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INDUSTRY 4.0: IMPROVING AND INCREASING THE COMPETITIVENESS AND SUSTAINABILITY OF ORGANIZATIONS THROUGH THE DIAGNOSIS OF MANAGEMENT INDICATORS, USE OF ARTIFICIAL INTELLIGENCE AND OPTIMIZATION METHODS IN MANUFACTURING, LOGISTICS AND SERVICES

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BRIEF INTRODUCTION

The industry has undergone major technological changes over time, these commonly called industrial revolutions. Known as the first industrial revolution (1760 to 1850), it was marked by the replacement of artisanal labor by machines, mainly steam-powered. Later, the second industrial revolution (1850 to 1945) was popularly marked by electric energy in industries. With the third industrial revolution (1945 to the present day) physical and mechanical systems began to be replaced by digital systems. And we are currently experiencing the transition to the fourth industrial revolution, called industry 4.0, which proposes to bring communication and intelligence to industry processes (LASI; FETTKE; KEMPER; FELD et al., 2014).

The term Industry 4.0 is derived from industry 4.0. It was created in Germany in 2011 as a high technology strategy for the year 2020. Entrepreneurs, politicians and universities collaborated so that their ideas would stimulate competitiveness among the country's industries. Today, the fourth industrial generation is expected to offer improvements in industrial processes involving: operation, engineering, production planning and control, logistics, and continuous analysis during the life cycle of products and services. The essence of industry 4.0 is based on cyber-physical systems (CPS) and the Internet of Things (IoT), which will lead factories to reach a new level of production. CPS is based on the dynamic configuration of manufacturing. Unlike traditional production methods, dynamic configuration is above production and the processes involved. Because the dynamism makes the system capable of changing the initial design of the product at any time. The fourth industrial generation presents as main characteristics: data interconnection, integration and innovation. In addition, the fourth industrial generation is based on nine pillars, which are: 1. Big data; 2. Cloud computing; 3. Integration of vertical and horizontal systems; 4. Artificial intelligence; 5. Industrial Internet of Things; 6. Virtual reality; 7. Autonomous robots; 8. Cybersecurity. 9. 3D simulation and printing.

Industry 4.0 is mainly characterized by Cyber-Physical Systems and Industrial Internet of Things that aim to create an intelligent environment and one of the key technologies to bring intelligence to these processes is artificial intelligence (EROL; JÄGER; HOLD; OTT et al, 2016).

Artificial intelligence techniques have been applied to the manufacturing sector, allowing for more efficient processes, sustainability with reduced waste and material consumption, safer work environments and higher quality and productivity. Artificial intelligence-based manufacturing can offer several innovations providing failure detection and prediction, automation and other process improvements (ANGELOPOULOS; MICHAILIDIS; NOMIKOS; TRAKADAS et al., 2020).

Thus, it is notable that artificial intelligence is one of the technologies that can facilitate the implementation of Industry 4.0 concepts in industries, bringing intelligence to processes in order to generate knowledge through the large amount of data generated in this new industry.

The way in which processes are developed in the industry is fundamental to the success of organizations and especially in the challenging Brazilian and global economic scenario after the coronavirus pandemic. It is imperative that strategies to reduce costs and increase the efficiency of operations are adopted as a way to make the competitiveness of manufactured products viable.

In the universe of Industry 4.0 and the large amount of data generated and underused by organizations, important questions, inquiries and problems arise: a) How the use of Industry 4.0 technologies can help in identifying and measuring indicators and consequently increase managerial effectiveness in the decision-making process of organizations?; b) How can the application of artificial intelligence and its sub-areas, as well as optimization methods contribute to improve organizational processes?; c) How the similarities and differences of these tools (management indicators and artificial intelligence) could be translated into hybridizations applied to the organizational management of different productive sectors related to Industry 4.0 (manufacturing industry, logistics and services)? In order to investigate and seek to answer the questions presented, this project intends to: a) investigate and identify the indicators and guides of the efficiency of decision-making processes; b) investigate the application of artificial intelligence and its sub-areas as well as optimization methods in the improvement of organizational processes.

Within this context and in accordance with the research fellow's work plan, an attempt was made to focus on literature review activities and on the development of a model for identifying managerial indicators in the decision-making process through the use of artificial intelligence, particularly in neural networks artificial.

LITERATURE REVISION

In the following topics, industry 4.0 and industry artificial intelligence and management indicators will be dealt with conceptually.

INDUSTRY 4.0

The concept of Industry 4.0, according to Moeuf et al. (2018), it is difficult to describe, as in the literature there are more than 100 different definitions. However, the term is usually defined as a combination of technologies such as the Internet of Things (IoT), the Industrial Internet of Things (IIoT), cloud-based manufacturing and smart manufacturing, which seek to transform the manufacturing process into an environment fully digitized and intelligent (EROL; JÄGER; HOLD; OTT et al., 2016).

Still, according to Hermann, Pentek and Otto (2016), Industry 4.0 is the combination of production, information and communication technologies and is a subject of great repercussion in the academic community. The fascination with this subject is mainly due to two factors: (1) for the first time the industrial revolution is somehow planned and not simply defined at a point of technological advancement, this gives and brings opportunity to researchers and companies to shape the future, (2) the economic impact of this technological advance must be significant and enormous, as it promises the improvement of industrial processes, allowing the creation of new business models, services, products and professions.

Industry 4.0 is still based on nine pillars: (1) data analysis, (2) robotics, (3) simulation, (4) systems integration, (5) internet of things, (6) cybersecurity, (7) computing cloud, (8) additive manufacturing and (9) augmented reality (VAIDYA; AMBAD; BHOSLE, 2018).

In addition, decision-making technologies, especially those based on artificial intelligence and big data, bring countless benefits to companies in the context of Industry 4.0, as better decisions are made and the production process becomes faster. more effective, cost reduction, better process management, among other benefits (XIA; XI; DU; XIAO et al., 2018).

In this scenario, the high integration between business environments is capable of generating huge amounts of data (big data) that can be used in a predictive approach, through regression techniques, neural networks and other algorithms that use past data to predict scenarios futures (KIPPER; FURSTENAU; HOPPE; FROZZA et al., 2020). However, most scientific studies are related to data infrastructure and few to data-driven organizational culture, which allow managers to make more accurate decisions based on data and not on intuition. Therefore, it is necessary to encourage and propose solutions in this context to improve the use of data-based decision-making (FURSTENAU; SOTT; KIPPER; MACHADO et al., 2020).

ARTIFICIAL INTELLIGENCE (NEURAL NETWORKS)

The history of Artificial Intelligence began in the 1950s as an academic area of study. From the 1980s, the term Machine Learning began to emerge, characterized by the study of pattern recognition and machine learning theory, enabling computers to learn without having to be programmed directly for this purpose. Finally, more recently, around the 2010s, the term Deep Learning began to spread as a branch of Machine Learning with the proposal to learn complicated patterns in a large volume of data (HALDORAI; MURUGAN; RAMU, 2020). (Deep Learning is a learning method in artificial neural networks).

MACHINE LEARNING AND NEURAL NETWORKS

The so-called Machine Learning technologies have several applications in modern society, from web searches to filtering content on social networks and recommendations on e-commerce sites, and it is increasingly present in consumer goods such as cameras and smartphones. These systems are used to identify and classify objects in images, perform audio transcription or even relate news, posts or products with user interests to recommend relevant results (LECUN; BENGIO; HINTON, 2015).

Conventional Machine Learning techniques were limited in their ability to process natural data in its raw form. For a long time modeling a Machine Learning algorithm required careful handling and considerable knowledge to generate a feature extractor that transformed the raw data into a suitable optimized representation or feature vector which the system could process efficiently. With the advancement of research in the area, representation learning algorithms were proposed and developed, which are methods that allow a machine to be fed with raw data and automatically discover the characteristics of the problem (LECUN; BENGIO; HINTON, 2015).

Artificial Neural Networks are the main representatives of Machine Learning, they are methods based on the functioning of the human brain, through nodes, or artificial neurons, interconnected with each other, as well as the network of neurons in the human brain. Node connections are defined with a weight attribute, determining the strength of that connection with the next node. Artificial neurons perform mathematical functions considering the received signal and generating an output that will serve as input for the next one, thus making an analogy with the synapse of natural neurons. Learning happens through repetition and the ability to adapt and correct the weights of the node connections (SCHMIDHUBER, 2015).

(Indicated reference for ANNs: HAYKIN, Simon. Neural networks: a comprehensive foundation. Upper Saddle River: Prentice Hall, 1994. 696 p.)

(Indicated reference for Machine Learning: MARSLAND, Stephen. Machine learning: An Algorithmic Perspective. New York: Chapman & Hall/CRC. 2015. 437 p.)

MANAGEMENT INDICATORS

An important way for companies to gain a competitive advantage, especially micro and small companies - MSE is the use of better environmental practices, reducing costs and achieving a competitive advantage in the marketing area (D'SOUZA and TAGHIAN, 2017). Obtaining a competitive advantage depends on a strategy to align your actions in an agile and solid way with your competitors, in order to better take advantage of your virtues, seeking to leave your weaknesses inert.

To create a model, relating competitiveness to the types of innovation, it is necessary to define which competitive criteria one intends to study. For Slack, Chambers and Johnston (2002), the competitive criteria of productive operations are: reliability, cost, flexibility, quality and speed. These competitive criteria were also used in research by González-Benito and Dale (2001) and Siluk et al. (2017).

Other authors present more concepts in relation to the competitive criteria. Even if each author highlights some different competitive criteria, there is great similarity between all the authors who converge on five main objectives of competitiveness, which are: speed, quality, flexibility, cost and reliability. This convergence served to define the competitive criteria in this work and will allow the assembly of the theoretical model, based on neural networks.

FUNDAMENTAL VIEWPOINTS (FVP)

Through the construction of a Decision Tree structure, the so-called PVFs are implemented, which correspond to the dimensions that at least one decision maker considers fundamental to evaluate the context of actions (ENSSLIN; NETO; NORONHA, 2001; ZAMCOPÉ et al., 2010; SOUSA and CARMO, 2015).

The PVFs show the strategic objectives of certain scenarios, as they point out, among so many actions, which are the potential for decision-making (RECK and SCHULTZ, 2016). Partial values can be assigned to each PVF (PINHEIRO; DE SOUZA; DE CASTRO, 2008), and these values are the importance given by decision-makers to that particular action (ENSSLIN; NETO; NORONHA, 2001). For Ensslin, Neto and Noronha (2001), the PVFs can be considered as being the axes for evaluating a problem, where after its definition, the multicriteria model can be applied to analyze potential actions and help decision makers. They can be presented individually or in branches to be evaluated separately (PINHEIRO; DE SOUZA; DE CASTRO, 2008). The authors Ensslin, Neto and Noronha (2001), state that PVFs can analyze an independent fundamental action, however, without losing the relationship with the whole. Siluk et al. (2016) listed four PVFs to measure the performance of incubated technology-based companies: cost, quality, flexibility and reliability. Silva et al. (2016) use the PVFs as families and within each family the concepts of the same nature are grouped, with the families generated: structure, assets, groups and actors. It can be seen from this that in each decision modeling elaborated, a research must be carried out to verify which are the FVPs relevant to the study. Slack, Chambers and Johnston (2010) presented five competitive criteria that productive operations need to pursue: reliability, cost, flexibility, quality and speed.

CRITICAL SUCCESS FACTORS (CSF)

They are the path an organization must follow to achieve its goals (ELWAKIL, 2017), or even the essential factors for the company to continue achieving its goals (TOOR and OGUNLANA, 2009). They are crucial elements to be examined and monitored to ensure effective management and the achievement of an organization's objectives (ROCKART, 1979; OAKLAND, 2014). These are those areas of activity in which the company necessarily needs to obtain positive results by transforming strategies into concrete actions to achieve the proposed objectives (ROCKART, 1980; LU, SHEN and YAM, 2008; GUPTA, et al. 2018). The FCS can represent a project or areas of a company that are considered fundamental to the success of the whole, requiring greater attention (JAHANGIRIAN et al., 2017).

ACTIVITIES DEVELOPED AND NOT DEVELOPED

According to the work plan, the planned activities were:

a. Carry out an extensive bibliographical review on management indicators and their impacts on the decision-making process;

b. Identify the main variables that manage the investigated process;

c. Collaborate in proposing a model for solving the problem;

d. Analyze the results of the proposed solution;

e. Collaborate for the publication of the results.

Among the planned activities, most of the activities were fully developed, such as items a, b and c mentioned above. The other items were partially developed and are still under development.

METHODOLOGY ADOPTED BY THE SCHOLARSHIP HOLDER

Considering its prescriptive nature and focused on designing innovative solutions to practical and relevant problems, this research will be conducted using the Design Science Research (DSR) method.

It must be noted that the DSR seeks to guide research whose objective is to prescribe solutions, considering the design and evaluation of artifacts aimed at solving practical problems in different contexts (DRESCH, LACERDA, & ANTUNES JR., 2015). Among the contexts in which DSR fits as an appropriate methodological approach, research carried out in the field of operations management, information technology, engineering, among others (DRESCH; LACERDA; CAUCHICK-MIGUEL, 2019), which aligns with to this work proposal.

Still within the scope of this work, it must be noted that the artifacts are understood as models, algorithms and other solutions that will be developed with a focus on improving processes for the industry. These developments aim, above all, to minimize costs, increase operational efficiency and reduce environmental impacts in order to increase the competitiveness and sustainability of the activity.

In this sense, in order to ensure the required methodological rigor and, at the same time, generate solutions for organizations focused on Industry 4.0, the work method presented is based on the methodological steps proposed by Dresch, Lacerda and Antunes Jr. (2015).

To develop the methodology proposed and adopted by the fellow, a Systematic Literature Review (SLR) was initially conducted, using explicit and systematic procedures to identify, select and critically evaluate the relevant literature for the present work (KITCHENHAM and CHARTERS, 2007). Bibliographies related to industry 4.0, performance indicators and artificial intelligence were searched, in particular on neural networks.

Then, the concepts and main elements from RSL were selected to guide the construction of managerial identifiers.

Afterwards, data were collected at the company and based on previous studies and RSL. To guide this stage of the method, modeling procedures were employed, which allow the researcher to define the variables and their mathematical relationships to describe the behavior of the system under study.

In the sequence, the proposed modeling uses artificial neural networks to identify the critical success factors and their ordering.

Preliminary results demonstrate the potential of using the proposed modeling to identify relevant factors in the decision-making process.

Although not yet carried out in the context of this scientific initiation scholarship, it is intended to carry out a first evaluation of the model through validation of the indicators in its functional state, considering its technical characteristics and evaluating its quality and efficiency with regard to the expected satisfactory solution.

From this first evaluation, it will be possible to refine the indicators in order to meet the demands arising from the companies.

Finally, the results obtained by this project can be disseminated in two ways.

There was preliminary dissemination through a presentation at a scientific initiation event at the Universidade Franciscana de Santa Maria.

RESULTS OBTAINED

The main objective of this table was to understand whether there is any kind of relationship and influence between innovation activities and competitive criteria based on data from Micro and Small Enterprises (MSEs) in the southern region of Brazil. Using multicriteria analysis as a solution method in the classification of different KPIs in conjunction with ANNs, which have the capacity to receive several inputs at the same time and distribute them in an organized way, allowing the modeling, evaluation and simulation of scenarios. In the theoretical model, all KPIs were related to innovation activities (FCS), and after the innovation activities identified in the bibliographical research, they were related to competitive criteria (PVF), seeking greater ease of control. After data collection, these links will be checked one by one. Thus,

> KPIs (key performance indicators) are assigned by organizations in their processes in order to obtain a better control and managing your data and goals. They are measurable measures that need to be aligned with the company's objectives, in order to evaluate or compare their performances to achieve strategic goals and operational.

KPI 1	Indicator of interaction with the supply chain
KPI 2	Order delivery indicator on time agreed with the customer
KPI 3	Order delivery speed
KPI 4	Raw material cost indicator
KPI 5	Raw Material Quality Indicator
KPI 6	Work attendance indicator of employees
KPI 7	Indicator of use and training, by employees, of the PPE indicated for their function
KPI 8	How important is it to monitor the employee satisfaction rate with your role within the company?
KPI 9	Indicator of the existence of product pricing strategies according to the market
KPI 10	Idea suggestion indicator collaborators
KPI 11	Working capital control indicator
KPI 12	Earnings reinvestment indicator in the company
KPI 13	Customer Opinion Indicator and consumer
KPI 14	Indicator of needs not identified by consumers
KPI 15	Brand Importance Indicator
KPI 16	Brand Application Indicator
KPI 17	Indicator Indicator of the percentage of active customers
KPI 18	Indicator of customers loyal to the company

Finally there are the E's which are the areas and sectors of the company to be analyzed.

	KPI1	KPI2	KPI3	KPI4	KPI5	KPI6	KPI7	KPI8	KPI9	KPI10	KPI11	KPI12	KPI13	KPI14	KPI15	KPI16	KPI17	KPI18
E1	4	3	4	3	5	5	5	4	4	5	2	3	4	5	4	5	3	4
E10	5	5	5	5	5	5	5	5	5	5	4	4	4	4	5	4	4	4
E11	4	3	4	3	4	5	5	4	3	4	3	3	4	5	4	5	4	3
E12	5	5	4	3	4	5	4	4	4	5	5	3	4	4	4	4	5	4
E13	4	3	4	4	3	4	2	3	4	4	3	3	3	5	4	4	3	4
E14	4	3	2	3	4	4	3	4	5	5	3	4	4	4	3	5	5	3
E15	4	3	4	3	3	5	2	3	4	5	2	4	4	4	3	4	4	4
E16	5	3	5	5	5	3	4	4	5	5	4	3	4	5	4	4	3	4
E17	4	4	3	4	3	2	3	3	5	5	3	2	3	5	4	3	3	4
E18	4	2	3	4	4	5	5	5	4	5	4	3	3	4	4	4	4	2
E19	4	4	3	3	4	4	3	4	3	4	4	3	2	4	4	3	3	3
E2	3	3	4	3	4	4	4	4	5	5	4	5	5	5	4	5	4	4
E20	4	3	5	4	4	5	4	4	4	5	2	4	4	5	3	3	4	3
E21	4	4	3	3	4	5	3	4	4	4	4	3	3	5	3	3	3	3
E22	4	3	4	4	4	5	4	5	4	5	5	5	5	5	3	5	4	4
E23	5	4	4	3	4	5	4	3	5	5	3	4	4	5	3	5	4	3
E24	5	3	3	4	4	5	3	5	5	5	1	4	4	5	4	5	4	4
E25	5	4	4	2	3	5	4	3	4	5	2	4	3	5	4	4	4	3
E26	5	5	4	3	4	4	3	4	5	5	4	4	4	5	4	5	4	4
E27	4	4	4	4	5	4	5	4	4	5	5	4	4	5	4	4	5	5
E28	2	2	2	2	2	5	1	3	5	3	3	1	2	5	1	2	2	1
E29	4	4	3	3	3	3	3	3	3	3	3	5	5	5	5	5	5	5
E3	3	4	3	3	3	4	4	3	4	4	4	4	3	4	3	4	4	4
E30	5	2	3	4	3	5	5	5	5	5	4	3	4	5	4	4	4	3
E31	5	3	3	2	4	5	4	3	3	4	4	4	4	4	3	5	3	3
E32	3	4	2	3	4	2	4	4	5	5	4	5	4	5	4	4	3	4
E33	4	4	2	2	4	4	4	4	4	3	4	5	4	4	4	4	4	5
E34	4	3	3	4	4	4	4	5	5	4	5	5	3	4	4	4	3	3
E35	4	4	4	4	5	4	4	4	4	4	3	4	4	4	5	4	4	3
E36	5	3	3	3	4	5	4	2	3	4	1	2	3	5	4	4	5	3
E37	3	3	2	2	2	2	1	3	4	3	1	3	4	3	4	3	3	4
E38	5	5	5	5	5	4	3	4	5	5	4	4	4	5	3	4	4	3
E39	4	4	4	3	3	4	3	4	5	4	4	3	3	5	4	5	4	3
E4	4	3	4	3	4	4	4	5	4	5	4	3	4	4	4	4	4	4
E40	5	4	4	3	3	5	5	4	3	5	2	5	5	3	3	4	5	5
E41	4	5	2	4	4	5	5	5	4	5	4	3	5	4	4	5	3	3
E42	5	5	3	5	3	5	4	5	2	4	2	5	5	4	4	3	4	4
E43	5	3	4	4	4	4	3	5	5	5	3	3	2	3	4	4	4	4
E44	3	2	2	2	3	4	3	3	5	4	4	4	4	4	2	5	4	2
E45	5	5	4	3	4	5	5	5	5	5	5	4	5	5	5	5	5	5
E46	5	4	4	5	5	5	5	5	5	5	5	4	4	5	4	5	3	3

E47	5	4	3	3	3	4	3	3	5	5	4	3	4	5	4	4	5	4
E48	5	4	2	2	4	4	3	3	5	4	1	3	3	5	4	5	4	4
E49	4	4	3	5	4	2	2	2	5	5	5	5	4	5	5	4	3	3
E5	5	3	4	3	3	4	3	5	5	5	5	5	3	5	5	4	4	5
E50	4	3	4	2	4	5	5	5	4	4	5	2	2	4	5	4	3	3
E51	5	3	4	4	5	5	4	5	4	5	5	5	4	5	5	4	5	3
E52	4	4	5	4	5	5	4	5	5	5	5	4	4	5	4	4	5	4
E53	5	5	5	4	5	5	5	4	4	5	2	3	2	2	4	4	4	4
E54	5	3	4	4	5	5	5	5	5	5	5	5	5	5	5	5	5	3
E55	4	5	2	1	5	5	5	5	5	4	5	3	4	5	4	5	3	3
E56	5	4	5	4	4	5	5	5	5	5	3	3	4	5	5	5	4	5
E57	5	5	4	4	4	5	4	4	5	5	4	4	5	5	5	4	4	4
E58	4	4	3	3	3	4	2	3	2	2	2	1	2	4	2	2	2	3
E59	4	3	3	3	4	5	4	5	4	5	5	5	4	4	4	5	4	5
E6	3	4	2	5	4	3	4	3	5	2	4	4	3	2	5	4	3	3
E60	5	5	4	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
E61	4	3	3	3	3	4	4	5	5	4	4	4	4	5	5	4	4	4
E62	5	5	4	4	3	5	5	5	4	5	5	5	5	4	5	5	4	4
E63	5	4	2	4	3	5	4	5	3	4	5	4	5	5	4	5	4	5
E64	5	4	3	2	4	5	5	4	3	5	4	3	3	5	4	3	4	4
E65	5	4	4	4	4	5	5	5	5	5	5	5	5	4	5	5	5	5
E66	2	3	2	2	4	5	3	5	3	4	4	3	3	4	2	5	3	4
IT'S 67	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
E68	5	5	5	3	4	5	5	5	5	5	5	4	4	5	4	5	5	4
E69	5	4	2	2	5	5	4	4	3	5	2	4	5	5	3	4	4	4
E7	4	4	4	5	3	4	4	5	5	5	4	4	4	5	4	4	4	5
E70	4	5	3	3	5	5	4	4	5	4	5	4	4	4	3	4	3	5
E71	3	4	3	2	3	5	2	3	3	5	4	4	4	5	3	2	3	4
E72	4	3	4	4	5	5	5	4	5	5	4	3	3	4	4	5	4	3
E8	5	4	3	3	4	5	3	4	5	4	3	2	4	4	4	5	3	3
E9	5	4	5	5	4	4	5	4	5	4	4	5	4	4	4	4	5	5

The results range from 1 to 5 representing the degree of importance and influence on the company's success.

DISCUSSIONS/CONCLUSIONS

The relationship and influence between innovation activities and competitive criteria were evaluated through multicriteria analysis, with the final results shown in the table, which also presents the KPIs that were directly related to innovation activities. The evaluations also allowed the deepening of the theoretical model.

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