

Article

GIANN—A Methodology for Optimizing Competitiveness Performance Assessment Models for Small and Medium-Sized Enterprises

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Abstract: The adoption of models based on key performance indicators to diagnose and evaluate the competitiveness of companies has been presented as a trend in the operations' management. These models are structured with different variables in complex interrelationships, making diagnosis and monitoring difficult due to the number of variables involved, which is one of the main management challenges of Small and Medium-sized Enterprises. In this sense, this article proposes the Gain Information Artificial Neural Network (GIANN) method. GIANN is a method to optimize the number of variables of assessment models for the competitiveness and operational performance of Small and Medium-sized Enterprises. GIANN is a hybrid methodology combining Multi-attribute Utility Theory with Entropy and Information Gain concepts and computational modeling through Multilayer Perceptron Artificial Neural Network. The model used in this article integrates variables such as fundamental points of view, critical success factors, and key performance indicators. GIANN was validated through a survey of managers of Small and Medium-sized Enterprises in Southern Brazil. The initial model was adjusted, reducing the number of key performance indicators by 39% while maintaining the accuracy of the results of the competitiveness measurement. With GIANN, the number of variables to be monitored decreases considerably, facilitating the management of Small and Medium-sized Enterprises.

Keywords: multi-attribute utility theory; artificial neural network; entropy; information gain; small and medium-sized enterprises



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1. Introduction

Competitiveness is a broad term that combines managers' concerns related to market share, profitability, outputs, exports, and employment levels (Carbone and Rivers 2020). Furthermore, the competitiveness and innovation of companies directly depend on improvements in their productivity, quality (Liu et al. 2022; Bhat et al. 2021), and the formation of dynamic and entrepreneurial environments (Baierle et al. 2021). These concerns heavily impact SMEs that form the backbone of development in most nations (Soni et al. 2022). The main challenges are industrial transformation and developing a high-quality production style (Villa and Taurino 2018). However, SMEs cannot identify the causes of these difficulties and challenges due to the lack of management control systems and difficulties measuring management performance (Kim et al. 2021), demonstrating the need for SMEs to have optimized and simplified models for diagnosing and measuring competitiveness.

The rapid industrial and technological development has increased competitiveness among companies, which have sought to establish strategies such as monitoring competitiveness through management metrics (Rodrigues et al. 2021) to improve decision-making

(Baierle et al. 2019). The companies' competitive performance must be measured to verify if the objectives are being reached (Kim et al. 2021). Therefore, this measurement becomes a basic requirement to effectively improve the competitiveness of companies (Yadav et al. 2020). In this sense, to measure competitiveness and assist in the decision-making process, Key Performance Indicators (KPIs) can be used as a set of metrics to manage and seek continuous improvement and effectiveness in productivity, quality, operational performance, and efficiency of an enterprise (Kang et al. 2016; Chytilova et al. 2019). KPIs must be defined based on business strategy, allowing organizations to translate abstract performance objectives into concrete, measurable metrics (Gilsing et al. 2021). There is no consensus among the authors regarding the number of KPIs to be used; Kaplan and Norton (1996) recommend less than 20 KPIs, while Hope and Fraser (2013) recommend less than 10. Thus, one must discern the appropriate number of KPIs to be used; often, many KPIs can end up generalizing specific problems. In contrast, a very small number may not effectively present the perceived reality of an enterprise.

In addition to KPIs, other metrics such as Critical Success Factors (CSFs) and Fundamental Points of View (FPVs) can be used to diagnose and assess companies' competitiveness, bringing a qualitative-quantitative view to the model used. In this sense, CSFs are those areas where a company needs to achieve positive results to achieve its goals (Gupta et al. 2018; Rockart 1982) being used as a basis for adapting and improving company actions and processes (Swarnakar et al. 2020). These CSFs can compose models of diagnosis and measurement of competitive performance together with other variables, such as FPVs (Schaefer et al. 2022). The FPVs are those aspects considered fundamental to evaluate the possible actions to be taken, defining what is important in the decision-making context and what actions must be taken (e Costa et al. 1999) to ensure efficient and effective management of companies (Schaefer et al. 2021). Thus, FPVs make up the main group of variables in companies' decision-making models (Ishizaka and Nemery 2013), enabling a direct assessment of companies' business objectives. Therefore, the relevance of structuring models for diagnosing and measuring the competitiveness of companies is perceived. These models can encompass KPIs, CSFs, and FPVs in a multilevel structure (Silva Júnior et al. 2022). It is necessary to define which and how many these KPIs, CSFs, and FPVs will be, as well as how to integrate them into a competitiveness measurement model (Rodrigues et al. 2021).

The models for measuring the competitive performance of companies can be structured with the help of Multicriteria Decision Making (MCDM) methods. MCDM methods are commonly used to classify options and alternatives and solve problems where a decision needs to be made, such as choosing the best option, eliminating alternatives, and identifying or creating new strategies (Santos et al. 2022). To find a solution in a decision-making process, hierarchizing the variables in a decision tree format is a crucial step (Laforest et al. 2013), thus making it possible to carry out the intended diagnoses and evaluations. To solve this decision tree, an MCDM approach like Multi-attribute Utility Theory (MAUT) can be used. MAUT uses subjective decision-making judgments given by managers and experts to establish preferences about different consequences (da Silva et al. 2022). The results of applying the MCDM methods to models for measuring and evaluating competitiveness may differ depending on the method chosen, and to overcome this difficulty, hybridization with other methodologies is an option that should be considered. (Aktaş and Demirel 2021). Therefore, allying an MCDM technique, such as MAUT, with mathematical and computational techniques to aid the management and decision-making process can be successfully performed.

Based on these initial considerations, it can be said that SMEs are naturally concerned with monitoring and measuring their competitive and market performance. Managers of these companies should seek to develop simple and optimized models to measure the competitiveness of these companies, enabling easier management and being in line with what is required at the market level. The use of metrics, such as KPIs, associated with decision-making methodologies can become an important tool to monitor and measure the competitive performance of SMEs. In addition, structuring this tool by adding a

methodology to optimize this modeling could further facilitate the management process of these companies.

Thus, this research aims to present the GIANN method. GIANN can be used to optimize and adjust the number of variables present in assessment models and frameworks that evaluate competitiveness in SMEs. To validate and show how GIANN can be applied, a case study was developed with SMEs from the South of Brazil. The companies' competitiveness rates were calculated using the MAUT method based on an evaluation model that integrates variables such as FPVs, CSFs, and KPIs. The correlation between the KPIs and the competitive rates and the tests to optimize the initial evaluation model were operationalized through the Artificial Neural Network (ANN) Multilayer Perceptron (MLP), keeping the variation of the values of the competitiveness rates within limits previously defined as acceptable. Thus, GIANN can reduce the number of KPIs, CSFs, and FPVs, keeping the correlation coefficient between KPIs and competitiveness rates above a predetermined level.

The main contribution of this article is that, through GIANN, the number of variables to evaluate the competitiveness of the companies can be optimized and adjusted, demanding the monitoring and control of a smaller number of KPIs to accompany the evaluation of the companies' competitiveness. It can also be highlighted that GIANN combines the multicriteria analysis method MAUT with mathematical techniques, such as entropy and information gain, and computational modeling through ANN MLP. From the SME's point of view, it can be highlighted that the article presents a proposal for the assessment of competitiveness with a direction of which variables are more critical and unstable in companies of this size.

The remainder of the paper is organized as follows: Section 2 details the GIANN Method, Section 3 shows a case study, Section 4 presents the discussion and managerial implications, and Section 5 presents the conclusion of this paper.

2. GIANN Method

The GIANN method is subdivided into eight stages, as seen in Figure 1. Each one of these stages is detailed in the sequence.

2.1. Stage 1—Integration of KPIs, CSFs, and FPVs

The initial model for evaluating the competitiveness of SMEs used in this research is the one proposed by (Schaefer et al. 2020), which uses interdependent and correlated concepts such as FPVs, CSFs, and KPIs, integrating and hierarchizing them in a decision tree format. This decision tree makes it possible to calculate replacement rates using the MAUT method, thus measuring the SMEs' competitiveness. Table 1 presents this initial model.

Figure 2 presents KPIs, CSFs, and FPVs in a decision tree format diagram. This diagram represents the initial variable integration used in this case study.

2.2. Stage 2—Data Collection

The second stage of the proposed methodology consists of surveying to collect data with specialists in the research area. The case study of this article was developed from a survey sent by e-mail to 67 managers of industry SMEs linked to productive extension programs of the Secretary of Economic Development Science and Technology of Rio Grande do Sul, Brazil. The survey questions to SME managers used a 5-point Likert Scale (1 = not important until 5 = extremely important). In these questions, SME managers pointed out the level of importance that each of the 18 KPIs of the competitive performance measurement model to effectively assess these companies' competitiveness rate.

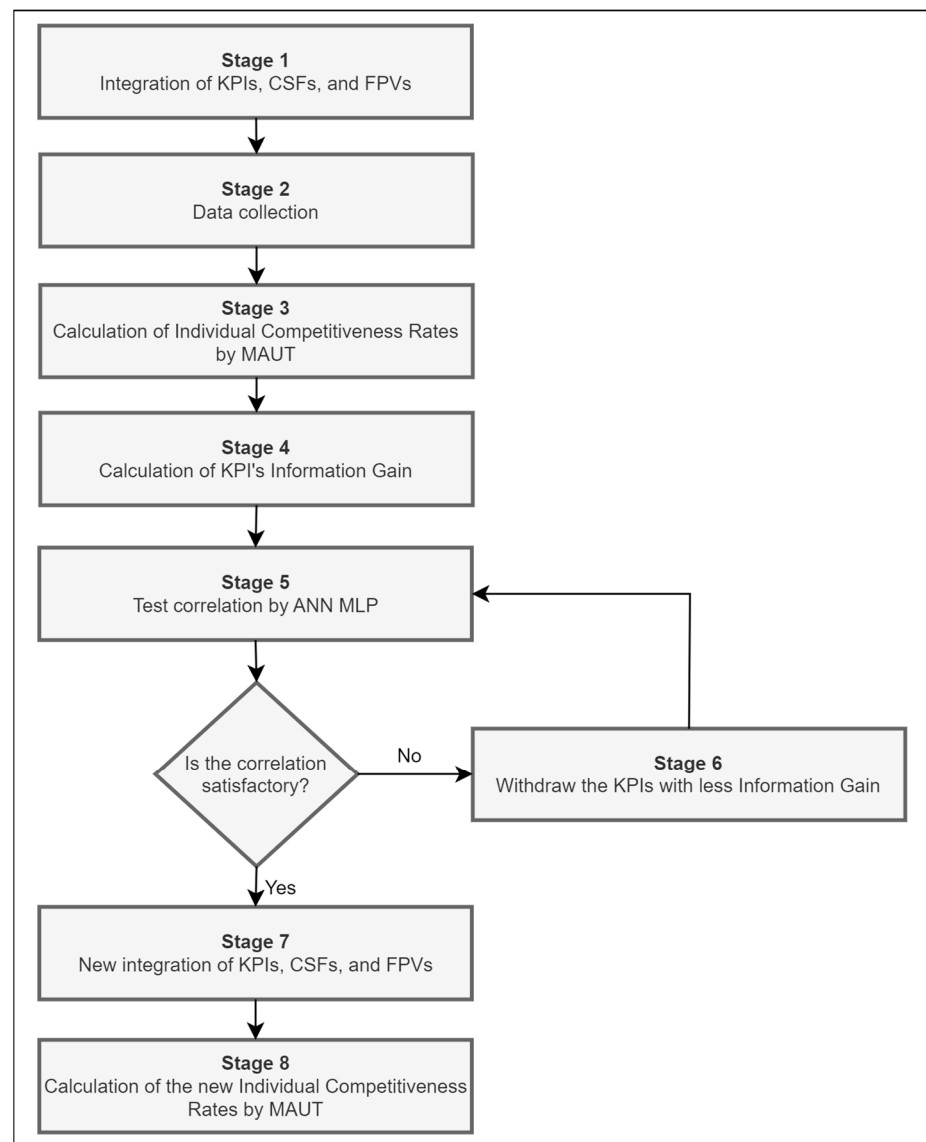


Figure 1. GIANN method stages.

Table 1. KPIs, CSFs, and FPVs integration (Schaefer et al. 2020).

Fundamental Point of View	Critical Success Factor	Key Performance Indicator
FPV1 RELIABILITY	CSF1 ORGANIZATIONAL STRATEGY	KPI1—Customer satisfaction indicator
		KPI2—Indicator of the existence of price strategies of products according to the market
		KPI3—Percentage of active customers indicator
		KPI4—Customer loyalty indicator
FPV2 COST	CSF2 RESOURCES	KPI5—Reinvestment of profits in the enterprise indicator
		KPI6—Raw material cost indicator

Table 1. Cont.

Fundamental Point of View	Critical Success Factor	Key Performance Indicator
FPV3 FLEXIBILITY	CSF3 TRAINING AND EDUCATION	KPI7—Indicator of the use, by employees, of the personal protective equipment indicated for their function
FPV4 QUALITY	CSF4 MANAGEMENT AND LEADERSHIP	KPI8—Control of the enterprise working capital indicator
		KPI9—Attracting new customers indicator
	CSF5 PROCESSES	KPI10—Quality of products indicator
		KPI11—Indicator of warranty products returned by defects
		KPI12—Machine availability indicator
FPV5 SPEED	CSF6 PERFORMANCE MEASUREMENT	KPI13—Production capacity utilization indicator
		KPI14—Indicator of the order delivered in the combined period with the customer
		KPI15—Customer complaints indicator
	CSF7 MOTIVATION	KPI16—Sales results indicator
		KPI17—Employee productivity indicator
		KPI18—Employee attendance indicator

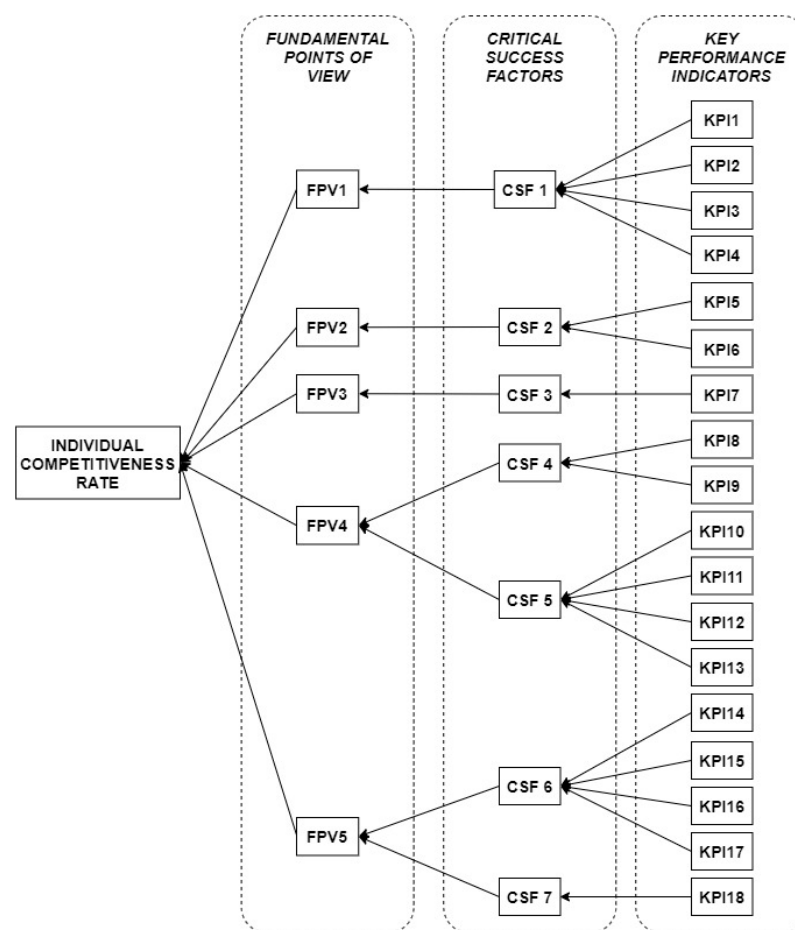


Figure 2. Initial integration of KPIs, CSFs, and FPVs (Schaefer et al. 2020).

2.3. Stage 3—Calculation of Competitiveness Rates Using the MAUT Method

MAUT (Fishburn 1970; Keeney and Raiffa 1976) has one of the best theoretical bases for applications involving risk and uncertainty since it not only deals with the choice of an alternative but also allows analyzing the decision (Monte and de Almeida-Filho 2016). The MAUT allows the establishment of an evaluation scale of alternatives (Aktaş and Demirel 2021); from this, the utility values for each alternative are calculated (Ozkaya et al. 2021). The ease of combining with other optimization methods in the search for an optimal solution (Wu et al. 2012) was the reason why this method was chosen for this research.

The MAUT method allows the proposition of decision models with more variables, and replacement rates are used to carry out the transition of calculations from one level to another. The replacement rates demonstrate the differences in importance between each criterion of the modeling, allowing them to be evaluated quantitatively (de Almeida 2013). They can be obtained by ordering the evaluation criteria and then constructing the semantic matrix of the value judgment in the same scale used for the value function (Ensslin et al. 2000). In the case study, to calculate the ICRs of SMEs, it is necessary to calculate the local replacement rates of KPIs, CSFs, and FPVs, allowing for assessing the competitiveness perception of SME managers at each level of the proposed model according to Equation (1) (KPIs), Equation (2) (CSFs), and Equation (3) (FPVs) initially proposed in Schaefer et al. (Schaefer et al. 2020).

$$LRR_{KPI} = \frac{KPI}{k} \quad (1)$$

where:

- LRR_{KPI} : KPI local replacement rate;
- KPI : the value of KPI responses;
- k : number of KPIs within the CSF.

$$LRR_{CSF} = \sum_1^n LRR_{KPI} * \frac{k}{w} \quad (2)$$

where:

- LRR_{CSF} : CSF local replacement rate;
- n : number of KPIs of the CSF;
- LRR_{KPI} : KPIs' local replacement rate;
- k : number of KPIs within the CSF;
- w : number of KPIs within the FPV.

$$LRR_{FPV} = \sum_1^n LRR_{CSF} * \frac{w}{x} \quad (3)$$

where:

- LRR_{FPV} : FPV local replacement rate;
- n : number of CSFs within the FPV;
- LRR_{CSF} : CSF local replacement rate;
- w : number of KPIs within the FPV;
- x : total number of KPIs.

FPVs' local replacement rates allow for calculating the SMEs' ICRs (Equation (4)).

$$ICR = \sum_1^n LRR_{FPV} \quad (4)$$

where:

- ICR : individual competitiveness rate;
- LRR_{FPV} : FPV local replacement rate;
- n : number of FPVs.

The ICR values provide a view of the perception of managers about the SMEs' competitiveness which takes into account the variables presented in the evaluation model initially

proposed in Table 1 and Figure 2. This article aims to propose a methodology that allows for optimizing these competitiveness assessment models, reducing the number of variables to be monitored by managers, and keeping the results of the competitiveness assessment similar to the initial model. For this, the GIANN method proposes using the information gain each KPI brings to the model.

2.4. Stage 4—Calculation of KPIs Information Gain

To obtain the information gain that each KPI brings to the modeling, it is necessary to calculate the entropy of the system, which is a measure of how uncertain the content of information is in a random variable (Bermudez-Edo et al. 2018). The maximum entropy principle determines the least informative probability distribution for a random variable given previous information about itself (Mendes et al. 2016). The calculation of the entropy is given by Equation (5):

$$E(S) = \sum_{i=1}^n -p_i \log_2(p_i) \quad (5)$$

where:

- $E(S)$: general network entropy;
- n : number of elements;
- p : the probability of occurrence of the element p .

With entropy, it is possible to calculate the information gain that each KPI brings to the model (Equation (6)). The information gain is calculated for each attribute (KPI), and the attribute with the highest information gain is designated as the root node (Kumar Pal and Pal 2013). In this research, we used the Weka software (WEKA 2022) to calculate the entropy and information gain each KPI provides to the initial competitiveness assessment model.

$$G(S, A) = -E(S) - \sum_{Values(A)} \frac{|S_v|}{|S|} E(S_v) \quad (6)$$

where:

- $G(S, A)$: attribute A information gain as a function of the set S ;
- $E(S)$: general network entropy;
- S_v : number of occurrences of the element p in attribute A ;
- S : total number of occurrences in attribute A ;
- $E(S_v)$: individual element entropy.

From the values of the information gains, it becomes possible to carry out the correlation tests of the model, removing the KPIs one by one and verifying if the values of the competitiveness rates remain above the desired values. The methodology proposed in this article uses the ANN for these tests.

2.5. Stage 5—Test Correlation by ANNs

ANN is a computational model based on biological neural networks which use multiple simple processors interconnected to learn the relationships between sets of variables (Hemmat Esfe et al. 2022). There are different types of ANNs, and the MLP network was chosen because it is a classification tree with at least three nodes: input, hidden, and output (Li et al. 2022), and each node of a layer has a connection to all nodes of the next layer through adaptive synaptic weights (Sarkar et al. 2019). This configuration partially approximates the initial measurement model presented in Figure 2. A backpropagation ANN was used to dynamically predict competitiveness rates, considering the uncertainties of the model (Lu et al. 2022) and predicting new data from supervised learning based on existing data. The mechanism used in learning functions as a sequential process iterative where information feed-forward, error calculation, error backpropagation, and weight adjustment occur (Kwon et al. 2018; Wong and Chan 2015). This process is repeated until the output error value converges to a minimum value.

Weka software (WEKA 2022) was used in this research to model the ANN. Modeling through Weka results in the weights and bias for each node, and a sigmoidal function is used for activation. Still, in cases where the data behaves linearly, the values of “S” provided by Weka must be considered linearly according to Equation (8). To obtain the general equation of the network, it is necessary to use Equations (7) and (8). Figure 3 graphically shows where the weights and bias influence the network, which is a simplified ANN with four inputs (x_1 , x_2 , x_3 , and x_4), a hidden layer with two nodes (S1 and S2), and one output (ICR):

$$ICR = W_0 + \sum_1^n W_n \cdot S_n \quad (7)$$

where:

- ICR: Individual competitiveness rate obtained by ANN;
- W_0 : Linear Node 0—Bias node 0;
- W : Linear Node—Node synaptic weight;
- S : Sigmoid Node—S function result.

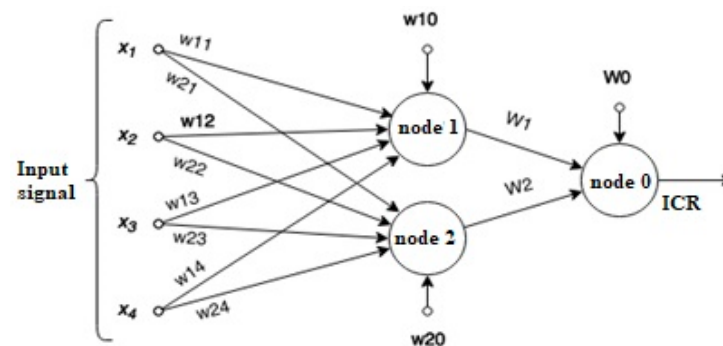


Figure 3. ANN representation (Nara et al. 2019).

For each node in the ANN hidden layers, it must calculate the value of S , which is the result of the linear function described by S (Equation (8)):

$$S = w_0 + \sum_1^n w_n \cdot x_n \quad (8)$$

where:

- S : Node sigmoid—linear function result;
- w_0 : Node 1 sigmoid—Node 1 bias;
- w_n : Node n sigmoid—Attribute x_n synaptic weight;
- x_n : x values (KPIs).

To obtain the correlation between KPIs and ICRs, it was necessary to provide the values of the ICRs calculated using the MAUT method. These parameters must be provided to the MLP ANN so that it is trained (Fetene et al. 2018). The dataset obtained through the survey can be considered small to be applied to the ANN. However, with a smaller dataset, the network can be trained with a high level of performance, set with a learning rate of 0.01 and momentum of 0.01, allowing the tests to be performed quickly. The cross-validation mode was applied to optimize the available data set and to train ANN once it divides the dataset into training and validation objects. It is used when the dataset is too small to be divided into training and validation datasets (Xu et al. 2018). The input attributes for the ANN were the responses of the SME managers to the survey KPIs. We obtained the correlation coefficients between the KPIs and the competitiveness rates (ICRs) as output.

2.6. Stage 6—Withdraw the KPI with Less Information Gain

With the KPIs ranked according to the information gains, the exclusion tests can be carried out, starting with the exclusion of the ones with less information gain towards the ones with greater information gain. Thus, the network was tested again for each excluded

KPI to verify the new correlation coefficient. The stopping point of the tests was when the pre-established correlation coefficient was reached. Pearson's correlation coefficient measures the linear dependency between two random variables, where 0.9 indicates a very strong correlation (Ly et al. 2018). Wu et al. (2018) say that above 0.7 the Pearson Correlation coefficient is already considered satisfactory. Thus, for this research, it was proposed a correlation coefficient of 0.950. In this case study, the KPIs were removed until only one was left, and the correlation coefficient was calculated for demonstration.

2.7. Stage 7—New Integration of KPIs, CSFs, and FPVs

Once the correlation coefficient was reached, a new hierarchy in a decision tree format was structured with the remaining KPIs, CSFs, and FPVs, giving rise to an optimized model for diagnosing and measuring the SMEs' competitiveness.

2.8. Stage 8—Calculation of the New ICRs by MAUT

Finally, the new ICRs from the optimized model were calculated by the MAUT method using Equations (1)–(4).

3. Case Study with Small and Medium-Sized Enterprises

The initial model for diagnosing and measuring competitiveness was presented in Figure 1, consisting of 18 KPIs, 7 CSFs, 5 FPVs, and the ICR as output.

3.1. KPIs' Information Gain Ranking

To make it possible to carry out tests that reduce the number of KPIs needed for the model and establish an order for removing KPIs, a ranking was generated (Table 2) with the average information gain each KPI brings to the model.

Table 2. KPI ranking.

POSITION	KPI	INFORMATION GAIN AVERAGE
1°	KPI11	1.072 ± 0.046
2°	KPI4	1.039 ± 0.038
3°	KPI15	0.935 ± 0.057
4°	KPI3	0.914 ± 0.034
5°	KPI18	0.900 ± 0.071
6°	KPI2	0.889 ± 0.035
7°	KPI7	0.888 ± 0.035
8°	KPI12	0.886 ± 0.040
9°	KPI8	0.880 ± 0.044
10°	KPI13	0.874 ± 0.052
11°	KPI9	0.815 ± 0.057
12°	KPI1	0.756 ± 0.055
13°	KPI6	0.738 ± 0.052
14°	KPI5	0.745 ± 0.041
15°	KPI17	0.731 ± 0.033
16°	KPI16	0.705 ± 0.040
17°	KPI14	0.563 ± 0.039
18°	KPI10	0.451 ± 0.059

3.2. Correlation Tests by ANN

To perform the ANN tests, Weka automatically generated the model in Figure 4. This model, represented by the ANN shown in this figure, uses 18 KPIs as inputs, a hidden layer with nine nodes, and the ICR as the output. It is worth mentioning that, in the MAUT method, each KPI influences only one CSF, and each CSF influences only one FPV, while in the ANN, each KPI influences all nodes of the hidden layer, distributing the weights among these nodes. By applying the results of the competitiveness rates obtained by the MAUT method as parameters for the ANN, it was possible to obtain the correlation coefficient

between the KPIs and these rates and the absolute and quadratic errors, both provided by Weka.

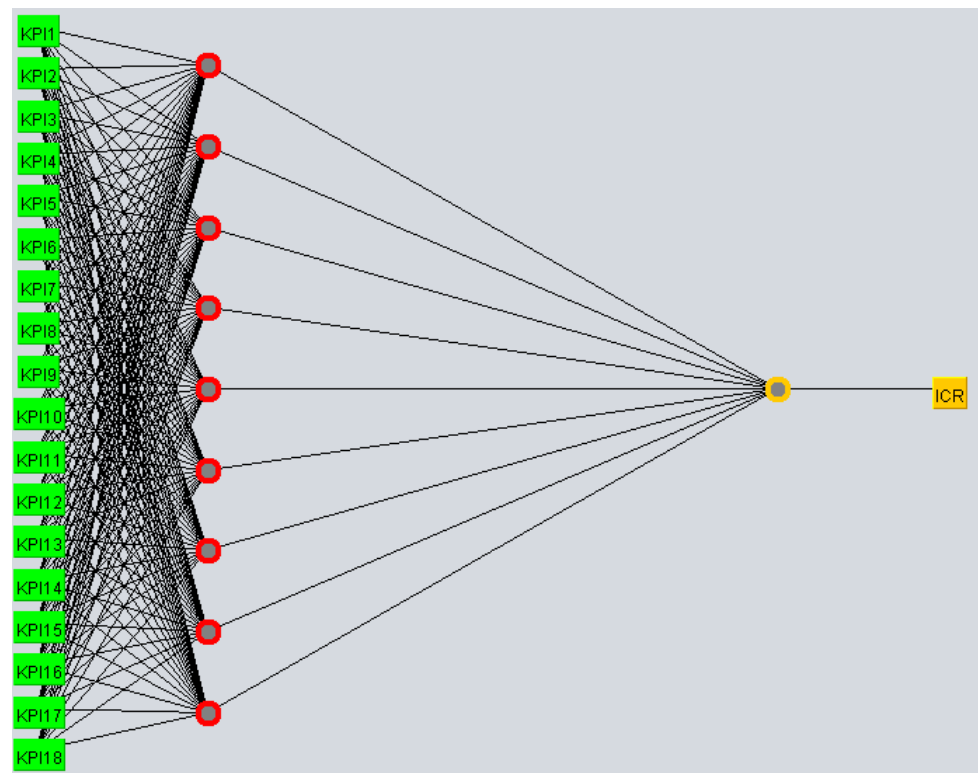


Figure 4. Competitiveness measurement model through Artificial Neural Network.

The GIANN method, after stage 5, has a decision point where it is checked whether the correlation coefficient is satisfactory. In this paper, for correlation to be considered satisfactory, it should be above 0.950. However, as a way of exemplifying, we presented in Figure 5 the tests until there was only one KPI in the model. This way, we made the tests by removing KPI by KPI, starting with the last one placed in the ranking (KPI10), followed by KPI14, and successively until there was only one KPI in the model (KPI11). Figure 5 is a graph with the progression of the correlation coefficients and the absolute and quadratic errors according to the KPI reduction tests.

In this paper, the remaining KPIs' correlation coefficient is defined as equal to or greater than 0.950 regarding the initial ICR. The optimization proposed for the competitiveness assessment model was to exclude 7 KPIs with the lowest information gain. In this proposal, the correlation coefficient reached was 0.9501, and the absolute error was 0.0969. The following KPIs were excluded: 10, 14, 16, 17, 5, 6, and 1. It is possible to perceive a good performance of the proposal due to the following factors: the reduction in the number of KPIs maintains the correlation between the variables and a level of error low; and the fact that the KPIs that were excluded have little variability, bringing little information to the model.

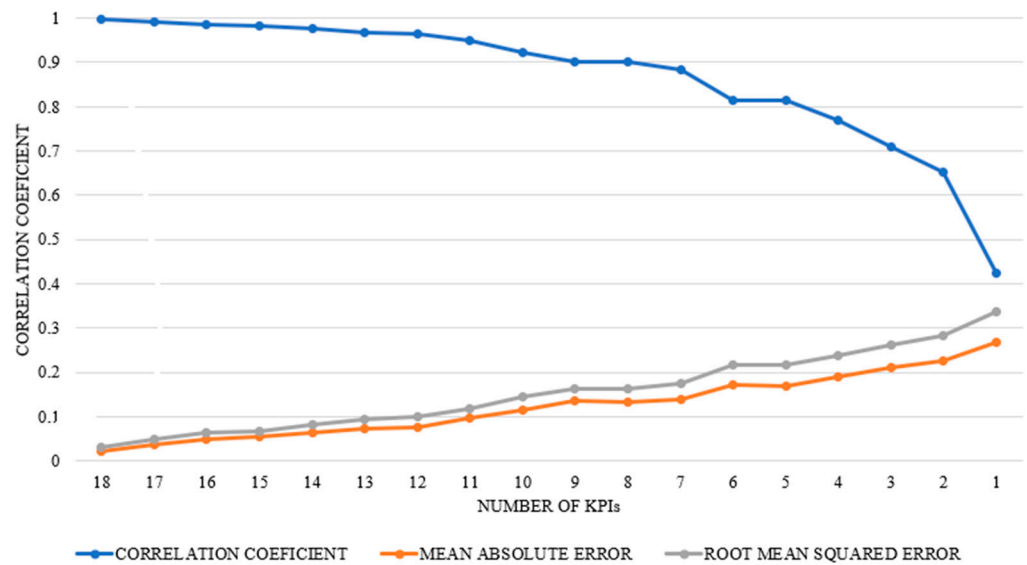


Figure 5. Progression of correlation coefficient and error levels.

3.3. New Integration of KPIS, CSFs, and FPVs

At this stage of the GIANN method, a new integration between KPIS, CSFs, and FPVs is performed, generating an optimized competitiveness measurement model. This new model is structured considering the decrease in the number of KPIS of the competitiveness measurement model from 18 to 11 and maintaining a correlation between the KPIS and the companies’ competitiveness rates at 0.9501. With the decrease in KPIS, CSF2 and FPV2 could also be excluded. Figure 6 shows the optimized model for measuring the competitiveness of SMEs.

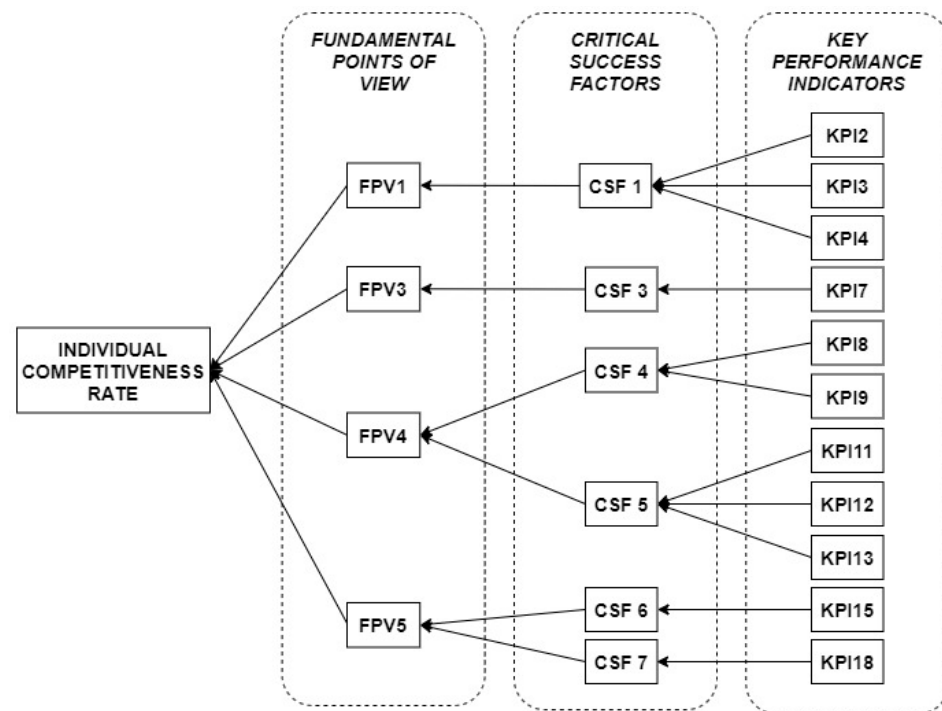


Figure 6. Optimized competitiveness measurement model.

3.4. New Competitiveness Rates by MAUT

With the optimized model to measure the competitiveness of SMEs, the new ICRs were calculated by the MAUT method. Table 3 presents the first results of SMEs’ ICR and

the new SMEs' ICR calculated by MAUT (the SMEs are coded by the letter E followed by numbers, and the ICR scale is the same as the survey, from 1 to 5).

Table 3. SMEs' ICR and New ICR by MAUT.

RANK	SME	ICR	SME	NEW ICR	RANK	SME	ICR	SME	NEW ICR
1°	E67	5.000	E67	5.000	35°	E1	4.000	E4	3.818
2°	E60	4.944	E60	4.909	36°	E35	4.000	E29	3.818
3°	E65	4.722	E65	4.727	37°	E42	4.000	E53	3.818
4°	E45	4.722	E10	4.636	38°	E61	4.000	E30	3.818
5°	E54	4.667	E45	4.636	39°	E47	3.944	E33	3.818
6°	E10	4.611	E62	4.636	40°	E4	3.944	E55	3.818
7°	E68	4.611	E9	4.545	41°	E34	3.944	E72	3.818
8°	E62	4.556	E68	4.455	42°	E20	3.889	E1	3.636
9°	E46	4.500	E54	4.455	43°	E29	3.889	E20	3.636
10°	E52	4.500	E7	4.364	44°	E49	3.889	E23	3.636
11°	E56	4.500	E46	4.364	45°	E64	3.889	E24	3.636
12°	E9	4.444	E52	4.364	46°	E69	3.889	E39	3.636
13°	E51	4.444	E56	4.364	47°	E11	3.889	E43	3.636
14°	E57	4.444	E57	4.364	48°	E33	3.833	E47	3.636
15°	E27	4.389	E27	4.273	49°	E32	3.833	E50	3.636
16°	E22	4.333	E5	4.182	50°	E18	3.833	E11	3.545
17°	E7	4.278	E22	4.182	51°	E39	3.833	E18	3.545
18°	E38	4.278	E51	4.182	52°	E43	3.833	E3	3.545
19°	E12	4.222	E2	4.091	53°	E8	3.778	E64	3.545
20°	E26	4.222	E16	4.091	54°	E14	3.778	E8	3.455
21°	E59	4.222	E38	4.091	55°	E25	3.778	E17	3.455
22°	E5	4.222	E59	4.091	56°	E50	3.778	E69	3.364
23°	E63	4.222	E63	4.091	57°	E31	3.667	E13	3.364
24°	E53	4.167	E70	4.091	58°	E3	3.611	E14	3.364
25°	E2	4.167	E12	4.000	59°	E15	3.611	E21	3.364
26°	E16	4.167	E26	4.000	60°	E21	3.611	E25	3.364
27°	E41	4.111	E41	4.000	61°	E48	3.611	E15	3.273
28°	E70	4.111	E42	4.000	62°	E13	3.556	E31	3.273
29°	E72	4.111	E61	4.000	63°	E17	3.500	E19	3.273
30°	E23	4.056	E34	4.000	64°	E19	3.444	E71	3.273
31°	E24	4.056	E32	3.909	65°	E71	3.444	E48	3.091
32°	E30	4.056	E35	3.909	66°	E66	3.389	E66	3.091
33°	E40	4.056	E40	3.909	67°	E44	3.333	E44	3.000
34°	E55	4.056	E49	3.909					

The variation between the values obtained for the ICRs and the new ICRs was between 0.101 (+2.27%) for more, up to 0.525 (−14.4%) for less, with a medium variation of 0.173 (4.42%). A slight tendency for a decrease in the ICR values of the SMEs could be observed.

Remembering that the scale of the ICRs ranges from 1 to 5, E9 had the highest positive variation, ranging from 4.444 to 4.545, and E69 had the greatest negative variation, ranging from 3.889 to 3.364. The variation of the ICRs' mean, called Global Competitiveness Rate (GCR), is shown in Table 4.

Table 4. Global Competitiveness Rate by initial and optimized modeling.

	Initial Model	Optimized Model
MAUT GCR	4.066	3.893
MAUT standard deviation	0.376	0.459

Another observation that can be made is that 10 SMEs occupy the same position in the two rankings, and another 10 had their positions changed only one position, more or

less. This little variation can be considered positive given the large number of variables involved in the model, thus bringing safety to the GIANN method.

4. Discussion and Managerial Implications

The model optimization by the GIANN method reduced the number of KPIs to be monitored and controlled by order of 39% (from 18 KPIs to 11 KPIs) and has a direct impact on the SMEs management, which, considering their financial and technological limitations, may measure and control their competitiveness by making use of a smaller number of metrics, facilitating their managerial decision-making processes. Given the low variability between initial and optimized competitiveness rates, it can also be understood that KPIs that can be excluded do not need to be monitored and controlled to maintain the enterprise's competitiveness because the desired level of efficiency will be maintained given the high correlation obtained between the variables and the competitiveness rates.

The ranking of the SMEs was performed to demonstrate that applying the GIANN method to optimize the competitiveness measurement model reduced the number of necessary KPIs, CSFs, and FPVs, and did not substantially modify the positions obtained by the SMEs. The initial model, which had 18 KPIs, 7 CSFs, and 5 FPVs, was optimized, resulting in an optimized model, maintaining a correlation coefficient above 0.950 and, therefore, a satisfactory mathematical accuracy. The optimized model consists of 11 KPIs, 6 CSFs, and 4 FPVs. GIANN enabled a 39% reduction in the number of KPIs in the model while maintaining a 95,01% correlation between the KPIs and the calculated competitiveness rates, demonstrating the reliability of the proposed method. GIANN method reduces the number of variables in such competitiveness measurement models, and it can be applied to other situations, exemplifying how the model can be simplified to aid decision-making while maintaining satisfactory results.

5. Conclusions

This article presented the GIANN method, a methodology used to optimize and adjust the number of variables present in models for measuring and evaluating the competitiveness of companies. The article focused on demonstrating an application of the proposed methodology in a case study with SMEs from the industry in southern Brazil. The management variables that served as the basis of the competitiveness measurement model presented were the KPIs, CSFs, and FPVs, which, after being ranked, were modeled to diagnose and assess the competitiveness of SMEs.

GIANN uses the MAUT multicriteria method, the concepts of entropy and information gain, and the ANN MLP in a hybrid way to evaluate and optimize models to measure the competitiveness of companies such as SMEs. Previously, the MONNA method was proposed to verify the quality of modeling to measure competitiveness (Baierle et al. 2020), de Moraes et al. (2019) used the Naive Bayes algorithm to simulate the probabilities of trade associations getting more members, and Immawan et al. (2019) proposed a KPI-based model to measure the performance of SMEs related to customers. In this sense, it is clear that the GIANN method, in addition to allowing the measurement of competitiveness, also allows optimizing the measurement model.

About the GIANN method, it can be said that the methodology streamlines and simplifies the monitoring and controlling variables such as KPIs. The application of the method defines a minimum set of variables that can satisfy the management needs of companies. With GIANN, KPIs that have little influence on business results are identified and do not need to be monitored regularly. Assuming that it is a fact with negative repercussions and greater variability in the KPIs, knowing how to select which these indicators are of paramount importance for good management of companies. In addition, a company can reapply the method when the set of controlled indicators no longer varies greatly. At this point, the company can reapply the method to verify if any indicator controlled in its management model can be replaced by another showing greater information gain.

This article had limitations regarding the level of specificity of the metrics and variables used, once in this article, three variables were used to measure the competitiveness of SMEs: KPIs, CSFs, and FPVs. However, in other applications, these variables may receive other nomenclatures and be applied to measure other objectives, such as innovation capacity. The number of model levels can be changed if the equations are suitable. It is suggested that, in the future, the GIANN method be applied to optimize the use of variables in applied models such as innovation in SMEs or the use of technology in SMEs.

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