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The Impact of Generic Positioning Strategies on the Configuration of Firms' Resources

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Resumo
This research aims to analyze the influence of generic positioning strategies, adopted in a pure or hybrid way, in the configuration of firms' resources, in order to investigate how such strategies act on the formation of a superior operational performance, based on accounting metrics as resource proxies. We used accounting information from publicly listed firms located in G20's countries (from 2008 to 2019). The principal component analysis technique is applied to measure strategic positioning (Banker et al. 2014; Tripathy, 2006). Logistic regression models and Catboost and SHAP algorithms are used to assess the positioning effect on the relationship between resource configuration and performance. The results showed that the strategy adopted influences the impact of resource variables on performance. Firms that apply a differentiation strategy are more sensitive to variations in the indexes. Although the hybrid positioning provides less impact of changes in resources on performance, in this strategy, the influence of factors that were not significant in the other strategies was observed. In addition to exploring the use of financial metrics to measure aspects related to strategic positioning and resource configuration, this research applies robust machine learning techniques to identify the impact of each variable in shaping operational performance.

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Abstract

This research aims to analyze the influence of generic positioning strategies, adopted in a pure or hybrid way, in the configuration of firms' resources, in order to investigate how such strategies act on the formation of a superior operational performance, based on accounting metrics as resource proxies. We used accounting information from publicly listed firms located in G20's countries (from 2008 to 2019). The principal component analysis technique is applied to measure strategic positioning (Banker et al. 2014; Tripathy, 2006). Logistic regression models and Catboost and SHAP algorithms are used to assess the positioning effect on the relationship between resource configuration and performance. The results showed that the strategy adopted influences the impact of resource variables on performance. Firms that apply a differentiation strategy are more sensitive to variations in the indexes. Although the hybrid positioning provides less impact of changes in resources on performance, in this strategy, the influence of factors that were not significant in the other strategies was observed. In addition to exploring the use of financial metrics to measure aspects related to strategic positioning and resource configuration, this research applies robust machine learning techniques to identify the impact of each variable in shaping operational performance.

Keywords: Generic strategies positioning; Hybrid strategy; Firm operational performance; Firms' resources.

1. INTRODUCTION

This study analyzes the effect of generic positioning strategies, in cost leadership and in differentiation, adopted in a pure and hybrid form, on the configuration of firms' resources. In this way, it investigates the role played by these strategic positions on the relationship between business conduct and the formation of superior operational performance. To this end, accounting metrics from financial information are used to measure the generic strategy adopted, as well as to measure performance.

According to Porter (1980), to defend against market forces and achieve competitive advantage, the firms need to position itself through a strategy of product differentiation (offering a unique product with high added value) or cost leadership (providing standardized products with the lowest market price). As these positioning strategies have a construction process that involves different productive structures and contradictory activities, it is unlikely that a firm will be able to adopt both strategies efficiently (Lapersonne, 2018).

Although some research has verified the existence of a trade-off between generic positioning strategies (Hansen et al., 2015; Kim & Lim, 1988; Thornhill & White, 2007), studies such as those by Acquaah and Yasai-Ardekani (2008), Kim et al. (2004) and Sofia and Augustine (2019) present results in which the adoption of a hybrid strategy is possible and may be superior. From this perspective, it is argued that the idea raised by Porter (1980) presents a restricted view that does not consider aspects of an unstable market, subjected to rapid transformations and high competitiveness, a context in which firms are forced to implement a more complex and dynamics strategy approach (Chakravarthy, 1997; Lapersonne et al., 2015).

In order to face the forces imposed by the market structure, firms must draw up a strategic plan that guides managerial policies and the actions of managers in order to guarantee not only their presence in this market, but also the achievement of satisfactory performances. The adoption of such policies and actions affects the configuration of its productive resources which, in turn, are reflected in the financial statements generated by the accounting processes.

By strategically positioning themselves, firms configure their processes around two main objectives: to maximize their operational efficiency, producing goods at the lowest possible cost, or to achieve a high level of product quality. Such configuration of productive resources is reflected by the financial information generated by the accounting processes. Thus, while ex-ante strategy aims to identify which set of actions and policies lead firms to their success (Besanko et al., 2013), ex-post accounting presents financial, operational and economic metrics that enable evaluate business performance, as well as measure the effects of managerial decisions (Palepu & Healy, 2008). Knowing the effect that strategic positioning has on the way these factors are arranged is a possible way to understand the determinants of superior performance.

Given the above, this study aims to answer the following question: What is the effect of adopting generic strategies, in cost leadership and product differentiation, whether in a pure or hybrid form, on the relationship between resource configuration and operational performance?

This research, through the accounting model, brings together the fields of economics, administration and business strategy, contributing to advances in these areas of knowledge. Such approximation is achieved as the financial metrics offered by accounting are explored for the evaluation of the effects of strategic decisions on the management of the productive resources and the superior operational performance of firms. Therefore, these metrics allow the empirical verification of the theoretical formulations of the Industrial Organization, of the Vision Resource-based and Generic Positioning. Based on Tripathy (2006), Banker et al. (2014) and Tang and Liou (2010), the information contained in the financial statements are taken as a starting point for the analysis of the strategic positioning adopted by firms and the way in which resources are organized, giving accounting science a fundamental role for the diagnosis and evaluation of management actions and their influence on operating results. It is also interesting to emphasize that in addition to using regression, a technique commonly observed in empirical analyzes in the strategy field, this study applies machine learning algorithms that have high predictive power and are still little applied in this field.

2. THEORETICAL FRAMEWORK AND HYPOTHESIS CONSTRUCTION

2.1. Strategic positioning and configuration of resources

Studies in the research field of business strategy have sought to identify and understand the factors that lead to heterogeneous performance behavior (Ghemawat, 2002). Porter (1980) argues that, to be successful, firms must define a strategy to defend themselves from market forces. Therefore, the best way to do this would be by positioning themselves through a cost leadership or product differentiation strategy. Firms that adopt a generic strategic positioning based on cost leadership seek to offer simplified and standardized products, providing a greater sales volume at the lowest price in the market (Banker et al., 2014; Campbell et al., 2011). On the other hand, firms that opt for a differentiation strategy offer an exclusive product, which awakens the customer's perception of the presence of benefits and advantages that go beyond its usefulness (Sashi & Stern, 1995). In this way, such firms can obtain high margins since their target audience is willing to pay a premium price to access such products (Hambrick, 1983).

Porter (1980) considers unlikely that a firm will efficiently establish both generic strategies simultaneously. For the author, when trying to implement a hybrid strategy, firms are not able to apply any of the strategies in a well-defined way, which results in a diffuse culture, poorly oriented and based on conflicting actions that make it difficult to assimilate them by different hierarchical levels of firms (Miles & Snow, 1978; Porter, 1985; Jones & Butler, 1988).

Although some studies have suggested that choosing pure strategies is always more advantageous than combining positioning strategies (Hansen et al., 2015; Kim & Lim, 1988; Thornhill & White, 2007), others dispute the trade-off between generic strategies and argue that a hybrid strategy is capable of creating a competitive advantage and providing high profitability (Acquaah & Yasai-Ardekani, 2008; Allen & Helms, 2006; Kim et al., 2004). Datta (2010) claims that Porter's (1980) failure to reject the possibility of the coexistence of strategies producing superior performance lies in his basic premise, which considers cost leadership as the only path to market share leadership and presents a narrow view of differentiation, based on exclusivity and premium value. For Lapersonne et al. (2015), the fact that the positioning school performs its analysis from a stable environment does not consider aspects of an unstable market, subjected to rapid transformations and high competitiveness, characteristics of the current era of globalization. In this context, firms are forced to implement a more complex and dynamic approach to strategy (Chakravarthy, 1997).

By assuming a strategic positioning, firms structure their internal configuration, allocating their resources in order to achieve a high level of quality or maximum efficiency in the production process. Therefore, the investigation of the way in which these resources are organized in face of each adopted position can be of great relevance for the elaboration of management policies that aim at maximizing operational results. In order to trace relationships between competitive advantage, resource configuration and sustainable superior performance, Tang and Liou (2010) argue that such relationships can be understood through the analysis of financial indicators, since they reflect the set of resources that which the firm applies in its operations. For the authors, such resources are organized around five management policies: customer relationship, supplier relationship, government relationship, intellectual property, and fixed asset management. According to Tang and Liou (2010), the management of these policies, which they call resource configuration, is the potential source of competitive advantage. Financial indicators reflect such policies and, consequently, shape performance.

With the aim of investigating the influence of generic positioning strategies on the configuration of firms' resources, from accounting metrics as proxies of resources, this research uses as a reference for the configuration of resources the management policies proposed by Tang and Liou (2010). In view of the arguments presented by the literature review, this study considers the following research hypothesis:

H1: The adoption of different positioning strategies is reflected in the configuration of firms' resources, when analyzed from their financial information and influences the relationship between management policies and performance.

Knowing the effect that strategic positioning has on the way these resources are arranged is a possible way to understand the determinants of superior performance (Bowman & Helfat, 2001).

2.2. The use of accounting information

Issues related to the study of performance are part of the strategy and accounting study fields, which differ in focus of interest and unit of analysis. Strategy focuses on the analysis of choices, decisions and resources in the firm's environment, aiming to relate the firm's competitive advantage to the characteristics of its environment (Rumelt et al., 1991). Accounting, on the other hand, provides financial, operational metrics and economic that, when combined, have the proposition of measuring the firm performance in an ex-post-facto perspective (Penman, 2009), and also allows the support or the repositioning of the choices and decisions of the managers in the use of their resources (O' Connor et al., 2015).

Most studies that aim to investigate the relationship between generic strategies and performance measure positioning through the application of questionnaires (Acquaah & Yasai-Ardekani, 2008; Hansen et al., 2015; Kaliappen et al., 2019; Khedmati et al., 2019; Thornhill & White, 2007; Yasa et al., 2019). Some authors use accounting metrics for this measurement, but they are limited to a single indicator for each strategy (Sofia & Augustine, 2019; Spanos et al., 2004). In this context, Tripathy (2006), Banker et al. (2014) and Fernando et al. (2016), present a more robust approach based on the principal components analysis with a set of accounting indicators.

The strategic decisions that agents must make in their day-to-day management can be basically summarized in those that deal with raising and allocating resources and, therefore, are related to changes in assets (application of resources) and liabilities (origin of financing)

(Palepu & Healy, 2008). Analyzing the resource bundle concept, the firm definition for the theory of resources, from the perspective of the accounting field we find a parallel with the definition of asset adopted by the IASB (2019). For the Board, an asset is a resource controlled by the entity as a result of past events and from which future economic benefits are expected to result. Therefore, every firm is necessarily composed of a set of assets (resources), which are within its domain, and which, when combined, are capable of generating economic results. Therefore, the accounting system, through its techniques, identifies, measures and highlights the resources controlled by firms.

Thus, assuming that economic and financial information are the main references for decision-making in the context of the firm and, considering the financial statements one of its main sources (Healy & Palepu, 2001; Penman, 2009), the study of the relationship between competitive advantage and the firm's operating performance using metrics contained in the structure of financial statements becomes relevant.

3. METHODOLOGY

3.1. Sample selection and data processing

The sample used was extracted from the Refinitiv Eikon™ database and is formed by publicly traded firms with shares traded on the main stock exchanges of the G20 countries, a group formed by the 19 largest economies in the world and the European Union. Annual data corresponding to the period from 2008 to 2019 were analyzed for firms in the following sectors: cyclical consumer goods and services, non-cyclical consumer goods and services, and technology, sectors 53, 54 and 57 of the Thomson Reuters Business Classification (Reuters, 2013). Understanding that these sectors are less influenced by government regulation, are more exposed to market laws and customer choices, we believe that in them the concepts of strategic approaches are more evident.

For the composition of the final sample, observations that presented missing data in the variables that formed the positioning proxies were excluded. Based on Tripathy (2006), observations with negative profit were not considered and observations with values for sales less than 1 million dollars were excluded in order to restrict the analysis to large firms. Observations with values of any variable above or below the 0.5% distribution were discarded to suppress the effect of outliers (Chen & Dixon, 1972). The final sample totaled 7778 firm-year observations. Table 1 presents the description of the adjustments made in the collected sample and the distribution of observations and firms in the sectors considered for the final sample. For the application of the analyses, the variables were standardized.

Table 1
Description of the adjustments made to the initial sample collected and the final sample

	Observations	
Initial sample	**172 596**	
Economic sectors selection:	115 980	
Cyclical Consumer Goods & Services	53 376	
Non-Cyclical Consumer Goods & Services	21 324	
Technology	41 280	
Data cleaning:		
Missing data	66 567	
Exclusion parameters: Negative profit and/or sales less than US$1,000,000.00	41 331	
Outliers	304	
Final sample	**7 778**	
Sample distribution by sector	**Observ.**	**Firms**
Cyclical Consumer Goods & Services	**3 813**	**710**
Automobiles & Auto Parts	1 297	223
Textiles & Apparel	422	80
Homebuilding & Construction Supplies	365	74
Household Goods	204	44
Leisure Products	143	25
Hotels & Entertainment Services	320	63
Media & Publishing	286	70
Diversified Retail	231	43
Specialty Retailers	545	88
Non-Cyclical Consumer Goods & Services	**2 079**	**362**
Beverages	270	47
Food & Tobacco	1 016	187
Personal & Household Products & Services	305	50
Food & Drug Retailing	488	78
Technology	**1 886**	**405**
Semiconductors & Semiconductor Equipment	400	87
Communications Equipment	189	43
Electronic Equipment & Parts	237	51
Office Equipment	85	17
Computers, Phones & Household Electronics	266	63
Software & IT Services	709	144

Note: Firm-year observations, referring to annual data, from 2008 to 2019.
Source: Prepared by the authors from data collected from Refinitiv Eikon™.

3.2. Variables

3.2.1. Dependent variables

The dependent variable used is the firms' operational performance. We considered the RNOA (return on net operating assets) as a performance metric. This indicator is obtained by the ratio between net operating income and total assets. The RNOA is used as a categorical variable (Performance), classified as "Good performance" and "Poor performance". To classify firms as successful or unsuccessful, Delen et al. (2013) divides the sample into firms that perform above or below the median, respectively. Similar to the approach used by the authors, it was determined that median performance values (RNOA) corresponding to 10% of the distribution above and below the median are not considered for the analyses. This was done considering that this intermediate group would refer to a performance considered average, neither characterized as good nor bad. Thus, observation groups with performance above and below the intermediate group were classified as “Good performance” and “Poor performance”, respectively.

3.2.2. Independent variables

a) Strategic positioning

In the literature that addresses the measurement of strategic positioning, six financial indicators are identified as measures of positioning. Of these, three evidence the firm's effort to create a favorable image and products with high added value (David et al., 2002; Kotha & Nair, 1995), which indicates a positioning aimed at product differentiation (Banker et al., 2014). The other three indicators are capable of evidencing the efficiency of the use of capital investments in the firm's production process, thus, they are related to a strategic positioning based on cost leadership (David et al., 2002; Hambrick, 1983). Such indicators are described in Table 2. In order to eliminate the effect of seasonality, the calculation of these indicators considers the average of the values obtained in the last five years.

Table 2
Strategic positioning indicators and their respective variables

Indicators	Strategic positioning
SGA / SALES	Differentiation
R&D / SALES	Differentiation
SALES / CGS	Differentiation
SALES / CAPEX	Cost leadership
SALES / P&E	Cost leadership
EMPL / P&E	Cost leadership
Variables	**Description**
SGA	Sales, general, and administrative expenses
SALES	Net revenue (total sales)
R&D	Research and development expenses
CGS	Cost of goods sold
CAPEX	Fixed capital expenditures
P&E	Book value of plant and equipment
EMPL	Total employees

Source: Prepared by the authors based on Balsam et al. (2011), Banker et al. (2014) and Fernando et al. (2016).

From the calculation of the indicators, based on Banker et al. (2014), Fernando et al. (2016) and Tripathy (2006), the Principal Component Analysis (PCA) technique was used. Initially, data adequacy was verified: the KMO statistic obtained was 0.61, considered reasonable (Hair et al., 1998), and Bartlett's sphericity test also showed favorable results (approximate chi-square: 3525 .26, with 15 degrees of freedom, $\rho < 0.001$). Then, PCA was performed together with the Varimax rotation technique. The results obtained are shown in Table 3. The extraction of 2 components followed the Kaiser criterion and the accumulated explained variance (which exceeded the minimum level of 60% with the determination of the second component). The first and second components were named as differentiation factor and cost leadership factor, respectively, in accordance with the theoretical evaluation of the indices that compose them.

Table 3
Results obtained in Principal Component Analysis (PCA)

Variables	Loads of the Differentiation factor	Loads of the cost leadership factor	Commonality
SGA / SALES	0.837		0.703
R&D / SALES	0.742		0.550
SALES / CGS	0.861		0.742
SALES / CAPEX		0.712	0.507
SALES / P&E		0.864	0.751
EMPL / P&E		0.717	0.514
Explained Variance (EV) (%)	2.038	1.729	
EV accumulated (%)	33.96%	62.78%	
Cronbach's alpha	0.745	0.647	

Source: Authors.

From the components found and the loads attributed to the variables, the differentiation and cost leadership factors were calculated for each observation in the sample, which allowed the measurement of the efficiency of each firm when adopting each of the generic positioning strategies. Based on the studies by Yamin et al. (1999) and Lapersonne (2018), the factors were standardized in the range between -1 and 1 (values above 0 considered "high" and values below 0, "low") and classified as follows: high score in differentiation and low in cost leadership (High-Low) characterizes a positioning in differentiation; low value in differentiation and a high value in cost leadership (Low-High), represents a positioning in cost leadership; firms that apply the two generic strategies simultaneously efficiently (High-High) are considered to have a hybrid positioning strategy; and the group called "stuck in the middle", when the differentiation and cost leadership strategies are not applied efficiently (Low-Low).

With the grouping performed, before proceeding with the analyses, it was verified whether there is, in fact, a significant association between the adopted position (characterized by the group) and the performance obtained. When performing the chi-square test for independence, it was found that there is a relationship between performance and the strategy adopted (chi-square: 223.027; ρ-value <0.001). Then, after measuring the strategic positioning, the positioning categorical variable (P) was established to be inserted in the model as a dummy variable (for each category), in which the value 1 or 0 is assigned, indicating whether the observation presents this characteristic or not, respectively.

b) Management policies indicators

For the configuration of resources analysis, the management policies proposed by Tang and Liou (2010) are used as a reference, which consider that firm's resources are organized around five management policies (customer relationship, supplier relationship, government relationship, intellectual property, and fixed asset management). In this way, the financial indices that form these policies are inserted into the model, as shown in Table 4.

Table 4
List of variables used to analyze the configuration of resources

Variable	Indicator	Policy
CR	SALES / AR (accounts receivable turnover)	Customer relationship
SR1	SALES / AP (accounts payable turnover)	Supplier relationship
SR2	SALES / INV (inventory turnover)	
SR3	CGS / SALES	
IP1	R&D / SALES	Intellectual property
IP2	SGA / SALES	
FAM1	SALES / P&E	Fixed asset management
FAM2	DEPR / SALES	
GR	TAX/ SALES	Government relationship

Note: SALES - Total sales; AR- Accounts Receivable; AP - Accounts Payable; INV - Inventory; CGS - Cost of Goods Sold; R&D - Research and development expenses; SGA - Sales, general and administrative expenses; P&E - Book value of plant and equipment; DEPR - Depreciation; TAX - Taxes payable.
Source: Authors, based on Tang and Liou (2010).

3.2.3. Control variables

Based on previous studies (Banker et al., 2014; Fernando et al., 2016; Tripathy, 2006), the following variables were chosen: Leverage (the firm's leverage measured by the value of total long-term debt divided by equity total); Book to market (the book-to-market ratio at the beginning of the year); and Size (the ratio of firm's sales to total sector's sales). The following variables were also considered: Sector, referring to the industry sector in which the firm operates, as competitors and the nature of competition vary in different markets and industries (Thornhill & White, 2007); Life cycle, phase of the life cycle that the firm is in (Dickinson, 2011; Gort & Klepper, 1982); and Country, as countries have regulatory environments that can affect the firm's profitability (Healy et al., 2014).

3.3. Empirical analysis

3.3.1. Logistic regression

To empirically examine the hypothesis presented by this research, Logistic Regression (LOGIT) models are used. The dependent variable used is performance, determined by calculating the RNOA and classified as “Good performance” or “Poor performance”, as described in item 3.2.1. In Model 1 (Equation 1), the independent variables correspond to the financial indexes that are components of the five management policies in which firm resources are organized, according to Tang and Liou (2010). To assess the effect of each of the positioning strategies, the positioning variable (P) is entered by multiplying each of the variables of interest. As it is a categorical variable, with the categories of differentiation, cost leadership and hybrid, the variable P is inserted as dummy, one for each category. P receive the value equal to 1 if the respective strategic positioning is adopted or 0 otherwise. Then, in applying logistic regression, the relationship between each variable of interest and performance is analyzed considering the strategic positioning adopted.

$$\begin{aligned} \text{Performance} = \alpha_0 &+ \beta_1\ CR * P + \beta_2\ SR1 * P + \beta_3\ SR2 * P \\ &+ \beta_4\ SR3 * P + \beta_5\ IP1 * P + \beta_6\ IP2 * P \\ &+ \beta_7\ FAM1 * P + \beta_8\ FAM2 * P + \beta_9\ GR * P \end{aligned} \tag{1}$$

To consider specific aspects of the firms and the environment in which they operate, an analysis of the model is also carried out with the insertion of control variables (Model 2, Equation 2).

$$\begin{aligned} \text{Performance} = \alpha_0 &+ \beta_1\ \text{CR} * \text{P} + \beta_2\ \text{SR1} * \text{P} + \beta_3\ \text{SR2} * \text{P} \\ &+ \beta_4\ \text{SR3} * \text{P} + \beta_5\ \text{IP1} * \text{P} + \beta_6\ \text{IP2} * \text{P} \\ &+ \beta_7\ \text{FAM1} * \text{P} + \beta_8\ \text{FAM2} * \text{P} + \beta_9\ \text{GR} * \text{P} \\ &+ \gamma\ \textit{Control variables} \end{aligned} \tag{2}$$

3.3.2. Catboost and SHAP

Another analysis applied to assess the influence of the adoption of different positioning strategies on the relationship between management policies and performance, the Catboost (Categorical Boosting) and SHAP (SHapley Additive exPlanations) algorithms are used. Catboost is a decision tree-based machine learning algorithm that was developed by Yandex and is available as an open-source library. This algorithm uses a gradient boosting structure, a technique that produces a model with high predictive power from the construction of a set of prediction models considered weaker (Ghori et al., 2020; Huang et al., 2019). Thus, instead of performing the analysis through a single decision tree model, this technique builds a set of trees to achieve greater predictive power. In addition to providing superior results to those obtained with traditional techniques, Catboost works well with small or large databases and with complex dependencies between variables (Dorogush et al., 2018). Another advantage of this algorithm is the use of a new way to calculate leaf values when selecting the tree structure, which contributes to reducing overfitting (Prokhorenkova et al., 2018). This technique was chosen considering that this study uses performance as a categorical variable (“Good performance” and “Poor performance”).

In order to assess the predictive power of the generated models, the data sample for each group was randomly divided into a training sample (80%) and a test sample (20%). A parameter commonly used for this validation is the calculation of accuracy, proportion of hits when applying the model (generated from the training sample) in the test sample. However, according to Huang and Ling (2005) AUC (Area Under the Curve) is a more precise measure than accuracy. The AUC represents the area under the ROC curve, which in turn is a graphical representation that illustrates the performance of a binary model and considers false positives and negatives in the analysis. The closer to 1 the value of the AUC found, the better the performance of the model.

In many cases, less complex and commonly used methods, such as regressions, are applied because they clearly display the weights of the variables, which allows for later specific analyses. Machine learning models, such as boosting models, are difficult to understand and do not allow a deep analysis of the importance of variables in the decision, however, they manage to reach superior results (Caruana & Niculescu-Mizil, 2006; Huang et al., 2019).

A decision tree algorithm produces the path (or paths) from the root of the tree to the leaf, which consists of a series of decisions, guarded by a specific resource. As Catboost establishes a set of trees to compose a forecast model, the visualization and interpretation of the results becomes even more complex. In this context, SHAP is a method created by Lundberg and Lee (2017), designed to explain individual predictions from boosting models. This technique is intended to explain individual forecasts, calculating the contribution of each variable in the forecast, attributing to each variable used an importance value in determining the output variable (Molnar, 2019). Simply put, in addition to analyzing the importance of variables for each instance of the base, it also checks whether the influence of high and low values of the variables on the result is positive or negative. Besides that, the results obtained are presented in graphical form, which facilitates their interpretation.

4. RESULTS AND DISCUSSIONS

4.1. Regression results

Table 5 presents the results obtained for Models 1 and 2. The addition of control variables (Model 2) provided an improvement in the model, which presented an R^2 (Nagelkerke) of 0.796. It was possible to identify that some categories of the control variables Sector and Country were significant. However, for this analysis, no significant categories were found for the life cycle variable.

From the results shown in Table 5 part (b), it is noted that the variables of management policies that had a significant influence on the dependent variable (performance) were similar for the differentiation positioning and cost leadership positioning, they are: SR3, IP2, FAM2 and GR. In the case of positioning in a hybrid strategy, in addition to the variables SR3, IP2 and GR, the variables SR1, SR2 and FAM2 were also significant. Even with these similarities regarding the significance of the variables between the positioning strategies, the coefficient and the odds ratio (Odds Ratio) must be analyzed in a specific way.

Regarding the variable SR3, which corresponds to the proportion of costs in sales and is associated with the supplier relationship policy (Tang & Liou, 2010), its coefficient was negative for the three strategic groups, indicating that high values in this index contribute significantly and negatively to the probability of obtaining a good performance, which is expected and understandable. However, there is also a high value (in module) of the coefficient associated with SR3 for the differentiation groups (13.073) and cost leadership (11.792), being the highest value among the coefficients found. For the hybrid strategy group, even though this coefficient is not the highest (in module), it appears in second place, showing little difference for the coefficient of greater relevance (associated with the GR). In this way, the importance of managing this index to obtain a positive result for the three strategic groups is identified, being more expressive in the case of positioning in differentiation. These results indicate that the performance of firms that adopt the differentiation strategy, as they work with the practice of high profit margins (Balsam et al., 2011; Chaganti et al., 1989), are more sensitive to the variation of this index.

Associated with the second highest coefficient (in module), in the strategic differentiation and cost leadership groups, and the third highest in the case of the hybrid strategy, the IP2 variable also negatively influences the chances of a good performance. This variable, related with the firm's intellectual capital (Tang & Liou, 2010), represents the proportion of expenses in relation to sales. There is a greater effect of this index in the probability of obtaining a superior performance for firms that work with a differentiated product or service, and less influence for firms that manage to employ both generic positioning strategies, efficiently, simultaneously. It is understandable that the variable IP2 (sales, general and administrative expenses/sales value) impairs the chances of obtaining a good performance, regardless of the strategy adopted. However, to awaken the quality character of a differentiated product, firms that adopt the differentiation strategy tend to present large amounts of expenses (David et al., 2002; Hambrick et al., 1982), which can be a justification for its greater sensitivity to IP2 variation. On the other hand, firms that adopt a hybrid strategy are less sensitive to changes in this variable, which could possibly be due to the fact that they are able to combine the two generic strategies, providing a quality product without the need for high investments.

In a general analysis, another important variable is the GR, which is associated with the relationship policy with government institutions, as it represents the proportion of tax expenditures in relation to the value of sales (Tang & Liou, 2010). As the other indexes already analyzed, its effect on performance is negative, but there is no significant difference in its magnitude between the positioning strategies (coefficients: -6.646, -5.465 and -5.743, for differentiation, cost leadership and hybrid strategy, respectively). In the case of firms that position themselves with a hybrid strategy, the GR variable appears as the one with the greatest influence on the probability of obtaining a good result. Then, the results indicate that the fact of adopting a certain positioning strategy does not influence the relationship between firms and the conditions established by the government.

Table 5
Logistic regression results - Models 1 and 2

		Model 1				Model 2			
Variables		Coef	Wald	p-value	OR	Coef	Wald	p-value	OR
Constant		6.973	346.223	0.000 ***	1.07E+03	9.047	30.782	0.000 ***	8.49E+03
Differentiation	CR	-2.430	5.774	0.016 **	0.088	-1.941	2.625	0.105	0.144
	SR1	-0.199	6.004	0.014 **	0.819	-0.066	0.156	0.693	0.937
	SR2	-4.522	5.097	0.024 **	0.011	-2.134	0.423	0.515	0.118
	SR3	-13.236	426.684	0.000 ***	0.000	-13.073	340.396	0.000 ***	0.000
	IP1	0.044	0.239	0.625	1.045	-0.020	0.028	0.867	0.981
	IP2	-9.072	410.419	0.000 ***	0.000	-9.077	331.253	0.000 ***	0.000
	FAM1	0.562	1.987	0.159	1.754	0.508	1.217	0.270	1.662
	FAM2	-0.811	60.658	0.000 ***	0.445	-0.954	46.967	0.000 ***	0.385
	GR	-6.795	313.019	0.000 ***	0.001	-6.646	239.298	0.000 ***	0.001
Cost leadership	CR	0.307	2.700	0.100	1.360	0.149	0.510	0.475	1.160
	SR1	-0.043	0.258	0.611	0.958	-0.154	2.660	0.103	0.857
	SR2	-0.430	0.842	0.359	0.651	0.053	0.036	0.849	1.054
	SR3	-10.980	325.672	0.000 ***	0.000	-11.792	262.735	0.000 ***	0.000
	IP1	-0.194	0.332	0.565	0.824	-0.538	1.792	0.181	0.584
	IP2	-7.248	209.129	0.000 ***	0.001	-7.360	158.675	0.000 ***	0.001
	FAM1	0.120	2.446	0.118	1.127	0.142	2.653	0.103	1.153
	FAM2	-0.909	8.607	0.003 ***	0.403	-1.802	37.793	0.000 ***	0.165
	GR	-5.140	164.158	0.000 ***	0.006	-5.465	136.265	0.000 ***	0.004
Hybrid	CR	0.408	0.197	0.657	1.504	1.020	1.005	0.316	2.773
	SR1	0.503	6.748	0.009 ***	1.653	0.504	7.379	0.007 ***	1.656
	SR2	0.212	7.001	0.008 ***	1.236	0.199	6.142	0.013 **	1.220
	SR3	-5.402	151.871	0.000 ***	0.005	-5.237	130.410	0.000 ***	0.005
	IP1	0.008	0.005	0.942	1.008	0.046	0.138	0.710	1.047
	IP2	-3.872	131.472	0.000 ***	0.021	-3.940	123.860	0.000 ***	0.019
	FAM1	-0.805	7.238	0.007 ***	0.447	-0.985	8.395	0.004 ***	0.373
	FAM2	0.375	1.049	0.306	1.455	0.351	0.819	0.365	1.420
	GR	-5.655	189.786	0.000 ***	0.004	-5.743	162.902	0.000 ***	0.003
Control		No				Yes			
Log likelihood					1781,744				1536,300
R^2 Cox & Snell					0,560				0,592
R^2 Nagelkerke					0,753				0,796

Note: *, **, and *** significant at 10%, 5%, and 1%, respectively; OR - Odds Ratio.
Source: Authors, with results from IBM SPSS Statistics 21.

In addition to the three variables described, the variable FAM2 (associated with the fixed asset management policy) presented significant coefficients considering a position in differentiation or in cost leadership. FAM2, which represents the proportion of depreciation of fixed assets in the value of sales, contributes negatively to the chance of obtaining a good performance. However, compared to the other variables analyzed (which were considered significant for the model), the magnitude of this negative effect is smaller. Furthermore, from the odds ratio (OR), it is noted that, for each unit variation in this index, there is a greater decrease in the chance of obtaining a good performance in the case of firms positioned in cost leadership than in firms that adopt the differentiation strategy.

Regarding the hybrid positioning strategy, the variables SR1 and SR2 were also significant (at a 5% significance level). These variables correspond to accounts payable turnover (sales/accounts payable) and inventory turnover (sales/inventory), respectively, and are associated with the supplier relationship policy (Tang & Liou, 2010). They showed positive coefficients, that is, the positive variation of their values generates an increase in the probability of obtaining a good performance. From the odds ratio (OR), we can see that this increase is around 65% for SR1 and 22% for SR2, when a hybrid strategy is adopted. Thus, in firms that choose this strategy, attention should be paid to the efficiency provided by the speed in the payment of suppliers, short-term debts, and the speed of inventory consumption, as these aspects significantly increase the chances of to obtain superior performance.

From the results and discussions presented, we can infer that, when opting for a hybrid positioning (working with a differentiated product or service, efficiently), firms obtain superior performance reaching satisfactory profit margins, through a quality product/service without high investments, and with high turnover of its operations.

4.2. Catboost and SHAP

The accuracy and AUC results (Table 6) show the predictive power of the models obtained by applying the Catboost algorithm to the strategy groups of differentiation, cost leadership and hybrid. The graphs generated by applying the SHAP technique are shown in Figures 1, 2 and 3, for the differentiation, cost leadership and hybrid strategy positioning groups, respectively. In these graphs, the influence of each variable in obtaining performance is plotted for each observation analyzed. The location of the points indicates whether the impact of each variable on performance is negative (the further to the left of the vertical axis, the greater the negative impact) or positive (the further to the right of the vertical axis, the greater the positive impact). It also indicates when the value of the variable is lower or higher, which is represented by the color scale that goes from blue (low value) to pink (high value). The variables are also displayed in order of influence (from highest to lowest) and in this case the SHAP value corresponds to the impact on the magnitude of performance. As they present several points, the analysis of this type of graph considers the predominance of points of each color, for each variable.

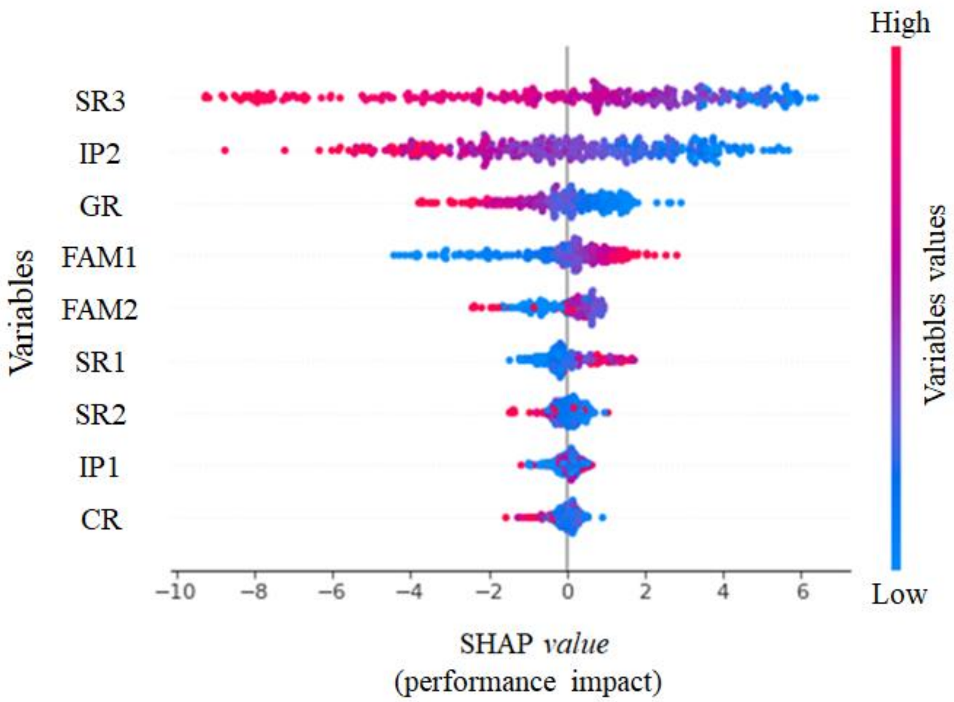
Table 6
Evaluation parameters of models generated by Catboost, for each strategic group

Strategic group	Accuracy (%)	AUC
Differentiation	95.69	0.979
Cost leadership	91.96	0.967
Hybrid	91.82	0.977

Source: Authors.

Figure 1 shows the results obtained for the observations corresponding to the positioning group in differentiation. We can identify that the first three variables (of greater influence), SR3, IP2 and GR, coincide with the results obtained with the regression (LOGIT), presented above. High values of these variables have a negative impact on performance (SHAP value), as also observed by the negative coefficients found through LOGIT (-13.073, -9.077 and -6.646, for SR3, IP2 and GR respectively). The next variable in the order of importance (Figure 1) was FAM1, which corresponds to the turnover of fixed assets (sales/value of plant and equipment). High FAM1 values contribute positively to achieving good performance. However, in the model calibrated with LOGIT, this variable was not considered significant, thus being identified as a divergence between the techniques applied. The fifth variable shown in the graph is FAM2, which has high values with negative and also positive influence (with lower magnitude), which indicates that there is no well-defined and expressive impact on the part of this variable. In the case of LOGIT, FAM2 had a negative impact, but with the smallest magnitude among the significant variables. The other variables (SR1, SR2, IP1 and CR) do not show great impact, in addition to not being considered significant in the model calibrated with LOGIT.

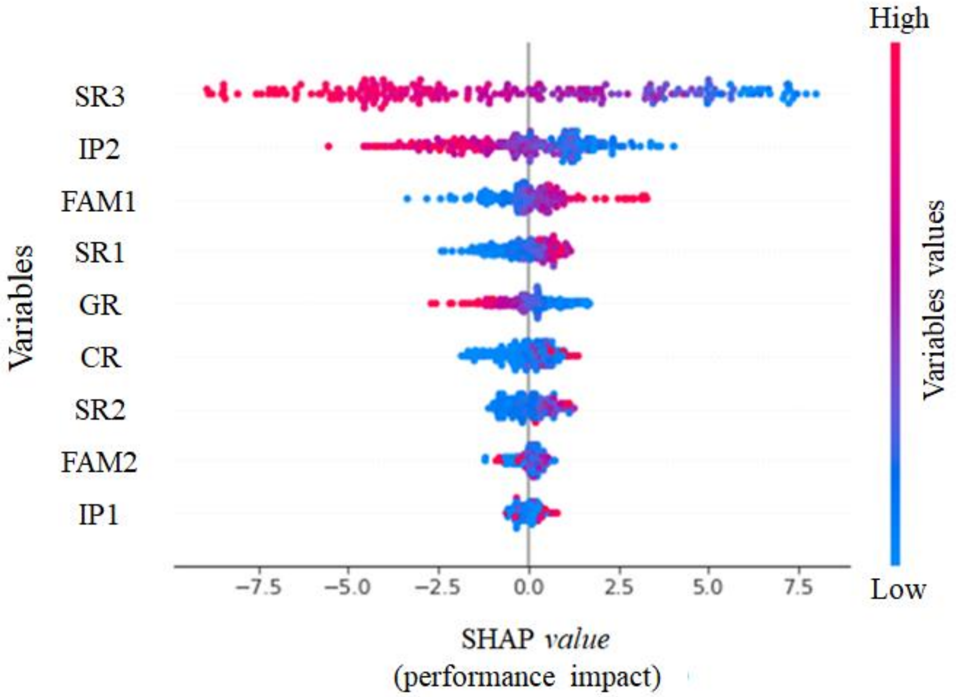
Figure 1
Positive or negative impact of variables on performance - Differentiation strategy



Source: Authors, results displayed using the SHAP algorithm.

Regarding the cost leadership positioning group (Figure 2), the two variables with the greatest impact are SR3 and IP2, which had a negative impact (high values of SR3 and IP2 have a negative impact to obtain good performance, as well as in the LOGIT results. Then, the variables FAM1 (fixed asset turnover) and SR1 (accounts payable turnover) appear, in both cases the high values of the variables have a positive impact on performance (with lower magnitude in the case of SR1). These variables were not considered significant in the model calibrated with LOGIT.

Figure 2
Positive or negative impact of variables on performance - Cost leadership strategy

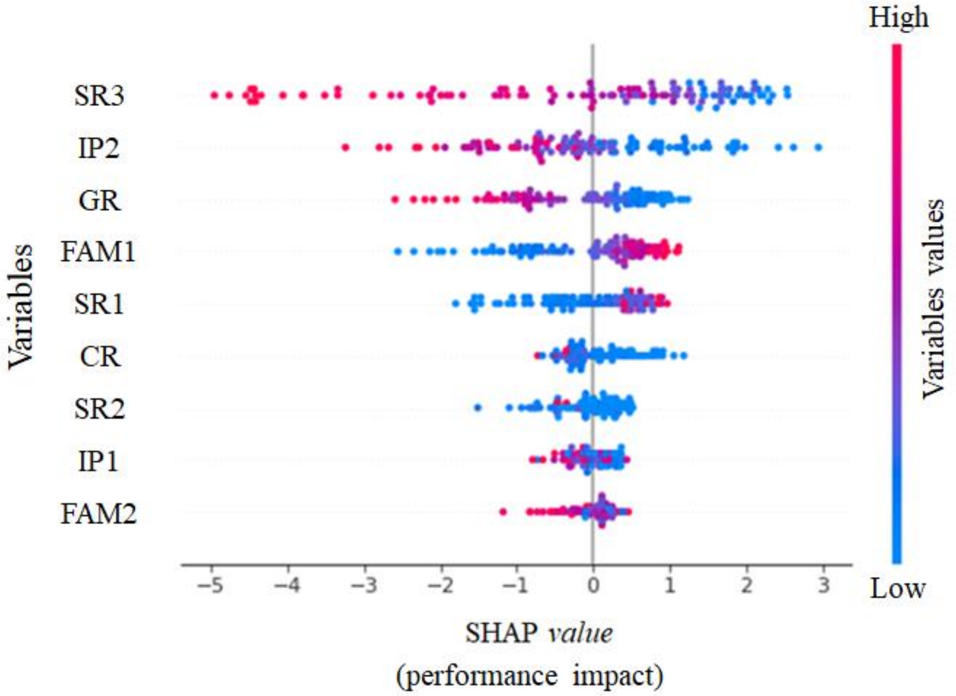


Source: Authors, results displayed using the SHAP algorithm.

In the case of the hybrid strategy (Figure 3), the points plotted on the graph are more dispersed. The five variables with the greatest influence on performance (SR3, IP2, GR, FAM1 and SR1) were similar to the five variables with the highest coefficient values (in module) presented by LOGIT. Also, in agreement with the previously calibrated model, high values in the variables SR3, IP2 and GR have a negative impact on performance, whereas in the case of the variable SR1 they have a positive impact (with lower magnitude). However, we can note that high values in FAM1 generate positive impacts. This result differs from the one obtained in LOGIT, in which this variable had a negative influence (-0.985) on the probability of obtaining a good performance.

Although some disagreements have been identified, if we consider the variables that have the greatest impact on obtaining superior performance, the two analyzes performed (LOGIT and Catboost associated with SHAP) showed similar results. It is interesting to note that some variables that were considered important in the second analysis (Catboost associated with SHAP), such as FAM1 and SR1 (in the cases of differentiation and cost leadership), had a positive impact on performance, but were not considered significant in LOGIT. In addition, in general, the variables considered less important in the SHAP analysis and with low impact values were not significant in the LOGIT.

Figure 3
Positive or negative impact of variables on performance - Hybrid strategy



Source: Authors, results displayed using the SHAP algorithm.

A data analysis using a machine learning algorithm produces a model with high predictive power that provides results superior to those obtained with traditional techniques. In addition, it considers the complex relationships between variables (Ghori et al., 2020; Huang et al., 2019). The analysis of the graphs generated through the SHAP algorithm is not as simple as an equation, but it makes it much clearer how the model is using the variables to arrive at the values of its predictions, and, in general, they offer better precision by using complex models (Dorogush et al., 2018). Thus, in this study, the results obtained through the SHAP algorithm also allow analyzes with greater specificity in relation to each variable, contributing to the identification of variables that do not have a clear influence (positive and negative), in addition to displaying graphical impacts referring to high and low values of the variables.

The results of the two analyzes showed that, although there are similarities in the variables that have the greatest effect on the chance of obtaining a good performance, between the positioning strategies, the magnitude of the impact of these variables is different. In this way, the strategic positioning influences the management of resources to obtain superior performance, which leads to the confirmation of the research hypothesis.

5. CONCLUSIONS

Seeking to evaluate the effect of strategic positioning on the relationship between management policies and performance, the results obtained showed similarities between the strategies in relation to the variables with the greatest effect on the probability of obtaining a good performance. However, it was identified that the magnitude of the influence of the variables is different between the strategic positions analyzed.

Firms that adopt the differentiation strategy are more sensitive to the variation of the analyzed variables, mainly in the proportion of costs in sales (SR3) and in the proportion of expenses in relation to sales (IP2). This result is possibly a consequence of the fact that firms that work with a differentiated product or service seek large profit margins and tend to make large investments in search of the quality of the product offered (David et al., 2002; Hambrick et al., 1982). On the other hand, when positioning themselves with a hybrid strategy, firms become less sensitive to changes in these factors, which may reflect a strategy that combines a quality and differentiated product/service, at a relatively low cost and without the need to of high investments. In addition, even though the hybrid strategy had a lower impact of variables, in general, two indicators associated with supplier relationship policies (SR1 and SR2) proved to be significant only for this strategy.

The analysis using the Catboost and SHAP algorithms made it possible to identify the impact of management policy variables on performance in a more comprehensive way, considering the influence of high and low values of each variable, in addition to presenting a graphical view of the results. Thus, it was possible to compare the results obtained for each strategic group, identifying the similarities and differences with the results found with the previously applied method (logistic regression). In general, considering the variables with the greatest impact on obtaining superior performance, the results of both methods were considered similar. However, it is noteworthy that boosting-type algorithms have a high predictive power, in addition to enabling the analysis of more complex relationships that may exist between variables. By associating the SHAP technique with Catboost, the restrictions regarding the complexity of analyzing these types of models are suppressed.

A limitation found in this study was the considerable reduction of the initial database due to the large number of missing data. In addition, the PCA technique was applied to measure strategic positioning considering the approach proposed in studies found in the literature. However, other clustering techniques are already widely used in the scientific environment, such as cluster analysis. Although this does not invalidate the results obtained, it is important to recognize the endogeneity of the analyzed data when measuring positioning and determining performance, an issue intrinsic to this study field.

By using machine learning algorithms, this study brings advanced methods of data analysis to accounting research. However, the investigations carried out did not take advantage of the full power of analysis provided by these tools. Thus, other aspects can be investigated in future studies, such as complexity, munificence and dynamism, dimensions related to the unpredictability of the market.

6. REFERENCES

Acquaah, M., & Yasai-Ardekani, M. (2008). Does the implementation of a combination competitive strategy yield incremental performance benefits? A new perspective from a transition economy in Sub-Saharan Africa. *Journal of Business Research*, 61(4), 346-354.

Allen, R. S., & Helms, M. M. (2006). Linking strategic practices and organizational performance to Porter's generic strategies. *Business Process Management Journal*.

Balsam, S., Fernando, G. D., & Tripathy, A. (2011). The impact of firm strategy on performance measures used in executive compensation. *Journal of Business Research*, *64*(2), 187–193.

Banker, R. D., Mashruwala, R., & Tripathy, A. (2014). Does a differentiation strategy lead to more sustainable financial performance than a cost leadership strategy? *Management Decision*, *52*(5), 872–896.

Besanko, D., Dranove, D., Shanley, M., & Schaefer, S. (2013). *Economics of strategy* (6th ed.). John Wiley & Sons.

Bowman, E. H.; Helfat, C. E. Does corporate strategy matter?. *Strategic Management Journal*, v. 22, n. 1, p. 1-23, 2001.

Campbell, D., Edgar, D., & Stonehouse, G. (2011). *Business strategy: an introduction*. Macmillan International Higher Education.

Caruana, R., & Niculescu-Mizil, A. (2006, June). *An empirical comparison of supervised learning algorithms*. In Proceedings of the 23rd international conference on Machine learning (pp. 161-168).

Chaganti, R., Chaganti, R., & Mahajan, V. (1989). Profitable Small Business Strategies under Different Types of Competition. *Entrepreneurship Theory and Practice*, *13*(3), 21–36.

Chakravarthy, B. (1997). A new strategy framework for coping with turbulence. *MIT Sloan Management Review*, 38(2), 69.

Chen, E. H., & Dixon, W. J. (1972). Estimates of parameters of a censored regression sample. *Journal of the American Statistical Association*, 67(339), 664-671.

Datta, Y. (2010). A critique of Porter's cost leadership and differentiation strategies. *Chinese Business Review*, 9(4), 37.

David, J. S., Hwang, Y., Pei, B. K., & Reneau, J. H. (2002). The performance effects of congruence between product competitive strategies and purchasing management design. *Management Science*, 48(7), 866-885.

Delen, D., Kuzey, C., & Uyar, A. (2013). Measuring firm performance using financial ratios: A decision tree approach. *Expert Systems with Applications*, *40*(10), 3970–3983.

Dickinson, V. (2011). Cash flow patterns as a proxy for firm life cycle. *The Accounting Review*, 86(6), 1969-1994.

Dorogush, A. V., Ershov, V., & Gulin, A. (2018). CatBoost: gradient boosting with categorical features support. Preprint arXiv:1810.11363.

Fernando, G. D., Schneible, R. A., & Tripathy, A. (2016). Firm strategy and market reaction to earnings. *Advances in Accounting*, *33*, 20–34.

Ghemawat, P. (2002). Competition and Business Strategy in Historical Perspective. *Business History Review*, *76*(1), 37–74.

Ghori, K. M., Abbasi, R. A., Awais, M., Imran, M., Ullah, A., & Szathmary, L. (2020). Performance analysis of different types of machine learning classifiers for non-technical loss detection. *IEEE Access*, 8, 16033-16048.

Gort, M., & Klepper, S. (1982). Time paths in the diffusion of product innovations. *The economic journal*, 92(367), 630-653.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (1998). *Multivariate data analysis* (Vol. 5, No. 3, pp. 207-219). Upper Saddle River, NJ: Prentice hall.

Hambrick, D. C. (1983). High Profit Strategies in Mature Capital Goods Industries: A Contingency Approach. *Academy of Management Journal*, *26*(4), 687–707.

Hansen, E., Nybakk, E., & Panwar, R. (2015). Pure versus hybrid competitive strategies in the forest sector: Performance implications. *Forest Policy and Economics*, *54*, 51-57.

Healy, P. M., & Palepu, K. G. (2001). Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *Journal of accounting and economics*, 31(1-3), 405-440.

Huang, G., Wu, L., Ma, X., Zhang, W., Fan, J., Yu, X., Zeng, W., & Zhou, H. (2019). Evaluation of CatBoost method for prediction of reference evapotranspiration in humid regions. *Journal of Hydrology*, 574, 1029-1041.

Huang, J., & Ling, C. X. (2005). Using AUC and accuracy in evaluating learning algorithms. *IEEE Transactions on knowledge and Data Engineering*, 17(3), 299-310.

IASB - International Accounting Standards Board (2019). *Conceptual framework for financial reporting*. Londres.

Jones, G. R., & Butler, J. E. (1988). Costs, revenue, and business-level strategy. *Academy of Management Review*, 13(2), 202-213.

Kaliappen, N., Chuah, F., Gorondutse, A. H., & Moktar, S. N. A. (2019). Hybrid competitive strategy, strategic capability and performance. *Journal of Business and Retail Management Research*, 13(4), 43-50.

Kim, E., Nam, D. I., & Stimpert, J. L. (2004). Testing the applicability of Porter's generic strategies in the digital age: A study of Korean cyber malls. *Journal of Business Strategies*, 21(1).

Kim, L., & Lim, Y. (1988). Environment, generic strategies, and performance in a rapidly developing country: A taxonomic approach. *Academy of Management journal*, 31(4), 802-827.

Kotha, S., & Nair, A. (1995). Strategy and environment as determinants of performance: evidence from the Japanese machine tool industry. *Strategic management journal*, 16(7), 497-518.

Lapersonne, A. H. (2018). *The Hybrid Competitive Strategy Framework: A Managerial Theory for Combining Differentiation and Low-Cost Strategic Approaches Based on a Case Study of a European Textile Manufacturer*.[Doctoral dissertation, The University of Manchester] The University of Manchester repository. Available in: https://www.research.manchester.ac.uk/portal/files/66046490/FULL_TEXT.PDF.

Lapersonne, A., Sanghavi, N., & De Mattos, C. (2015). Hybrid Strategy, ambidexterity and environment: toward an integrated typology. *Universal Journal of Management*, 3(12), 497-508.

Lundberg, S. M., & Lee, S.-I. (2017). A Unified Approach to Interpreting Model Predictions. In I. Guyon, U. V Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, & R. Garnett (Eds.), *Advances in Neural Information Processing Systems 30* (pp. 4765–4774). Curran Associates, Inc. http://papers.nips.cc/paper/7062-a-unified-approach-to-interpreting-model-predictions.pdf

Miles, R. E., & Snow, C. C. (1978). *Organizational strategy, structure, and process*. McGraw-Hill.

Molnar, C. (2019). *Interpretable machine learning*. https://christophm.github.io/interpretable-ml-book

O'Connor, N. G., Deng, F. J., & Fei, P. (2015). Observability and subjective performance measurement. *Abacus*, 51(2), 208-237.

Palepu, K. G., & Healy, P. M. (2008). *Business Analysis and Valuation: Using Financial Statements, Text and Cases*. Thomson South-Western.

Penman, S. H. (2009). Accounting for intangible assets: There is also an income statement. *Abacus*, *45*(3), 358-371.

Porter, M E. (1980). *Competitive Strategy: Techniques for Analyzing Industries and Competitors*. Free Press.

Porter, M. E. (1985). *Competitive advantage: creating and sustaining superior performance*. Free Press.

Prokhorenkova, L., Gusev, G., Vorobev, A., Dorogush, A. V., & Gulin, A. (2018). CatBoost: unbiased boosting with categorical features. In *Advances in neural information processing systems*, 6638-6648.

Reuters (2013), Thomson Reuters Business Classification (TRBC) , Reuters, New York, NY.

Rumelt, R. P., Schendel, D., & Teece, D. J. (1991). Strategic management and economics. *Strategic management journal*, 12(S2), 5-29.

Sashi, C. M., & Stern, L. W. (1995). Product differentiation and market performance in producer goods industries. *Journal of Business Research*, 33(2), 115-127

Sofia, I. P., & Augustine, Y. (2019). Does enterprise risk management and hybrid strategy affect to organizational performance?. *South East Asia Journal of Contemporary Business, Economics and Law*, 20 (5), 120-126.

Spanos, Y. E., Zaralis, G., & Lioukas, S. (2004). Strategy and industry effects on profitability: evidence from Greece. *Strategic management journal*, 25(2), 139-165.

Tang, Y.-C., & Liou, F.-M. (2010). Does firm performance reveal its own causes? the role of Bayesian inference. *Strategic Management Journal*, *31*(1), 39–57. https://doi.org/10.1002/smj.799

Thornhill, S., & White, R. E. (2007). Strategic purity: A multi-industry evaluation of pure vs. hybrid business strategies. *Strategic Management Journal*, 28(5), 553-561.

Tripathy, A. (2006). *Strategic positioning and firm performance*. Doctoral dissertation, The University of Texas at Dallas.

Yamin, S., Gunasekaran, A., & Mavondo, F. T. (1999). Relationship between generic strategies, competitive advantage and organizational performance: an empirical analysis. Technovation, 19(8), 507-518.

Yasa, N. N. K., Sukaatmadja, I. P. G., & Yuniari, I. G. G. N. W. (2019). The Influence of External Environment and Resource Capability on the Hybrid Business Strategy and Business Performance. *In Proceedings of the 7th International Conference on Entrepreneurship and Business Management (ICEBM Untar 2018)*. https://doi.org/10.5220/0008492903430349.