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Utilization of Artificial Intelligence in fiscal stress forecasting: evidence for Brazilian municipalities

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Abstract

Objective: Utilize the model proposed by Trussel and Patrick (2018), in conjunction with the factors introduced by Groves et al. (1981) and Groves and Valente (2003), tailored to the Brazilian context, to forecast fiscal stress in municipalities of Minas Gerais between 2016 and 2020.
Method: The Random Forest (RF) model, a machine learning technique from the Decision Trees family, was applied to predict fiscal stress in Minas Gerais municipalities. The selection of this model was motivated by its recent success in predictive applications, which warranted its use in this study.
Results and Discussions: The model displayed an average overall accuracy of 68.2%. Early precision rates reached up to 85% by defining particular threshold values. The model exhibited a greater efficacy in predicting the occurrence of fiscal stress than its absence, although outcomes exhibited notable variation across distinct analysis periods. Notably, variables associated with the liquidity category carried the highest significance, while organizational and environmental factors showed lower importance. These findings both corroborate and question prior literature, exceeding the findings of some previous studies.
Contributions: This article presents two innovative contributions: the use of Artificial Intelligence (AI) to analyze the Governmental Financial Condition in Brazil and the forecasting of fiscal stress in Brazilian municipalities.

Keywords: Governmental Financial Condition; Fiscal Condition; Subnational Entities; Artificial Intelligence; Random Forest.

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Introduction

Governmental Financial Conditions originated in the United States during the last century, particularly during local government crises (Clark, 1994). However, this topic is still relatively in its infancy within the Brazilian context and has only garnered attention in the domestic literature following the work of Lima and Diniz (2016). Guaranteeing financial well-being is vital for subnational entities, encompassing adherence to timely payment obligations and providing high-quality public services that meet societal expectations (Lima & Diniz, 2016).

A portion of the Government Financial Condition fiscal condition is solely linked to the financial outcome, assessing whether revenues are sufficient to cover expenses (Bowman & Calia, 1997). It is worth noting that a lack of resources can lead to a decline in the quality of essential activities that should be provided (McDonald & Larson, 2020). This is because a municipality experiencing fiscal stress faces difficulties such as restricted access to credit, high-interest payments, deteriorating liquidity, and the risk of worsening its financial situation (Leiser et al., 2021). Therefore, proper resource management promotes job and income generation and, consequently, reduces its own risk of default (Bisogno et al., 2019; Navarro-Galera et al., 2020).

As proposed by Dantas Junior et al. (2019), one approach for assessing whether governmental revenues effectively cover expenditures is the fiscal stress test introduced by Bowman and Calia (1997). If the test result is negative, it is concluded that the locality is under fiscal stress.

Trussel and Patrick (2018) presented a model incorporating 21 primarily financial variables, effectively categorizing the likelihood of fiscal stress in as much as 99% of American subnational entities. Chen (2021) utilized artificial intelligence techniques to predict fiscal stress in Chinese governments, yielding an accuracy rate of roughly 85%.

Global attention to the subject has been conspicuous, underscoring an increasing interest in the Brazilian context. This is exemplified by the initiative of the National Treasury Secretariat in collaboration with the National Transparent Treasury (Brasil, 2022), which has, since 2017, been issuing analyses of the consolidated debt.

In the scenario of municipalities in the state of Minas Gerais, there is a diversity in socioeconomic structures, leading to disparities in revenue (Costa et al., 2015; Vieira et al., 2021). It is worth noting that the mentioned state hosts the largest concentration of subnational entities in Brazil (Vieira et al., 2021).

Recognizing the importance of fiscal stress in public management and the necessity to enhance forecasting methods for this issue, we applied the Random Forest (RF) technique to predict fiscal stress in municipalities within Minas Gerais. This research was based on the framework introduced by Trussel and Patrick (2018), with modifications to adapt it to the Brazilian context and the inclusion of factors suggested by Groves et al. (1981) and Groves and Valente (2003).

The results indicated that the model exhibited higher accuracy in predicting fiscal stress (with an average success rate of 68.4%) than in predicting non-stress situations (49.2%). It is important to note that these results were affected by the COVID-19 crisis, leading to significant changes. The prediction accuracy of the issue also surpassed the initial classification of the 2011 sample proposed by Trussel and Patrick (2018). The overall average accuracy achieved by the model was 65.8%. However, when cutting points based on the probability of event occurrence were applied, the results improved, reaching an accuracy of 85%. Notably, this result is in line with what was found by Chen (2021).

Additionally, the three most significant variables are linked to liquidity, corroborating the findings of Iacuzzi (2022) and endorsing Lima and Diniz's (2016) viewpoint that the operational position variable should not be regarded as a dependent factor, as conducted in McDonald and Larson's (2020) research. However, the average significance of the state's mesoregions was the least among the variables, contradicting the results presented by Antulov-Fantulin et al. (2021).

Two significant contributions of this study to the literature merit attention: the utilization of Artificial Intelligence (AI) in this field and the prediction of fiscal stress in Brazilian municipalities — two aspects that, thus far, have not been investigated in the national literature.

An implication of this research is the early anticipation of fiscal stress, enabling policymakers to manage finances better and plan to avert the issue. The public can also monitor the condition of their municipality, thus preventing potential declines in the quality and quantity of essential services.

Despite these contributions, the limitations of this study encompass the sample size, the analysis period, and the reliability of the data. Notably, the full adoption of the accrual basis of accounting by Brazilian municipalities has not yet been achieved (Costa & Leão, 2021). This approach plays a crucial role in the public sector, offering insights into past transactions and future obligations and facilitating economic decision-making (Cruvinel & Lima, 2011). Nevertheless, it is essential to recognize that this limitation does not render the financial information invalid; on the contrary, it underscores the importance of meticulous analysis.

Besides the introduction, this article is organized as follows: Governmental Financial Condition and Fis

cal Condition as the theoretical framework; the methodology, which outlines the techniques utilized in the research; the findings; and, lastly, the conclusions.

2 Governmental Financial Condition

The discourse surrounding Governmental Financial Condition commenced in the United States after the fiscal crisis in New York City during the 1970s, which resulted in high inflation and posed challenges for local governments (Clark, 1994; Groves et al., 1981). Since then, there has been an increasing interest from both the general public and policymakers in this topic, as tumultuous economic periods can impact public administration and the provision of essential services (McDonald & Larson, 2020; Turley et al., 2020). However, it was only in the 1990s that scholars began to delve more deeply into this subject (Lima & Diniz, 2016).

As per Groves and Valente (2003), for a locality to be deemed financially sound, it is essential to guarantee the quality of vital services in both the short and long term and to withstand economic instability and population pressures. The seminal study by Groves et al. (1981) offers one of the most comprehensive methods for analyzing Governmental Financial Condition, which is influenced by financial, organizational, and environmental factors.

The ten-point evaluation for Financial Condition, developed by Brown (1993), comprises variables associated with revenue, expenditure, debt composition, and operational standing. Later, García-Sánchez et al. (2012) determined that the model established by Kloha et al. (2005), improved by the addition of two variables concerning financial autonomy, proposed by Zafra-Gómez et al. (2009), exhibited the most effective performance in financial condition assessment.

Despite the time that has elapsed in their development, research on the subject is still relatively recent in Brazil, with the study by Lima and Diniz (2016) being considered pioneering. This subject emerged during periods of economic volatility in the country, as witnessed in 2015 and 2016, characterized by sluggish economic growth (Dantas Junior et al., 2019). Additionally, the nation was navigating through a tumultuous political phase characterized by a presidential impeachment and a decline in confidence in the political establishment (Jucá & Fishlow, 2021).

Lima and Diniz (2016) state that a robust Governmental Financial Condition is attained when the government fulfills its payment obligations and sustains the effective delivery of public services, aligning with society's quality expectations. The authors emphasize that this subject is intricate and subject to influence from both internal and external factors. In essence, certain factors fall under the purview of government leaders, while others do not, such as periods of crisis.

This topic became significant during American municipal economic instability (Clark, 1994). Concerns about this subject escalated following the global financial crisis 2008 (Antulov-Fantulin et al., 2021; Chung & Williams, 2021). According to Afonso and Jalles (2020), instability exerted pressure on fiscal authorities to take proactive measures to control debt, functioning as a disciplining mechanism, as was the case post-2008. Consequently, subnational entities implemented policies to reduce the workforce (Shi, 2019).

Concerning the COVID-19 pandemic, available knowledge remains limited. Nonetheless, McDonald and Larson (2020) analyzed the effects of diminished tax revenues on the financial health of subnational entities in North Carolina, revealing concerning outcomes. Maher et al. (2020) argued that nonprofit organizations must maintain financial reserves for pivotal moments, with fiscal consequences possibly manifesting several years later. Nevertheless, the insights from the 2008 recession may place them in a more advantageous position.

This study aims to evaluate the financial condition of subnational entities in Brazil. Defining the Governmental Financial Condition using a single dependent variable based solely on financial data would not be practicable. This is due to variations in the demands of public services, which depend on the served population. Therefore, our approach involves an examination of the fiscal condition of municipalities.

2.1 Fiscal Condition

Addressing economic crises frequently necessitates fiscal adjustments, which can have a societal impact. This was exemplified by reduced healthcare and education expenditures in Brazil over 20 years (Vieira, 2016). Nevertheless, based on systematic reviews, the author concludes that such measures tend to exacerbate the situation. This underscores the significance of preserving social programs for essential services and achieving a quicker economic recovery. It is important to emphasize the relevance of involving the population and labor unions in municipal decision-making during fiscal stress (Warner et al., 2021).

Fiscal condition is a financial aspect that characterizes the challenges faced by local governments (Lima & Diniz, 2016). In other words, they have an intrinsic relationship (Magkonis & Tsopanakis, 2016), highlighting that a lack of resources can affect quality and even lead to cuts in essential services.

Various definitions of fiscal condition are observable. In the United States, a survey conducted among senior

officials in all 50 states demonstrated that only ten states had a formal definition for crises in local governments. In contrast, the remaining states employed more practical approaches or permitted subnational entities to establish their criteria (Honadle, 2003).

According to Stanley (1980), fiscal challenges can be classified into two primary categories: fiscal crisis, which involves a lack of resources to cover the immediate expenses of the entity and long-term decline, indicating a gradual economic deterioration over time. As a result, municipal governments encounter specific constraints. In the context of long-term issues, their choices are predominantly restricted to managing expenses and establishing procedural order. In the short term, governments may rely on assistance from other entities or implement cost-saving measures.

Miranda et al. (2018) found that high spending on interest and debt amortization affects the fiscal management of Brazilian states, impacting their liquidity and Government Financial Condition. In another study, Oliveira et al. (2021) investigated the factors influencing fiscal management in municipalities in Paraná. They identified a positive relationship between variables representing autonomy, net consolidated debt, and personnel expenses.

When a government faces spending pressures and cannot collect sufficient revenues, it is considered to be in a state of fiscal stress (Clark, 1977). This hinders the provision of essential services to the population due to the need for financing (Honadle, 2003). Various approaches are used to assess this situation in local governments.

McDonald and Larson (2020) define fiscal status using the variable total revenue over total expenses, dividing the results into five categories, from very stressed to very healthy. They suggest that policymakers balance current revenues, expenses, and indebtedness to achieve proper management (Bisogno et al., 2019). On the other hand, the stress test from Bowman and Calia (1997) uses a dummy variable to classify governments as stressed or not based on the sufficiency of current revenues to replenish assets committed to operational expenses.

Recent and relevant studies have been conducted in various world regions. In Italy, distinctions were observed between municipalities with and without debt regarding employee expenses, total revenue, short-term obligations, current revenue, and subsidies per capita (Cohen et al., 2017). Dantas Junior et al. (2019) delved into fiscal federalism and its relationship with the indebtedness of Brazilian municipalities. The findings indicated that during periods of economic instability, municipalities with a higher degree of financial reliance on other governing bodies are at a greater risk of facing fiscal stress challenges.

Trussel and Patrick (2018) devised a model for classifying fiscal stress risk in subnational governments within the United States. The model relied on 21 variables and attained a success rate of up to 99% within the sample, employing an error cost cutoff. Nonetheless, the model encompasses solely two variables linked to the environmental factor, while the remaining 19 are financial, with no variables associated with the organizational factor.

3 Methodology

The model in this study is grounded in Trussel and Patrick (2018) and integrates the three factors delineated by Groves et al. (1981) and Groves and Valente (2003). Additionally, it takes into account the Brazilian context, particularly the Fiscal Responsibility Law (LRF), and incorporates insights from Hendrick (2004), Dantas Junior et al. (2019), Silva et al. (2020), and Bolognesi et al. (2023). The dependent variable subject to analysis is Bowman and Calia's (1997) stress test, while the predictive model applies the RF technique.

Data from the Brazilian Institute of Geography and Statistics (IBGE) were used, including the municipality code, area, mesoregion, and population estimates, along with financial data from the National Treasury Secretariat, covering the period from 2014 to 2021.

3.1 Variables

As per Trussel and Patrick (2018), identifying fiscal stress involves three essential steps: detecting its occurrence, exploring potential causes, and assessing the probability. In this context, Bowman and Calia's (1997) stress test was employed as the dependent variable to evaluate the capacity to fulfill payment obligations about revenues, making it well-suited for the Brazilian context (Dantas Junior et al., 2019). The analysis process comprises four stages, followed by the evaluation of the indicators, as detailed in Table 1.

Initially, the financial surplus for the year is estimated. Then, its variation between two consecutive years is calculated. Next, the variation in operating expenses between the same years is computed. Finally, the stress test is determined, which is the ratio between the variation in the surplus and the expenses.

Table 1: Analysis of Results for Fiscal Condition

Result	Operational expenses	Condition
Stress test ≤ 1	Increasing	1
Stress test > 1	Decreasing	1
Stress test ≤ 1	Decreasing	0
Stress test > 1	Increasing	0

Notes: (i) If the financial surplus result is a deficit for both years necessary for the calculation, it is regarded as fiscal stress; (ii) If the condition result equals 1, the municipality is experiencing fiscal stress; otherwise, the municipality is not under fiscal stress.

Source: Adapted from Bowman and Calia (1997).

Table 2 displays the yearly count of municipalities

under examination, specifying the cases impacted by fiscal stress and those not affected. It is crucial to note that data were gathered from all 853 municipalities, but the sample size was reduced due to missing data.

Table 2: Research Sample Regarding the Dependent Variable

Accounting year	Sample	Forecast year	In stress	No stress
2014	483	2015	389	94
2015	495	2016	329	166
2016	485	2017	330	155
2017	600	2018	507	93
2018	704	2019	404	300
2019	725	2020	381	344
2020	720	2021	189	531

Note: Accounting year = year of the independent variables; Sample = number of municipalities with available data; Forecast year = year of the dependent variable; In stress = number of municipalities under fiscal stress according to the stress test; No stress = number of municipalities without fiscal stress.
Source: Research data.

The independent variables in the model were primarily derived by Trussel and Patrick (2018), with some adaptations made to suit the Brazilian context. Additionally, as outlined by Groves et al. (1981) and Groves and Valente (2003), environmental factors and governmental influences on the financial condition were considered. Indicators V18, V20, and V21 correspond to environmental factors, V22 relates to the organizational factor, while the remaining variables are all financial and are detailed in Table 1.

For clarity, we will only provide descriptions for the variables modified or newly incorporated into the model.

The variables for healthcare expenditures (V5) and education expenditures (V6) were adapted to the Brazilian context. Trussel and Patrick (2018) initially utilized variables that measured user charges for services and public expenditure on municipal roads. In alignment with these indicators, we opted to employ the variables introduced by Dantas Junior et al. (2019).

According to Groves and Valente (2003), the population tends to rely less on public services in regions with high employment rates, as they prefer to self-finance their expenses. Conversely, Dantas Junior et al. (2019) contend that the higher the investment in education or healthcare relative to total revenues, the greater the risk of Brazilian subnational entities encountering fiscal stress.

However, such services must be provided to society (Lima & Diniz, 2016). The curtailment of investments in essential areas can lead to significant social issues, such as unemployment, depression, and an increase in the number of suicides (Vieira, 2016). Additionally, it is essential to note that unemployment is impacted differently across sectors, with human services being the most affected by the cutbacks (Brien et al., 2021).

The employee expenditure variable (V16) was modified to align with the LRF, given that the original model included two variables associated with pension costs and employee benefits. This adjustment is warranted within the Brazilian context.

Table 1 - Independent Variables in the Model

	Category	Indicator	Account	Reference
V1	Indicators based on operations	Per capita revenue	Total revenue / Population	Trussel and Patrick (2018)
V2		Intergovernmental revenues	Revenues from other governments / Total revenue	
V3		Per capita expenses	Total expenditure / Population	
V4		Operational position	Total revenue / Total expenditure	
V5		Health expenditures	Healthcare expenditure / Total revenue	Dantas Juni-or et al. (2019)
V6		Education expendi-tures	Education expenditure / Total revenue	
V7	Indicators based on debt	Debt service	Interest and debt charges / Total revenue	Trussel and Patrick (2018)
V8		Debt to revenue ratio	Total debt / Total revenue	
V9		Per capita liability	Total liabilities / Population	
V10	Indicators based on capital structure	Debt to assets	Total debt / Total assets	Trussel and Patrick (2018)
V11		Equity to revenue	Equity / Total revenue	
V12		Equity to assets	Patrimônio Líquido / Total assets	
V13	Indicators based on liquidity	Cash to revenue	Cash+investments / Total revenue	Trussel and Patrick (2018)
V14		Cash to debt	Cash+investments / Total debt	
V15		Current liquidity	Total assets / Current liabilities	
V16	Employee-based indicator	Employee expendi-ture	Employee expenditure / Net Current Revenue	Adapted from LRF (2000)
V17	Tax-based indicator	Concentration of tax revenue	Tax revenue / Total revenue	Trussel and Patrick (2018)
V18	Other indicators and control variables	Population	Natural logarithm of the population estimate	Trussel and Patrick (2018)
V19		Capital expenditure share	Capital expenditure / Total expenditure	
V20		Population density	Population / Municipal area	Hendrick (2004)
V21		Location	Meso-regions of Minas Gerais	Adapted from Silva et al. (2020)
V22		Political ideology	Left or right-wing parties	Bolognesi et al. (2023)

Source: Prepared by the authors.

The LRF sets forth regulations for subnational entities to attain effective fiscal management, aiming to equilibrate income and outlays. Regarding personnel expenditures, the cap is 60% of net current revenue, a requirement applicable to municipalities and states. Audit courts warn the governing bodies when surpassing 90% of this threshold (54%) (LRF, 2000).

As suggested by the findings of Miranda et al. (2018), states with high personnel expenses frequently demonstrate a less favorable fiscal condition, a trend similarly observed in municipalities in Paraná by Oliveira et al. (2021).

Three supplementary variables were introduced in conjunction with the preexisting indicators and control variables. Population density (V20), recognized for its influence on the production and distribution of public services (Lima & Diniz, 2016), was included, notwithstanding Hendrick's (2004) contention that this variable may not encompass all investment needs.

Despite the similarity of this variable to population size, its effect on municipal expenditures in Australia varies, as demonstrated by Tran et al. (2019). Population size positively impacted local governments' economies of scale, while population density did not produce the same effect.

Trussel and Patrick (2018) included the municipality type as a control variable since these subnational entities in the United States are categorized into four distinct types: 'city,' 'borough' (a type of district), 'first-class municipality' (over 10,000 inhabitants), and 'second-class municipality' (between 1,500 and 9,999 inhabitants). This indicator addresses three crucial factors: population density, historical context, and the range of services available (Trussel & Patrick, 2018).

However, this division does not apply to Brazil. Thus, based on relevant studies (Antulov-Fantulin et al., 2021; Preston, 1985; Psycharis et al., 2016), the mesoregions of Minas Gerais (V21) were chosen for this research.

Kim and Warner (2018) discovered that the United States metropolitan and rural regions are vulnerable to fiscal stress. Aarsaether (1990) noted that spatial factors affect fiscal conditions in Norway, particularly about industrialization. Silva et al. (2020) highlight the importance of geographical location in fiscal management in Brazil. Therefore, incorporating this variable is warranted, as the mesoregions of the state may reveal significant distinctions.

The literature provides diverse findings regarding the impact of political ideologies on fiscal conditions. Municipalities governed by right-wing parties in Portugal tend to encounter financial challenges (Lobo et al., 2011). In Spain, however, a significant relationship has yet to be identified between the debt level and political ideology (Benito et al., 2010). Conversely, a recent study conducted by Navarro-Galera et al. (2020) unveiled that the political ideology of mayors influences financial risk, with those leaning toward the left demonstrating a greater propensity to face difficulties, as they tend to allocate more resources to social policies.

To classify the political ideology of parties (V22) as left or right, we adopted the methodology employed in the study by Bolognesi et al. (2023), based on a survey completed by political scientists in 2018. The survey utilized a scale from 0 to 10, where lower values indicated more left-leaning ideologies and higher values indicated more right-leaning ideologies. This variable is continuous, ranging from 0 to 10.

Thus, the general equation of the model is defined as follows:

$$P_{Y(i,t)} = \frac{1}{1 + e^{(\beta_0 + \beta_1 V_{i,t-1} + \varepsilon_{i,t-1})}}$$

Where $P_{Y(i,t)}$ is the probability of municipality i experiencing fiscal stress in year t, which is assigned a value of 1 if fiscally stressed and 0 otherwise; Vi,t-1 represents the independent variables of city i in year t-1; e $\varepsilon_{i,t-1}$ pertains to the error term

3.2 Artificial Intelligence

AI techniques have been extensively applied in contemporary finance, offering cost-effective and swifter financing solutions. Nevertheless, it is crucial to remain mindful of potential limitations, including data biases (Lin, 2019). Among these AI techniques, RF deserves particular attention, as it has demonstrated its efficacy across various knowledge domains (Cutler et al., 2012). Regarding predicting fiscal stress in local governments, RF consistently delivers superior results compared to logistic regression techniques (Jarmulska, 2022).

Although recent, AI techniques are beginning to be used in the analysis of the financial condition of local governments. Chen (2021) employed Neural Networks and Decision Trees to assess the risk of fiscal stress in subnational entities in China, achieving over 85% accuracy in early prediction of this issue. Antulov-Fantulin et al. (2021) identified the best techniques for predicting municipal bankruptcy in Italy, highlighting Gradient Boosting Machines and RF, while Lasso and Neural Networks yielded inferior results. Finally, Zarkova et al. (2023) forecasted the public debts of European Union countries using RF, highlighting the technique's potential for predictive purposes.

In this study, RF is employed. According to Breiman (2001), this technique exhibits several qualities: high accuracy, relative robustness to noise and outliers, and appropriate estimates for internal variables like correlation, strength, error, and variable importance. Additionally, the author asserts that the technique is unlikely to encounter overfitting issues, making it a reliable and easily implementable predictor.

On the other hand, the RF method may overestimate sample errors in situations with a low amount of data and low correlation between predictor variables (Janitza & Hornung, 2018). Furthermore, it has been observed that deep trees can lead to inconsistent models (Tang et al., 2018).

3.3 Results Analysis (Definition of the AI Forecasting Model)

The Python programming language was used to develop the model and analyze the results. Different periods were evaluated, including the three years before the 2020 global crisis, which was not affected by the COVID-19 pandemic in the data, while the fourth year was affected by the dependent variable, and the last year was also affected by the independent variables. A rolling window method was employed to analyze this situation.

Thus, two years of data were employed for model training, while the variables from the subsequent year were used for model validation. Consequently, five time intervals were established, with the initial one trained using data from 2014 and 2015, validated with data from 2016, and so on, until culminating in data from 2018 and 2019, utilized for model training and validation in 2020.

The rationale for the division mentioned above is based on the strategy of attaining roughly 70% of the data for training and 30% for testing, as observed by Antulov-Fantulin et al. (2021). The training data concerning the dependent variable were balanced, following the approach of Antulov-Fantulin et al. (2021), since an imbalanced sample can result in the model classifying based on the majority class. Therefore, the imblearn. over_sampling library was employed to rectify this concern.

To assess the model's performance, the Classification-Report from the sklearn.metrics library was utilized. It returns four metrics: precision, which represents the proportion of correct predictions to the total predictions; recall, which indicates the percentage of data correctly classified concerning the actual situations; F1-Score, which is a harmonic mean of precision and recall; and accuracy, representing the overall model accuracy (Chen, 2021).

The prediction results are presented as the probability of the occurrence or non-occurrence of fiscal stress. However, some probabilities are low, such as a 51% chance of fiscal stress occurring or covering the expenses for the period. This area is known as the gray zone, where it is uncertain what will happen. Therefore, this area can be excluded for a more accurate assessment (Altman et al., 2013).

The objective of this process is to mitigate type I and type II errors, which are a complement to recall. Type I error transpires when the examined municipality is forecasted to undergo fiscal stress, yet, in actuality, it does not encounter this problem. Conversely, type II error occurs when the subnational entity genuinely experiences fiscal stress, but the prediction suggests otherwise (Antulov-Fantulin et al., 2021). Consequently, type II error carries more significant consequences than type I error.

To evaluate the significance of the variables, we utilized the 'feature_importances_' function from the matplotlib. pyplot library, which offers percentage values for ranking the essential features.

4 Results

Table 3 shows that the model yielded promising results for predicting fiscal stress outside the pandemic period, with the F1-Score consistently above 0.7. However, it obtained results below 0.5 for predicting non-stress. During the pandemic years, the results were reversed, and it is essential to note that the dependent variable for 2019 refers to the year 2020, indicating that the data had already been affected by the health crisis.

Table 3: Model results

Validation	Condition	Precision	Recall	F1-Score	Quantity
2016	Não Estresse (0)	0.46	0.45	0.45	155
	Estresse (1)	0.74	0.76	0.75	330
	Acurácia			0.66	485
2017	Não Estresse (0)	0.23	0.54	0.32	93
	Estresse (1)	0.89	0.66	0.76	507
	Acurácia			0.65	600
2018	Não Estresse (0)	0.81	0.17	0.28	300
	Estresse (1)	0.61	0.97	0.75	404
	Acurácia			0.63	704
2019	Não Estresse (0)	0.65	0.51	0.58	381
	Estresse (1)	0.56	0.70	0.62	344
	Acurácia			0.60	725
2020	Não Estresse (0)	0.84	0.81	0.83	531
	Estresse (1)	0.52	0.57	0.54	189
	Acurácia			0.75	720

Note: Precision = the ratio of correct predictions to total predictions; Recall = the proportion of correctly classified data to actual situations; F1-Score = the harmonic mean of precision and recall; Quantity = Number of municipalities in a given condition and the total; Accuracy = Overall model accuracy.
Source: Research data.

The model's overall accuracy was consistently above 60%, as demonstrated in Table 3. Notably, in 2020, the accuracy reached 75%. It is important to emphasize that this was the sole year when the pandemic affected the dependent and independent variables.

Trussel and Patrick (2018) established cutoff points in their sample, taking into account the cost of error, and reported

results only for the case of fiscal stress. They obtained a result of 0.77 between 2007 and 2010 and 0.17 in 2011. In comparison, this study did not achieve better results than the first sample but had superior results in all years compared to the second.

However, it should be noted that this study makes predictions, whereas Trussel and Patrick (2018) only analyzed the factors affecting fiscal stress. Therefore, the results of this work are expected to be lower, but they managed to surpass the mentioned results in some aspects.

4.1 Gray area

Such areas are characterized by imprecision, with a low probability of the predicted outcome occurring (Altman et al., 2013). Therefore, the removal of these is implemented to improve accuracy rates. To do so, five cutoff points were applied: in the first one, all values within the range of 45% to 55% were removed; in the second, between 60% and 40%; in the third, between 65% and 35%, in the fourth, between 30% and 70%, and finally, between 25% and 75%.

The results obtained can be viewed in Appendix 1. As the range of cutoff points expands, the accuracy values of the models also increase, signifying that the elimination of low probabilities yielded the anticipated outcomes. Remarkably, in the final cutoff point, all accuracy values surpassed 0.8, indicating a high overall accuracy, exceeding 80%. These values closely resemble those in Chen's work (2021), which achieved an accuracy rate of 85%. Additionally, in 2020, an accuracy rate of 0.85 was attained, matching the reference.

Furthermore, Appendix 2 includes five figures that depict the quantity of type I and type II errors and correct fiscal and non-fiscal stress predictions. The graphs have the X-axis representing the number of municipalities and the Y-axis representing the probability of fiscal stress. It is important to note that when this probability is less than 50%, the prediction indicates that the subnational entity will not face issues. The graphs are divided into four sections, always starting at identifiable values on the X-axis, making them easy to read.

Upon reviewing the five figures provided, it becomes evident that there was a higher incidence of type I errors compared to type II errors, except for the prediction year 2017. Additionally, it is clear that as probabilities increase, the chances of fiscal issues occurring decrease. Minimizing these occurrences and improving the overall model accuracy has been effectively achieved.

Considering the analysis, only seven municipalities predicted not to face fiscal stress experienced the issue when analyzed above 85% (or below 15% in the graphs), and only one when analyzed above 90%. It is noteworthy that in the year 2019, everything was correct of this type above 80%. On the other hand, when the subnational entity was predicted not to face the issue but did, there were a higher number of occurrences, with 42 instances above the 85% cutoff, 13 instances above 90%, and no such errors occurred in three years of analysis with the 95% cutoff.

The visual analysis further corroborates the variations in the model's performance concerning the periods before and during the pandemic. From 2016 to 2018, a significantly higher accuracy rate in predicting fiscal stress is evident, at least four times greater. In 2019, the accuracy rates for both predictions were nearly identical, while in 2020, the model correctly predicted the absence of the issue approximately four times more frequently.

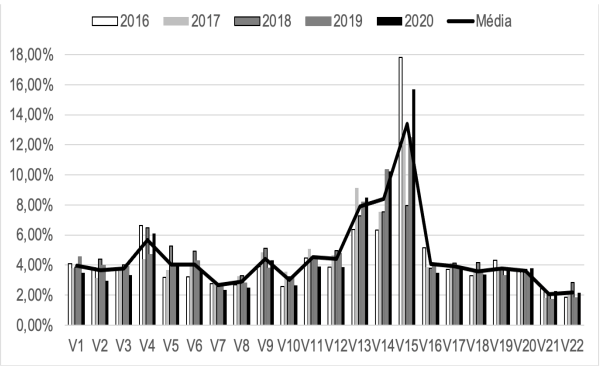
4.2 Variable importance

Upon analyzing Figure 1, it becomes evident that, on average, the most crucial variables, specifically V13, V14, and V15, were related to liquidity over the years. This finding aligns with the observations of Iacuzzi (2022), who identified a concentration of liquidity-related indicators among the variables examined in this domain. Additionally, Variable 15 consistently maintains its primary significance in all years.

The mean importance of the variables averaged 4.55%. In addition to the three variables mentioned earlier, only Variable V4 exceeded this mean. This finding supports the perspective put forth by Lima and Diniz (2016), emphasizing that, despite the significance of the operational position, it should be considered independent, as suggested by McDonald and Larson (2020). The genuine concern arises when a consistent pattern of expenditures surpassing revenues over several consecutive periods or when reserves are established without a justifiable rationale. Therefore, this variable can be employed to assess prolonged deterioration and aligns with the core objective of the LRF, which is to balance revenues and expenditures.

Among the model variables, V21 and V22 stand out as the least important, with the former related to the environmental factor and the latter to the organizational factor. This result does not align with the studies of Groves and Valente (2003), which attribute significant importance to environmental and organizational indicators in predicting fiscal balance.

Figure 1: Importance of Variables



Source: Developed by the authors.

This outcome also contradicts the research by Antulov-Fantulin et al. (2021), who deem specific region-related indicators to be more crucial than financial data for forecasting, and it diverges from the conclusions of Silva et al. (2020), who view the region as a fundamental factor in evaluating fiscal management in Brazil. Moreover, the other two environmental variables (V18 and V20) also exhibited below-average significance.

This variable's relative lack of significance is observed in the context of political ideology (V22). Therefore, this result aligns with the research of Benito et al. (2010), which also did not identify a significant association between this variable and debt. However, it contrasts with the findings of Lobo et al. (2011) and Navarro-Galera et al. (2021), who established a significant relationship. Hence, it is possible that financial indicators already encompass the effects of environmental and organizational variables.

The variables related to health and education expenses, which scored below average, deserve attention due to their importance. This result is significant in light of the lessons learned from Vieira (2016) as if such resources do not significantly impact fiscal stress, there is no justification for promoting fiscal austerity programs that may lead to social problems.

Nevertheless, caution is warranted since, as per Dantas Junior et al. (2019), these expenditures impacted Brazilian municipalities' fiscal stress. This inconsistency is likely linked to the analysis, as assessing influencing factors relies on variables from the same year, while the prediction utilizes variables from the subsequent period.

4.2.1 Variable Importance During Different Periods

The results unveiled significant fluctuations during the global health crisis. Furthermore, the 'cash to debt' variable exhibited variations, with its values hovering around 7% from 2016 to 2018 but exceeding 10% in the last two years. This outcome aligns with the conclusions of Maher et al. (2020), underscoring the importance of nonprofit organizations maintaining financial reserves to navigate periods of economic turbulence.

Throughout the health crisis period, the 'capital expenditure' variable displayed alterations compared to the preceding period, albeit with reduced volatility and a decline in its significance. The values hovered around 4% in the initial three years, while in the last two years, they stood at approximately 3.5%.

The other variables did not change the results significantly between the two periods analyzed. Therefore, in percentage terms, the 'cash to debt' variable gained importance during the crisis, while capital expenditure decreased. However, the first variable underwent a more significant change.

5 Conclusions

Government financial health has been thoroughly examined and discussed on a global scale. In recent years, this subject has received growing attention in the Brazilian literature. Fiscal health is closely linked to governments' financial well-being and can decrease public services when an entity experiences fiscal stress. As a result, crises and innovative methodologies can stimulate researchers to seek new insights and analyses in this field.

Therefore, this study adopted a contemporary model to examine the factors influencing the fiscal condition of municipalities and utilized the artificial intelligence technique, random forest, to assess the outcomes, as this approach has recently demonstrated favorable results.

This study sought to forecast the fiscal state of municipalities in Minas Gerais, with a one-year lead time, to evaluate the probability of fiscal stress. This enabled a comparison of the findings with other research endeavors that aimed to make similar predictions or verify their accuracy for the corresponding period.

The initial outcome surpassed one of the primary datasets employed by Trussel and Patrick (2018) as a foundation for customizing this model, even though these authors intended to explore the factors impacting fiscal conditions. By implementing probability thresholds within the model, a comparable result was obtained by Chen (2021), who likewise forecasted this scenario.

The model presented distinct results for the different periods analyzed, as there was a significant change in the prediction of fiscal stress and the absence of this problem when the influence of pandemic-related data (independent and dependent) was considered.

When assessing the significance of the variables, it becomes apparent that the most crucial factors are linked to the liquidity of municipalities, aligning with the findings of Iacuzzi (2022) and supporting Lima and Diniz's (2016) perspective on the importance of the operational position, which, though significant, should not be regarded as the sole determining factor. However, the mesoregion variable exhibited lower importance, in contrast to the results of Antulov-Fantulin et al. (2021).

Lastly, it is relevant to underscore the constrained impact of political ideology on fiscal stress, aligning with the results of Benito et al. (2010) and deviating from the conclusions of Lobo et al. (2011) and Navarro-Galera et al. (2021). Consequently, environmental and organizational factors are needed to demonstrate significance in this analysis, contrary to the assertions presented by Groves et al. (1981) and Groves and Valente (2003).

Even with the enhancements introduced in this study, it is imperative to acknowledge its constraints. The analysis period was delimited by the data availability of SICONFI, which spans from 2014 onwards, and the examination was centered on municipalities within a single Brazilian state.

As a direction for future research, it is suggested to extend the analysis period, including the post-pandemic period, and expand the analysis to include all municipalities in Brazil. Furthermore, exploring other AI methodologies and including additional variables to enhance the understanding of fiscal stress in municipal contexts is also possible.

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Appendix 1: Gray Area Results

Table 4: Model Results After the Removal of Specific Probabilities

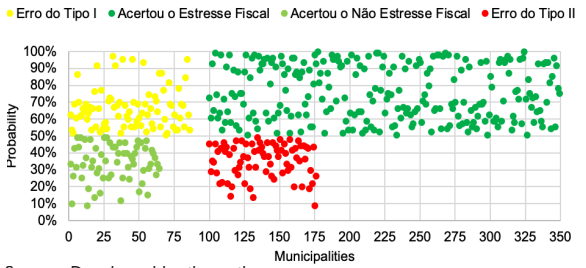
		Cut of 45% to 55%				Cut of 40% to 60%				Cut of 35% to 65%				Cut of 30% to 70%				Cut of 25% to 75%			
Validation	Condition	Precision	Recall	F1-Score	Quantity	Precision	Recall	F1-Score	Quantity	Precision	Recall	F1-Score	Quantity	Precision	Recall	F1-Score	Quantity	Precision	Recall	F1-Score	Quantity
2016	No Stress (0)	0.46	0.42	0.44	124	0.47	0.40	0.43	95	0.49	0.42	0.46	73	0.46	0.45	0.46	40	0.42	0.38	0.40	26
	Stress (1)	0.76	0.78	0.77	287	0.77	0.82	0.80	235	0.80	0.84	0.82	197	0.86	0.87	0.87	160	0.88	0.90	0.89	134
	Accuracy			0.67	411			0.70	330			0.73	270			0.79	200			0.81	160
2017	No Stress (0)	0.21	0.54	0.30	65	0.22	0.58	0.32	45	0.20	0.67	0.31	27	0.22	0.68	0.33	19	0.25	0.69	0.37	13
	Stress (1)	0.91	0.69	0.78	426	0.93	0.73	0.82	340	0.96	0.76	0.85	297	0.97	0.81	0.88	243	0.98	0.86	0.92	199
	Accuracy			0.67	491			0.71	385			0.75	324			0.80	262			0.85	212
2018	No Stress (0)	0.76	0.10	0.18	250	0.76	0.08	0.14	208	0.82	0.09	0.16	158	0.62	0.05	0.09	104	0.40	0.03	0.06	66
	Stress (1)	0.63	0.98	0.77	390	0.66	0.99	0.79	370	0.71	0.99	0.83	351	0.76	0.99	0.86	320	0.82	0.99	0.89	286
	Accuracy			0.64	640			0.66	578			0.71	509			0.76	434			0.81	352
2019	No Stress (0)	0.68	0.51	0.58	281	0.68	0.50	0.58	169	0.66	0.46	0.54	113	0.69	0.39	0.49	57	0.73	0.24	0.36	33
	Stress (1)	0.61	0.76	0.67	280	0.68	0.83	0.75	223	0.73	0.86	0.79	193	0.81	0.94	0.87	156	0.84	0.98	0.90	133
	Accuracy			0.63	561			0.68	392			0.71	306			0.79	213			0.83	166
2020	No Stress (0)	0.86	0.85	0.85	458	0.86	0.89	0.87	385	0.86	0.88	0.87	308	0.87	0.88	0.87	220	0.88	0.85	0.87	151
	Stress (1)	0.59	0.61	0.60	162	0.66	0.62	0.64	141	0.70	0.64	0.67	129	0.71	0.69	0.70	97	0.74	0.78	0.76	80
	Accuracy			0.79	620			0.81	526			0.81	437			0.82	317			0.83	231

Note: Precision = the ratio of correct predictions to total predictions; Recall = the proportion of correctly classified data to actual situations; F1-Score = the harmonic mean of precision and recall; Quantity = Number of municipalities in a given condition and the total; Accuracy = Overall model accuracy.

Source: Research data.

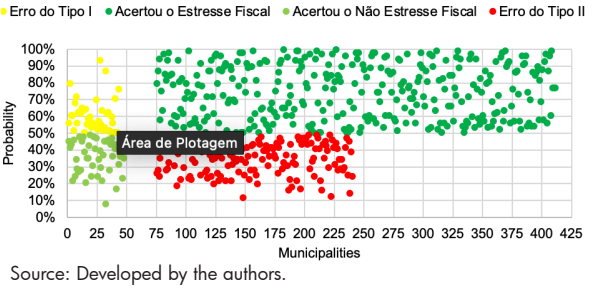
Appendix 2: Gray Area Figures

Figure 2: 2016 Prediction Result



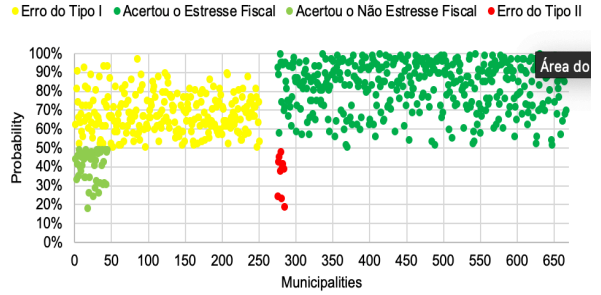
Source: Developed by the authors.

Figure 3: 2017 Prediction Result



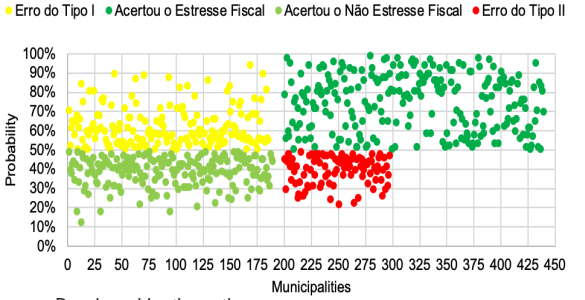
Source: Developed by the authors.

Fiaure 4: 2018 Prediction Result



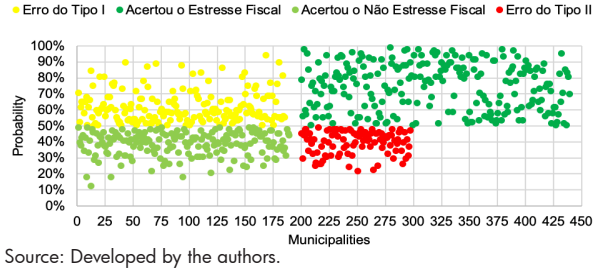
Source: Developed by the authors.

Fiaure 5: 2019 Prediction Result



Source: Developed by the authors.

Figure 6: 2020 Prediction Result



Source: Developed by the authors.