6	13
General	96	39	35	8	8	31

Note: E1 = Szymanski and Smith (1997) Indicator; E2 = Brazilian Championship Position; E3 = Earned points percentual; E4 = Division; E5 = Fans' Attendance; E6 = Size; E7 = Relegation; E8 = Promotion; E9 = Total Games. Authors' own elaboration.

Based on the indicator developed by Szymanski and Smith (1997), it can be noticed that solvent clubs present a higher indicator value, at the median, and, therefore, better positions than insolvent clubs. Additionally, the average attendance of solvent clubs was higher than that of insolvent clubs. These results are convergent with those of Alaminos and Fernández (2019), that, on average, solvent clubs presented higher sports performance indicators than insolvent ones.

The descriptive statistics of the financial variables are presented in Table 5. The variables that measure the liquidity of clubs show differences between solvent and insolvent clubs. From the I2 indicator, used to measure current liquidity, it is perceived that the median of solvent clubs is higher than that of insolvent clubs. The I3 indicator that reflects the net working capital, shows that less than 25% of the statements presented positive net working capital. The results converge with those suggested by Alaminos and Fernández (2019), in which solvent clubs presented higher liquidity than insolvent clubs.

Regarding fixed asset values, there is a difference of more than four times between solvent and insolvent clubs. Corresponding results were found by Alaminos and Fernández (2019), meaning that solvent clubs showed more resources in fixed assets than insolvent clubs. It is relevant to mention that fixed assets of clubs include stadiums, training centers, and facilities, for those that own such properties. Thus, the argument presented by Beech et al. (2010) is supported, as the authors state that clubs that do not own or lose stadium property are closer to insolvency.

The indicator I7, that identifies the representativeness of the intangible assets, in which clubs present the value of their athletes' registration rights, shows a higher relevance for insolvent clubs. In this study, approximately 51% of the clubs presented intangible assets representing more than 10% of total assets, being that for the club Santa Cruz, in 2012, this value reached a representation of 91% of total assets. When compared to the findings of Barabanov and Nakamura (2019), considering their sample of 27 Brazilian clubs, the share of clubs in which intangible assets represent more than 10% of total assets is slightly higher (66%). Additionally, the percentage found by the authors for this ratio was 45%.

Concerning indebtedness, the I8 indicator shows that insolvent clubs display higher representativeness in their obligations for loans and financing than solvent clubs. Such results are convergent with Alaminos and Fernández (2019), in which indebtedness indicators were superior for insolvent clubs as opposed to solvent clubs. Additionally, the majority of clubs present mostly long-term obligations, especially the insolvent ones.

4.2. Neural Network-Based Models

Through Spearman's method, a correlation greater than 0.7 is shown between variables I2 and I4, I12 and I13, I2 and I14, I13 and I14, E2 and E4. Additionally, variables E1 and E2; E1 and E4 show a correlation of less than -0.7. Thus, it was necessary to exclude some variables. For the model development, variables I2, I12, I13, E2, and E4 were excluded – as these presented a higher correlation with other used variables – in order to reduce the redundancy of the model.

From Table 6, results for the chosen models are presented. Accuracy measures the percentage of correct prediction achieved by the model, disregarding the proportion of errors for each type of error. Thus, if the proportion of solvent and insolvent balance sheets is not balanced, as in this study's sample, the error for the group with fewer observations may be underestimated. Therefore, it is argued that the ROC curve is more appropriate to measure the model's level of correctness because it considers type 1 and 2 errors for the calculation of the AUC.

Table 5
Financial Indicators Descriptive Statistics

Solvent	**I1**	**I2**	**I3**	**I4**	**I5**	**I6**	**I7**	**I8**	**I9**	**I10**	**I11**	**I12**	**I13**	**I14**
Minimum	0,00	0,00	-0,99	0,00	0,00	0,02	0,00	0,00	0,11	0,12	0,01	-4,47	-5,98	-1,88
First Quartile	0,00	0,09	-0,28	0,08	0,03	0,32	0,02	0,02	0,31	1,34	0,18	-0,11	-0,22	-0,15
Median	0,02	0,36	-0,18	0,21	0,08	0,53	0,06	0,06	0,43	2,28	0,30	-0,03	-0,07	0,01
Mean	0,05	0,42	-0,21	0,31	0,11	0,53	0,10	0,09	0,45	2,74	0,43	-0,12	-0,15	-0,07
Third Quartile	0,05	0,58	-0,09	0,48	0,16	0,74	0,15	0,14	0,55	3,41	0,46	0,05	0,03	0,09
Maximum	0,95	2,94	0,25	1,25	0,87	0,93	0,51	0,42	1,00	14,22	5,27	0,96	2,16	1,80
Std. Deviation	0,12	0,43	0,21	0,28	0,14	0,25	0,11	0,10	0,20	2,13	0,62	0,53	0,70	0,47
Insolvent	**I1**	**I2**	**I3**	**I4**	**I5**	**I6**	**I7**	**I8**	**I9**	**I10**	**I11**	**I12**	**I13**	**I14**
Minimum	0,00	0,01	-4,43	0,01	0,01	0,07	0,00	0,00	0,09	0,21	0,09	-0,90	-2,99	-2,75
First Quartile	0,00	0,10	-0,89	0,07	0,09	0,34	0,05	0,09	0,28	1,27	0,49	-0,07	-0,27	-0,12
Median	0,01	0,23	-0,50	0,12	0,16	0,57	0,12	0,20	0,38	2,27	0,85	-0,02	-0,05	0,01
Mean	0,08	0,30	-0,73	0,18	0,21	0,59	0,16	0,38	0,42	4,37	1,56	-0,03	-0,16	-0,09
Third Quartile	0,05	0,38	-0,26	0,22	0,27	0,84	0,21	0,38	0,51	4,19	1,35	0,01	0,03	0,11
Maximum	2,54	2,04	0,38	0,84	0,85	1,00	0,81	3,91	1,00	64,01	37,04	0,72	0,90	0,66
Std. Deviation	0,28	0,31	0,77	0,18	0,18	0,27	0,16	0,54	0,19	7,84	3,54	0,17	0,44	0,42
General	**I1**	**I2**	**I3**	**I4**	**I5**	**I6**	**I7**	**I8**	**I9**	**I10**	**I11**	**I12**	**I13**	**I14**
Minimum	0,00	0,00	-4,43	0,00	0,00	0,02	0,00	0,00	0,09	0,12	0,01	-4,47	-5,98	-2,75
First Quartile	0,00	0,10	-0,56	0,07	0,05	0,33	0,03	0,04	0,29	1,30	0,26	-0,08	-0,23	-0,13
Median	0,01	0,27	-0,27	0,15	0,11	0,55	0,09	0,11	0,40	2,28	0,48	-0,03	-0,05	0,01
Mean	0,07	0,37	-0,46	0,25	0,16	0,55	0,13	0,23	0,43	3,55	0,99	-0,09	-0,17	-0,07
Third Quartile	0,05	0,47	-0,14	0,33	0,21	0,79	0,19	0,24	0,53	3,97	0,93	0,03	0,03	0,11
Maximum	2,54	2,94	0,38	1,25	0,87	1,00	0,81	3,91	1,00	64,01	37,04	0,96	2,16	1,80
Std. Deviation	0,21	0,38	0,62	0,25	0,16	0,26	0,14	0,41	0,19	5,76	2,58	0,40	0,59	0,44

Note: I1 = Immediate Liquidity; I2 = Current Ratio; I3 = Net Working Capital; I4 = General Liquidity; I5 = Asset Composition; I6 = Fixed to Total Assets; I7 = Intangible to Total Assets; I8 = Total Debt; I9 = Debt Composition; I10 = Net Debt; I11 = Asset Turnover; I12 = Return on Assets; I13 = Net Margin; I14 = EBIT to Total Revenue. Source: Authors' own elaboration.

Table 6
Models Results

Model	Neurons	Sample	TP	TN	FP	FN	Type I error (%)	Type II error (%)	ACC (%)	AUC (%)
T-1	2	Training	111	103	0	0	0,00	0,00	100	–
		Test	12	16	3	3	20,00	15,79	82,35	95,79
T-2	2	Training	99	87	0	0	0	0	100	–
		Test	12	16	3	3	20,00	15,79	82,35	91,05
T-3	2	Training	79	69	0	0	0	0	100	–
		Test	11	13	6	4	40,00	21,05	71,59	81,58

Note: TP = True Positive; TN = True Negative; FP = False Positive; TN = True Negative, ACC = Accuracy. Source: Authors' own elaboration.

For the training sample, 100% of the observations were correctly classified in all three of the developed models. For the test sample, it is noticeable that the AUC value decreases as the training sample period moves away. A possible reason is that the number of observations decreases and can affect the network training. Such a pattern of hit reduction also occurred in the study of Alaminos and Fernández (2019), where the explanatory power of model t-1 was higher in that study and models t-2 and t-3 in this one.

As for the importance of the variables for the model, it is more appropriate to analyze the Olden algorithm than the weight of the connections and neurons. From this algorithm, it is possible to analyze the magnitude and relationship of the variables with respect to the model's classification. The values of the *y*-scale, represented in Figures 2, 3 and 4, hold a relationship with the weights of the connections between the variables and neurons of the model and it is suggested not to analyze them (Beck, 2018).

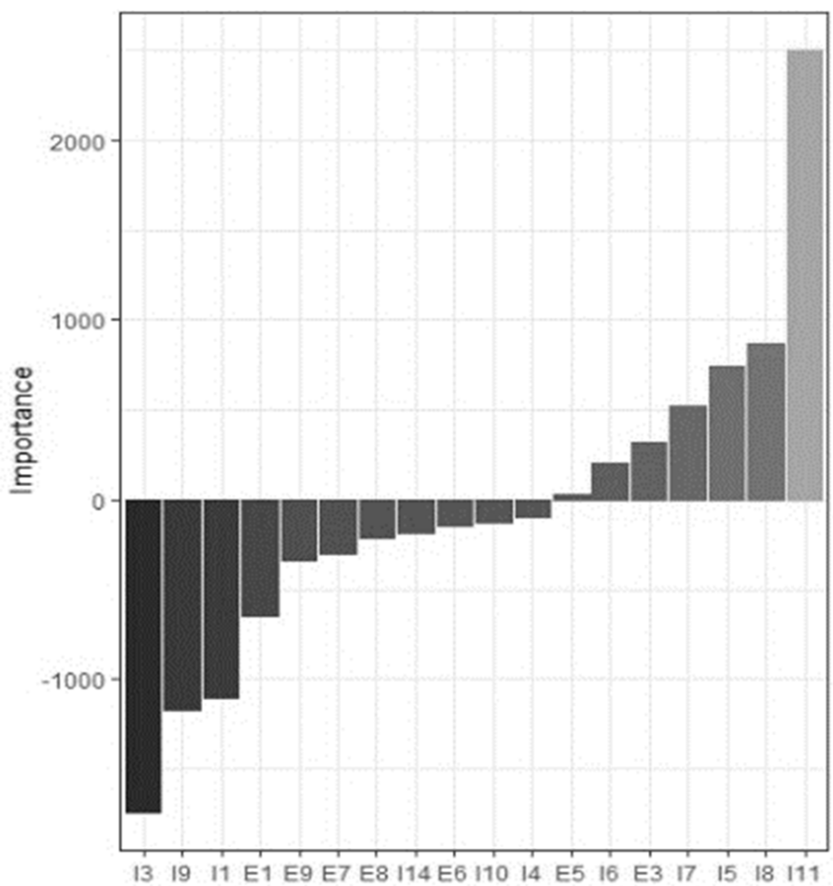

Figure 2. Importance of the variables (Model t-1)
Note: I1 = Immediate Liquidity; I3 = Net Working Capital; I4 = General Liquidity; I5 = Asset Composition; I6 = Fixed to Total Assets; I7 = Intangible to Total Assets; I8 = Total Debt; I9 = Debt Composition; I10 = Net Debt; I11 = Asset Turnover; I14 = EBIT to Total Revenue. E1 = Szymanski and Smith (1997) Indicator; E3 = Earned points percentual; E5 = Fans' Attendance; E6 = Size; E7 = Relegation; E8 = Promotion; E9 = Total Games. Source: Authors' own elaboration., software R NeuralNetTools package.

For model t-1, presented in Figure 2, the most important variable was the asset turnover (I11). This presents a direct relationship with insolvency; the clubs that present a higher indicator are more likely to be considered insolvent. We highlight that this result relates to the level of assets of the clubs, showing that insolvent clubs present lower fixed assets than solvent clubs. The second most important variable for the model, net working capital (I3), presents an inverse association. Therefore, clubs that display a lower value for this indicator are classified as insolvent. The sports variable indicator proposed by Szymanski and Smith (1997) (E1) showed an inverse behavior towards insolvency, as the clubs that performed better in the Brazilian Championship moved away from insolvency. In the study by Alaminos and Fernández (2019), it is highlighted that the financial variables were relevant for the model prediction and only one sports performance variable was considered relevant, according to the criteria adopted in the study.

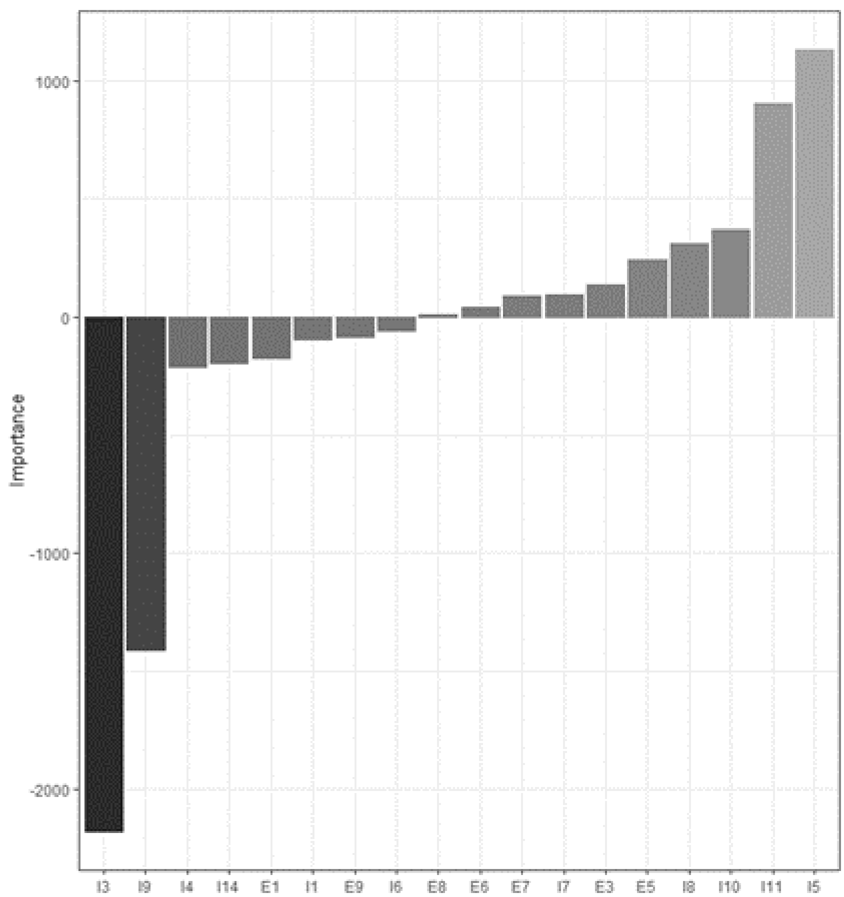

Figure 3. Importance of the variables (Model t-2)
Note: I1 = Immediate Liquidity; I3 = Net Working Capital; I4 = General Liquidity; I5 = Asset Composition; I6 = Fixed to Total Assets; I7 = Intangible to Total Assets; I8 = Total Debt; I9 = Debt Composition; I10 = Net Debt; I11 = Asset Turnover; I14 = EBIT to Total Revenue. E1 = Szymanski and Smith (1997) Indicator; E3 = Earned points percentual; E5 = Fans' Attendance; E6 = Size; E7 = Relegation; E8 = Promotion; E9 = Total Games. Source: Authors' own elaboration., software R NeuralNetTools package.

For model t-2, according to Figure 3, the variables net working capital (I3), debt composition (I9), and the asset turnover (I11) again proved to be important for the model, consistent with the results from model t-1. Distinctly, the asset composition variable (I5) proved to be important for the model. This result indicates that clubs that hold a higher value for intangible and fixed assets, proportionally in relation to total assets, move away from insolvency. The results of Alaminos and Fernández (2019) suggest that only financial variables were relevant for the t-2 model, most notably liquidity and debt variables.

For model t-3, presented in Figure 4, immediate liquidity (I1) and net working capital (I3), both liquidity indicators, proved to be the most important variables. Additionally, the total indebtedness variable (I8) is relevant and its relationship is direct. Thus, clubs that present higher total indebtedness are more likely to be classified as insolvent. We highlight that the variables asset turnover (I11) and debt composition (I9) were also relevant, as for models t-1 and t-2. Notably, the debt variables in model t-3 of the study by Alaminos and Fernández (2019), in addition to a sports performance variable and a governance variable, were shown to be significant for insolvency prediction.

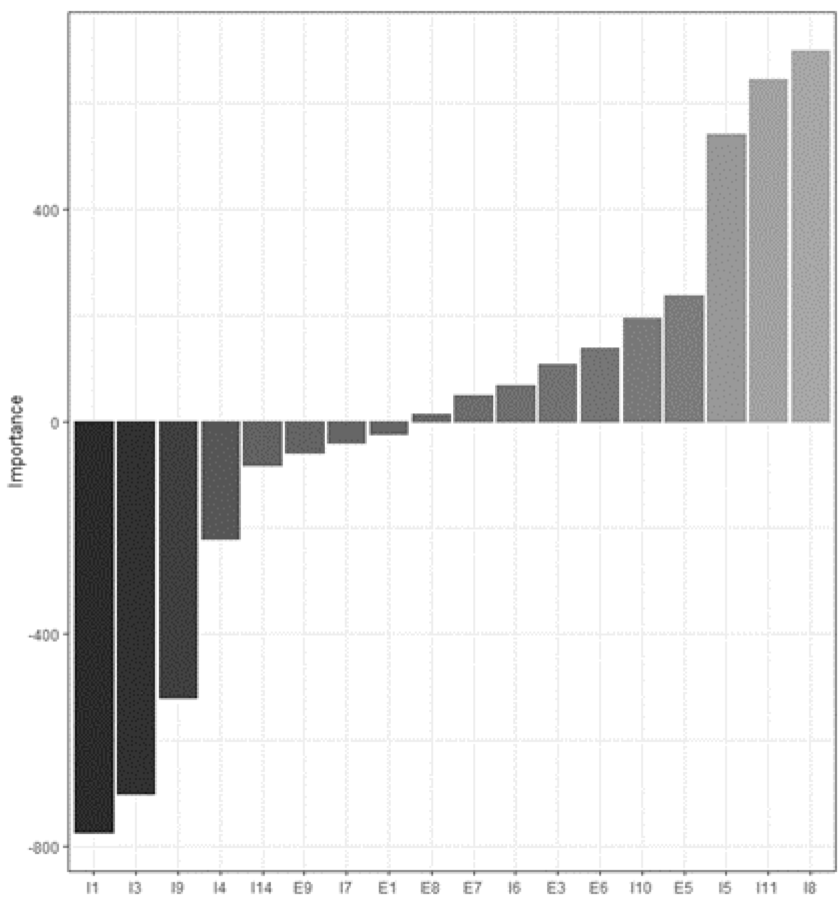

Figure 4. Importance of the variables (Model t-3)
Note: I1 = Immediate Liquidity; I3 = Net Working Capital; I4 = General Liquidity; I5 = Assets Composition; I6 = Fixed to Total Assets; I7 = Intangible to Total Assets; I8 = Total Debt; I9 = Debt Composition; I10 = Net Debt; I11 = Asset Turnover; I14 = EBIT to Total Revenue. E1 = Szymanski and Smith (1997) Indicator; E3 = Earned points percentual; E5 = Fans' Attendance; E6 = Size; E7 = Relegation; E8 = Promotion; E9 = Total Games. Source: Authors' own elaboration., software R NeuralNetTools package.

From the comparative analysis between the models, it can be noticed that some variables remained important for all three predictive models. It is worth noting that the variables immediate liquidity (I1) and net working capital (I3), which indicate the liquidity level of the clubs, proved to be important and maintained an inverse relationship with insolvency for two of the three models. Thus, the need for clubs to maintain a higher level of liquidity to stay away from insolvency is suggested. The variable asset turnover (I11) proved to be important for the three developed models. As for the sports variables, the Szymanski and Smith (1997) indicator stands out. This proved to be important for the t-1 model, being inversely related to insolvency. Thus, clubs that presented a better sports performance tend to move away from insolvency. These results converge with the research of Alaminos and Fernández (2019).

5. CONCLUDING REMARKS

The objective of this research was to propose insolvency prediction models for Brazilian football clubs. To this end, three models based on neural networks were developed with financial and sports indicators as input variables. The choice of this method was justified by the results presented in the literature (Ahmadpour Kasgari, Divsalar, Javid, & Ebrahimian, 2013; Alaminos & Fernández, 2019; Tseng & Hu, 2010).

The sport variables contributed to the model classification, according to Olden's algorithm. Within these, the one that presented the highest importance was the Szymanski and Smith (1997) indicator. Thus, solvent clubs presented a better sports performance in the Brazilian Championship than insolvent teams. Among the financial indicators, both net working capital and immediate liquidity stand out, demonstrating an inverse relationship with insolvency. The indicators asset turnover, debt composition, and total indebtedness showed significant importance for the models and hold a direct relation with the clubs' insolvency. Therefore, it appears that clubs should evaluate liquidity, indebtedness, profitability, and sports performance to move away from insolvency.

Research contributions include the fact that sporting and financial variables were significant for the development of a model based on neural networks for predicting the insolvency of Brazilian clubs with high accuracy. Such modeling used for European clubs by Alaminos and Fernández (2019) proved to be suitable for Brazilian clubs as well. Additionally, in the analyzed literature, no insolvency prediction model was found for Brazilian football clubs. Therefore, we sought to address a research gap, as existing models were developed only for European football clubs (Alaminos & Fernández, 2019). In their study, the authors recommend the development of models suitable for the South American reality.

Despite methodological differences between studies, it is noted that the sports performance was significant for the models presented by authors Alaminos and Fernández (2019) and, in a convergent manner, in this study. Differently, the indicator asset turnover proved relevant for the model developed for European clubs and for Brazilian clubs, but with an opposite relationship between studies. That is, whereas in this research the relationship of this indicator was direct, for European clubs the relationship proved to be reversed.

It is possible to state that, in the analyzed period, the presence of negative equity among the clubs has increased. Conversely, for those that already presented it, these values increased in the period, evidencing the financial deterioration of these clubs. The study by Dantas et al. (2015) revealed clubs with negative equity in the period from 2010 to 2012, a situation that persists. Football club's insolvency is observed and studied in Spanish (A. Barajas & Rodriguez, 2014), German (Szymanski & Weimar, 2019) and English (Beech et al., 2010) clubs and the presence of negative equity is a suitable indicator for insolvent football clubs (Á. Barajas & Rodríguez, 2010).

For future studies, we suggest adding indicators that reflect governance practices adopted by Brazilian football clubs, as performed by Alaminos and Fernández (2019) for European clubs, when formulating an insolvency prediction model. Indicators reflecting clubs' cash flows may be included, as well as information related to the external auditing, such as their opinion, may be of relevance.

REFERENCES

Agarwal, V., & Taffler, R. J. (2007). Twenty-five years of the Taffler z-score model: Does it really have predictive ability? *Accounting and Business Research*, *37*(4), 285–300. https://doi.org/10.1080/00014788.2007.9663313

Ahmadpour Kasgari, A., Divsalar, M., Javid, M. R., & Ebrahimian, S. J. (2013). Prediction of bankruptcy Iranian corporations through artificial neural network and Probit-based analyses. *Neural Computing and Applications*, *23*(3–4), 927–936. https://doi.org/10.1007/s00521-012-1017-z

Al-shayea, Q. K., El-refae, G. a, & El-itter, S. F. (2010). Neural Networks in Bank Insolvency Prediction. *IJCSNS International Journal of Computer Science and Network Security, VOL.10 No.5*, *10*(5), 240–245.

Alaka, H. A., Oyedele, L. O., Owolabi, H. A., Kumar, V., Ajayi, S. O., Akinade, O. O., & Bilal, M. (2018). Systematic review of bankruptcy prediction models: Towards a framework for tool selection. *Expert Systems with Applications*, *94*, 164–184. https://doi.org/10.1016/j.eswa.2017.10.040

Alaminos, D., & Fernández, M. Á. (2019). Why do football clubs fail financially? A financial distress prediction model for European professional football industry. *PLOS ONE*, *14*(12), e0225989. https://doi.org/10.1371/journal.pone.0225989

Alm, J., & Storm, R. K. (2019). Isomorphic Forces and Professional Soccer Standardizations: Instruments of Governance for Municipal Investments? *International Journal of Public Administration*, *42*(3), 185–194. https://doi.org/10.1080/01900692.2017.1422746

Altman, E. I. (1968). Financial Ratios, Discriminant Analysis and The Prediction Of Corporate Bankruptcy. *The Journal of Finance*, *XXIII*(4), 589–609.

Altman, E. I., & Hotchkiss, E. (2006). Corporate financial distress and bankruptcy. In *Foundations and Trends in Finance* (Vol. 5). Wiley.

Azme Khamis. (2001). The Effects of Outliers Data on Neural Network Performance. *Journal of Applied Sciences*, *14*(17), 1394–1398. https://doi.org/10.3923/jas.2005.1394.1398

Balcaen, S., & Ooghe, H. (2006). 35 years of studies on business failure: an overview of the classic statistical methodologies and their related problems. *The British Accounting Review*, *38*(1), 63–93. https://doi.org/10.1016/j.bar.2005.09.001

Barabanov, R., & Nakamura, W. T. (2019). *O intangível nos clubes brasileiros : uma análise dos gastos com jogadores nas demonstrações contábeis*. 119–133.

Barajas, A., & Rodriguez, P. (2014). Spanish football in need of financial therapy: Cut expenses and inject capital. *International Journal of Sport Finance*, *9*(1), 73–90.

Barajas, Á., & Rodríguez, P. (2010). Spanish football clubs' finances: Crisis and player salaries. *International Journal of Sport Finance*, *5*(1), 52–66.

Beck, M. W. (2018). NeuralNetTools: Visualization and analysis tools for neural networks. *Journal of Statistical Software*, *85*(11), 1–20. https://doi.org/10.18637/jss.v085.i11

Beech, J., Horsman, S., & Magraw, J. (2010). Insolvency events among English football clubs. *International Journal of Sports Marketing and Sponsorship*, *11*(3), 236–249. https://doi.org/10.1108/IJSMS-11-03-2010-B006

Bellovary, J., Giacomino, D., & Akers, M. D. (2007). A Review of Bankruptcy Prediction Studies : A Review of Bankruptcy Prediction Studies : 1930 to Present. *Journal of Financial Education*, *33*, 1–42.

Bishop, C. M. (1996). *Neural Networks for Pattern Recognition*. Oxford University Press.

Coelho, E. G., Edwards, C. M., Scherer, L. M., & Colauto, R. D. (2017). Gerenciamento de resultado em empresas insolventes: um estudo com os países do Brics. *Enfoque: Reflexão Contábil*, *36*(2), 95. https://doi.org/10.4025/enfoque.v36i2.31765

Dantas, M. G. da S., Machado, M. A. V., & Macedo, M. A. da S. (2015). FATORES DETERMINANTES DA EFICIÊNCIA DOS CLUBES DE FUTEBOL DO BRASIL. *Advances in Scientific and Applied Accounting*, *8*(1), 113–132. https://doi.org/10.14392/asaa.2015080106

Dias, P., & Monteiro, P. (2020). Sports Marketing and Perceived Value: an application of the conjoint analysis in the Fan Membership Programs of Football. *Brazilian Business Review*, *17*(3), 253–274. https://doi.org/10.15728/bbr.2020.17.3.1

Ecer, F., & Boyukaslan, A. (2014). Measuring Performances of Football Clubs Using Financial Ratios: The Gray Relational Analysis Approach. *American Journal of Economics*, *4*(1), 62–71. https://doi.org/10.5923/j.economics.20140401.06

Evans, R., Walters, G., & Tacon, R. (2019). Assessing the effectiveness of financial regulation in the English Football League: "The dog that didn't bark." *Accounting, Auditing and Accountability Journal*, *32*(7), 1876–1897. https://doi.org/10.1108/AAAJ-12-2017-3288

Freestone, C. J., & Manoli, A. E. (2017). Financial fair play and competitive balance in the Premier League. *Sport, Business and Management: An International Journal*, *7*(2), 175–196. https://doi.org/10.1108/SBM-10-2016-0058

Gajowniczek, K., Orłowski, A., & Ząbkowski, T. (2019). Insolvency modeling with generalized entropy cost function in neural networks. *Physica A: Statistical Mechanics and Its Applications*, *526*, 120730. https://doi.org/10.1016/j.physa.2019.03.095

GloboEsporte.com. (2019). Globoesporte.com.

Gool, S. (2019). Sr. Gool. Retrieved January 6, 2020, from http://www.srgoool.com.br

Guo, F., Kubick, T. R., & Masli, A. (2018). The effects of restatements for misreporting on auditor scrutiny of peer firms. *Accounting Horizons*, *32*(1), 65–85. https://doi.org/10.2308/acch-51934

Gutiérrez-Fernández, M., Talavero-Álvarez, F. J., & Coca-Pérez, J. L. (2017). Economic and Financial Analysis of Bankruptcy of Football Teams. In M. Peris-Ortiz, J. Álvarez-García, & M. de la C. Del Río-Rama (Eds.), *Sports Management as an Emerging Economic Activity* (pp. 155–182). https://doi.org/10.1007/978-3-319-63907-9_10

Heaton, J. (2012). *Introduction to the Math of Neural Networks*. Heaton Research. Inc.

Kanitz, S. C. (1976). *Indicadores contábeis financeiros – previsão de insolvência: a experiência da pequena e média empresa brasileira*. Universidade de São Paulo.

Lago, U., Simmons, R., & Szymanski, S. (2006). The Financial Crisis in European Football. *Journal of Sports Economics*, *7*(1), 3–12. https://doi.org/10.1177/1527002505282871

Martins, E., Diniz, J. A., & Miranda, G. J. (2017). *Análise avançada das demonstrações contábeis: Uma abordagem crítica*. Atlas.

Ogol. (2019). Ogol. Retrieved December 28, 2019, from http://www.ogol.com.br/

Pereira, M. C. (2019). Fim da gastança maluca no futebol? CBF quer Fair Play financeiro já em 2020. Retrieved January 5, 2020, from UOL Esporte website: https://blogdomaurocezar.blogosfera.uol.com.br/2019/02/19/fim-da-gastanca-maluca-no-futebol-cbf-quer-fair-play-financeiro-ja-em-2020/

Petrocilo, C. (2019). Clubes da Série A devem R$ 1,8 bilhão para a União; veja ranking. Retrieved September 9, 2019, from Folha de São Paulo website: https://www1.folha.uol.com.br/esporte/2019/04/clubes-da-serie-a-devem-r-18-bilhao-para-a-uniao-veja-ranking.shtml

Plumley, D., Wilson, R., & Ramchandani, G. (2017). Towards a model for measuring holistic performance of professional Football clubs. *Soccer & Society*, *18*(1), 16–29. https://doi.org/10.1080/14660970.2014.980737

Plumley, D., Wilson, R., & Shibli, S. (2017). A Holistic Performance Assessment of English Premier League Football Clubs 1992–2013. *Journal of Applied Sport Management*, *9*(1). https://doi.org/10.18666/jasm-2017-v9-i1-7353

Ruta, D., Lorenzon, L., & Sironi, E. (2019). The relationship between governance structure and football club performance in Italy and England. *Sport, Business and Management: An International Journal*, *ahead-of-p*(ahead-of-print). https://doi.org/10.1108/sbm-10-2018-0081

Scelles, N., Szymanski, S., & Dermit-Richard, N. (2018). Insolvency in French soccer: the case of payment failure. *Journal of Sports Economics*, *19*(5), 603–624. https://doi.org/10.1177/1527002516674510

Silva, J. O. da, Wienhage, P., Souza, R. P. S. de, Bezerra, F. A., & Lyra, R. L. W. C. de. (2012). Capacidade Preditiva De Modelos De Insolvência Com Base Em Números Contábeis E Dados Descritivos. *Revista de Educação e Pesquisa Em Contabilidade (REPeC)*, *6*(3), 246–261. https://doi.org/10.17524/repec.v6i3.268

Szymanski, S. (2015). Long-term and short-term causes of insolvency and English football. In *The Economics of Competitive Sports* (pp. 74–83). https://doi.org/10.4337/9781783474769

Szymanski, S. (2017). Entry into exit: insolvency in English professional football. *Scottish Journal of Political Economy*, *64*(4), 419–444. https://doi.org/10.1111/sjpe.12134

Szymanski, S., & Smith, R. (1997). The English football industry: Profit, performance and industrial structure. *International Review of Applied Economics*, *11*(1), 135–153. https://doi.org/10.1080/02692179700000008

Szymanski, S., & Weimar, D. (2019). Insolvencies in professional football: A German Sonderweg? *International Journal of Sport Finance*, *14*(1), 54–68. https://doi.org/10.32731/IJSF.141.022019.05

Taylor, M., & Koning, M. (2017). *Machine Learning with Neural Networks: An In-depth Visual Introduction with Python: Make Your Own Neural Network in Python: A Simple Guide on Machine Learning with Neural Networks.* (B. W. Media, Ed.).

Tseng, F. M., & Hu, Y. C. (2010). Comparing four bankruptcy prediction models: Logit, quadratic interval logit, neural and fuzzy neural networks. *Expert Systems with Applications*, *37*(3), 1846–1853. https://doi.org/10.1016/j.eswa.2009.07.081

Wilson, R. L., & Sharda, R. (1994). Bankruptcy prediction using neural networks. *Decision Support Systems*, *11*(5), 545–557. https://doi.org/10.1016/0167-9236(94)90024-8

Wilson, R., Plumley, D., & Ramchandani, G. (2013). The relationship between ownership structure and club performance in the English Premier League. *Sport, Business and Management: An International Journal*, *3*(1), 19–36. https://doi.org/10.1108/20426781311316889

AUTHORS' CONTRIBUTION

First Author: Contextualization, Method, Results, analyses, concluding remarks.
Second Author: Problem and Objective definition, literature review, and support in applying the method.

FINANCING

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) - Finance Code 001

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.