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Application of Machine Learning in Supply Chain Management in the Context of Transaction Costs

Aplicação do Machine Learning na Gestão da Cadeia de Suprimentos Sob o Contexto de Custos de Transação

Aplicación del Machine Learning en la Gestión de la Cadena de Suministro en el Contexto de los Costes de Transacción

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Abstract: This paper aims to identify the impact of supply chain performance on organizational performance through the application of machine learning in the relationships between constructs, in a context of transaction cost economics. The research was performed according to three stages: bibliographical; exploratory and qualitative research, with 11 supply chain professionals. Subsequently, a questionnaire with 72 statements was applied to 121 professionals who work with machine learning. Through exploratory factor analysis, significant variables were identified. The findings confirmed that the use of machine learning has a positive impact on the relationships between supply chain strategic orientation and transaction cost reduction, as well as between transaction cost reduction and supply chain performance. One concludes that the use of machine learning led to improved supply chain performance, which was passed on to the company's performance. As contributions the study brought the perception that the application of machine learning expands the understanding of the relationship between constructs; and it obtained subsidies to discover patterns in the data involved in supply chain processes through factor analysis that identified influential factors for the success of the supply chain.

Keywords: Machine Learning; Transaction Cost Economics Theory; Strategic Supply Chain Management Orientation; Supply Chain Performance; Firm Performance; Value Addition.

Resumo: Esse artigo teve como objetivo identificar o impacto do desempenho da cadeia de suprimentos no desempenho organizacional a partir da aplicação de aprendizado de máquina nas relações entre os construtos, em um contexto de economia dos custos de transação. A pesquisa teve três etapas: bibliográfica; pesquisa exploratória e qualitativa, com 11 profissionais de cadeia de suprimentos. Posteriormente, aplicou-se um questionário com 72 assertivas a 121 profissionais que atuam com aprendizado de máquina. Por meio de análise fatorial exploratória, foram identificadas as variáveis significativas. Os achados confirmaram que o uso de aprendizado de máquina tem impacto positivo nas relações entre orientação estratégica da cadeia de suprimentos e redução dos custos de transação e entre a redução dos custos de transação e o desempenho da cadeia de suprimentos. Pode-se concluir que o uso de aprendizado de máquina propiciou a melhoria do desempenho da cadeia de suprimentos, repassada para o desempenho da empresa. Como contribuições o estudo trouxe: a aplicação do aprendizado de máquina amplia o entendimento sobre a relação entre os construtos; obteve subsídios para descobrir

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padrões nos dados envolvidos nos processos de cadeia de suprimentos por meio de análise fatorial que identificaram fatores influentes para o sucesso da cadeia de suprimentos.
Palavras-chave: Aprendizado de máquina; Teoria da Economia de Custos de Transação; Orientação Estratégica da Gestão da Cadeia de Suprimentos; Desempenho da cadeia de suprimentos; Desempenho da empresa; Adição de Valor.

Resumen: Este artículo tuvo como objetivo identificar el impacto del desempeño de la cadena de suministro en el desempeño organizacional a partir de la aplicación del aprendizaje automático en las relaciones entre constructos, en un contexto de ahorro de costos de transacción. La investigación tuvo tres etapas: bibliográfica; Investigación exploratoria y cualitativa, con 11 profesionales de la cadena de suministro. Posteriormente, se aplicó un cuestionario con 72 aserciones a 121 profesionales que trabajan con machine learning. Mediante análisis factorial exploratorio se identificaron las variables significativas. Los hallazgos confirmaron que el uso del aprendizaje automático tiene un impacto positivo en las relaciones entre la orientación estratégica de la cadena de suministro y la reducción de los costos de transacción, y entre la reducción de los costos de transacción y el rendimiento de la cadena de suministro. Se puede concluir que el uso del machine learning proporcionó una mejora en el rendimiento de la cadena de suministro, trasladada al rendimiento de la empresa. Como contribuciones, el estudio aportó: la aplicación del aprendizaje automático amplía la comprensión de la relación entre constructos; Obtuvo subsidios para descubrir patrones en los datos involucrados en los procesos de la cadena de suministro a través del análisis factorial que identificó factores influyentes para el éxito de la cadena de suministro.
Palabras clave: *Machine Learning; Teoría de la Economía de los Costos de Transacción; Orientación Estratégica de la Gestión de la Cadena de Suministro; Rendimiento de la Cadena de Suministro; Desempeño de la Empresa; Agregado de Valor.*

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1. Introduction

Supply chain is a concept that has gained strength in the last three decades as a way of seeking better operational performance through proximity between links (suppliers, manufacturers, distributors, retailers, consumers) and has used technologies in this sense. Since then, the impacts on the performance of supply chains due to the technologies that emerged and were absorbed by their activities have been felt by changes in management methods and the increased accuracy of decision-making aid tools. Machine learning is a tool that, despite not being a new concept, has expanded its scope of applications.

Based on this constant advancement of technologies and the increase in their use in supply chain practices, the problem question of this work was:

- What is the influence of supply chain performance on organizational performance based on the application of machine learning in the relationships between the links in this chain, in a context of transaction cost economics theory?

As a general objective, this work aimed to identify the influence of supply chain performance on organizational performance through the application of machine learning in the relationships between the links in this chain, in a context of transaction cost economics theory.

Based on the general objective presented in the previous topic, the specific objectives outlined for this work were:

- Identify the characteristics (types) of machine learning used in companies.
- Study machine learning applications in the supply chain.
- Study the use of machine learning according to the strategic alignment of the supply chain.
- Identify what results are expected in supply chain performance management with the use of machine learning.

Expectations regarding organizational performance by managers have become increasingly higher due to an increasingly competitive market and demanding customers. Therefore, it is necessary to use technological tools that help in making decisions on how to best use available resources.

The study carried out had the following relevance:

- The need for knowledge regarding the interaction between supply chain orientation, transaction costs and chain performance.
- The increasing use of machine learning to generate predictions that improve organizational performance.
- Expand scientific production that analyzes the concept of supply chain management and the use of machine learning.
- Expanding knowledge of supply chain management as a way of improving organizational performance.
- Dissemination of the use of machine learning as an analysis and decision-making tool.

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This work was aimed at the interests of supply chain managers, students and researchers and public policy managers who seek to understand the improvement of supply chain performance through the use of machine learning in planning activities.

The originality of the work was based on searches carried out in the Web of Science (WoS) and Science Direct databases based on the constructs and moderating variable of the proposed model (supply chain orientation, economy transaction costs, supply chain performance, organizational performance). On the WoS basis, there was no return.

In the Science Direct database, 10 articles published between 2017 and 2021 were found, distributed as follows: 1 article in 2017, 2 articles in 2019, 4 articles in 2020, 3 articles in 2021, none in 2022. In the Web of Science, between 2017 and 2021, based on the combination of constructs, the results were:

- "Machine Learning" and "supply chain": 269 articles, of which 65 presented adherence to the study theme (operations research management science, management, business, business finance, interdisciplinary social sciences, social sciences mathematical methods), 46 were cited one or more times (sum of citations 586, h-index 12 and average citations 9.02).
- "Machine Learning" and "transaction costs": 24 articles with adherence (business finance, economics, operations research management Science, management, social sciences mathematical methods) 12 with 1 or more citations (488 citations, average number of citations per article 20, 33 and h-index 8).
- "Supply chain" and "transaction costs": found 122 articles, 82 with adherence (business, management, operations research management science, economics, business finance, social science disciplinary), of which 54 have 1 or more citations (sum of citations 477, h-index 11 and average number of citations 5.82).

This work sought to explore the gap by studying the relationship between supply chain performance and organizational performance through the moderation of the use of machine learning, with the mediation of transaction costs.

The complexity of the research was in the relationship between the constructs and the moderating variable, in light of the transaction cost theory; because there are no previous studies focusing on Brazilian industrial activity; and in building a machine learning model that is generally applicable in supply chains. Another point was the still low adherence of Brazilian companies to the use of machine learning, restricting the research universe.

2. Theoretical Foundation

2.1 Strategic Guidance for Supply Chain Management

The first step in discussing the strategic orientation of supply chain management was understanding the concept of supply chain. Stonebracker and Liao (2004)

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listed the characteristics of a supply chain: multiple echelons, focus on integration, service and profitability goals, collaborative processes and activities, and concern for adding value for the customer. Integration is important for improving business performance and can be achieved in several ways: by reducing costs, improving responsiveness, increasing the level of service and facilitation in decision making (ABUBAKER et al., 2017).

Burgess, Singh and Koroglu (2006) identified in the literature a lack of clarity and uncertainty as to whether supply chain management was based on a coherent theory. The authors compiled seven supply chain management constructs:

- **Leadership**: focused on strategy and the need for proactive involvement of managers.
- **Intra and inter-organizational relationships**: focused on economic and social associations with stakeholders, inside and outside the organization.
- **Logistics**: issues related to the movement of materials internally and between links in the chain.
- **Guidance for process improvement**: process arrangements that aim to facilitate interactions so that there is continuous improvement within and between organizations.
- **Information systems**: communication aspects throughout the chain and within companies.
- **Business results**: recording performance related to the results arising from the adoption of a strong supply chain orientation.

These constructs were also grouped by the authors into soft constructs, focused on people and relationships, and hard constructs, focused on technological and infrastructure issues. In the field of soft constructs, one can point out the construction and maintenance of elements of internal behavior, such as trust, commitment, organizational compatibility, cooperation norms and top management support for the elements of supply chain orientation (ESPER; DEFEE; MENTZER, 2010).

Esper, Defee and Mentzer (2010) also pointed out the lack of clarity in the definition of supply chain management and its boundaries, and identified the following common points in the view on supply chain definitions found in the literature of the area:

- Emphasis on coordination and collaboration with suppliers and customers.
- Highlighting the value of adherence between demand and supply.
- Adoption of a flow perspective.

Since the establishment of these concepts, there have been rapid changes. Aryal et al. (2020) pointed out the evolution of the supply chain due to the development of disruptive technologies, such as big data and IoT, which were implemented with the aim of optimizing routine activities and operations in logistics and customer support. The authors pointed out that the literature emphasized the critical role of using the accuracy and reliability of data for real-time understanding to aid supply chain decision making, process automation, integration and standardization.

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Esper, Defee, and Mentzer (2010) defined supply chain orientation as "a system of shared beliefs and values that helps understand how the organization can strategically manage its chain and the necessary behavioral norms within the organization" and proposed that the basis of supply chain orientation lies in the high degree of fit between the strategy and the structure of the supply chain, expanding to areas external to the company. The supply chain structure is composed, according to the authors, of four categories: organizational design, human resources, information technologies and organizational measures.

Lee and Nam (2016) reinforced the differences between strategic supply chain orientation and structural supply chain orientation: while strategic orientation presents tacit characteristics, emphasizing the understanding and perception of company members, structural orientation is more linked to formal characteristics.

Strategic orientation was conceptualized by Hsu and Tan (2016) as the set of decision-making designed to achieve stipulated goals, with the manager's interpretation and perspective having a great influence on strategic decision-making, in addition to the breadth of shared organizational actions.

Jüttner and Christopher (2013) indicated as results the positive impact of supply chain strategy coordination on the organization's customer focus; the support that marketing offers the strategic structure of the supply chain; the crucial role of information exchange between marketing and supply chain management.

For Liu et al. (2020), strategic orientation is a direction that leads the firm to adopt measures to improve its business performance, being a long-term commitment. Strategic orientation provides a guide for decision making within and across firm boundaries, reflecting the firm's strategic emphasis or priority.

Sriyakul, Prianto and Jermsittiparsert (2019) pointed out that inter-organizational associations provide the basis for supply chain management and supply chain guidance, with complementary and mutual efforts made by supply chain members acting as the drivers of creation of value. Both upstream and downstream resource flows within the supply chain cause the establishment of supply chain orientation. Identifying customers and suppliers as strategic partners came from a transactional approach, which refers to ongoing transactions within supply chain members to achieve collaborations.

2.1.1 Lean strategy and agile strategy

Qi, Boyer and Zhao (2009) split supply chain strategies into lean and agile. The lean strategy seeks to increase efficiency by eliminating waste in its inter and intra-organizational processes, reducing activities that do not add value, increasing flexibility and reducing costs, being linked to a stable product demand, which makes programming easier production, allowing the reduction of the order cycle, in-process stocks and finished product stocks (QI; BOYER; ZHAO, 2009; CARVALHO; DUARTE; MACHADO, 2011).

Santos, Reul and Gohr (2021) pointed out that lean supply chains are

DOI: https://doi.org/10.29327/2384439.2.4-3

characterized by practices that aim to strengthen customer-supplier integration based on information sharing in relation to inventory control, demand forecasting and operations scheduling. The agile strategy aims to maintain its competitive advantage in an environment of rapid change, through products with differentiated characteristics.

Rahimi et al. (2020), in their research, indicated that the agility of the supply chain by creating speed in response to market needs, the ability to produce in small or large categories and the ability to change the delivery time of the customer order supplier leads to reduced costs, increased speed and reduced inventory levels and customer satisfaction. The agile supply chain practices indicated by the authors included: use of information technology to integrate and coordinate projects, production and development; use of information technology to coordinate and integrate the supply chain; establish a relationship based on trust with suppliers and customers; create a flow of information throughout the entire chain; customize products; facilitate quick decision making; reduce product development cycle; increase delivery speed; be sensitive to the market; improve service level; ability to change production volumes.

Regardless of the type of strategic orientation, Kirchoff, Tate and Mollenkopf (2016) defined five behavioral dimensions of the chain:

- Trust in chain partners.
- Commitment to maintaining the relationship between the links in the chain.
- Cooperation standards that guarantee the pooling of efforts to achieve common objectives.
- Organizational compatibility, that is, they have similar corporate cultures.
- Support from senior management to maintain strong relationships with supply chain members.

This authors's view suggests that there are points in common between the two strategic orientations, which opens space for a more careful analysis.

2.2 Theory of transaction cost economics

Williansom (1985) reinforced that the economics of transaction costs would pose the problem of economic organization as a problem of contracts. According to the author, transaction costs could be divided into:

- **Ex ante costs**: costs for drafting, negotiating and safeguarding an agreement.
- **Ex post costs**: they would include maladaptive costs incurred when transactions fall out of alignment; the trading costs incurred to correct later misalignments.

Coase (1937) indicated that changes such as in communication technologies, which would tend to reduce the cost of spatial organization, would tend to increase the size of the company. Any changes that improved management technique would tend to increase the size of the company.

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For Siffert Filho (1995), economic organizations would be driven by transaction cost economies that represent expenses with the general functioning of the economic system. Augusto et al. (2013) conceptualized transaction costs as costs associated with the functioning of markets. Besanko et al. (2006) included the time and expense of negotiating, recording and enforcing contracts, arising when parties to a transaction act opportunistically, considering the adverse consequences as well as the costs of avoiding these opportunistic actions.

Farina, Azevedo and Saes (1997) presented behavioral assumptions about transaction costs, such as the rationality of economic agents and their opportunistic attitudes. Due to the inability of agents to foresee all future contingencies, the contract would be incomplete and, therefore, some elements of the transaction would not be contractable ex-ante. Opportunism would thus lead to a renegotiation of the contract, leading to losses for one of the parties, which is the transaction cost.

There are three levels of rationality (WILLIAMSOM, 1985; FARINA; AZEVEDO; SAES, 1997): maximization, or strong rationality; limited or semi-strong rationality; and organic or weak rationality.

Opportunism also received a three-point classification (WILLIAMSOM, 1985; FARINA; AZEVEDO; SAES, 1997): opportunism or strong self-interest; simple self-interest or without opportunism; obedience or lack of self-interest.

Opportunism would arise from possible adaptation problems due to the incompleteness of contracts, originating from limited rationality and would lead to future renegotiations, which would open space for opportunism through unethical actions, leading to losses for one of the parties (FARINA; AZEVEDO; SAES, 1997).

Therefore, according to Farina, Azevedo and Saes (1997) and also according to Dyer (1997), there are three dimensions of transactions:

a. **Specificity of assets**: those that could only be reused with loss of value, with investment in them being subject to risks and adaptation problems, which are directly proportional to specificity:
    i. Locational specificity: proximity to firms belonging to the same chain reduces transport and storage costs.
    ii. Specificity of physical assets.
    iii. Specificity of human assets.
    iv. Dedicated assets, those whose return on investment depends on the transaction with a specific agent.
    v. Brand specificity.
    vi. Temporal specificity, which depends on the moment in which the transaction would be carried out.
b. **Frequency**: in this dimension, the transaction duration attribute is considered.
c. **Uncertainty**: complexity, difficulty in measuring performance and costs of coordinating different transactions. There are three treatments for uncertainty:
    i. Risk refers to the variance of a probability distribution. In this

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case, the role of uncertainty would be to distinguish the different governance structures that are sensitive to variances.

ii. Unawareness of future events. In this case there would be no possibility of defining a probability distribution.

iii. Recognition of information relevant to the contract, which occurs when the information is incomplete and asymmetric.

In these last two treatments, one sought to identify the limits of rationality and, consequently, the incompleteness of contracts.

2.3 Machine Learning

The concept of machine learning has been expanded over time as information technology advances and allows the execution of increasingly complex algorithms. In Finlay's view (2017), machine learning would be the use of mathematical procedures, algorithms, in order to analyze data with the aim of discovering useful patterns (relationships or correlations) between different data items, so that they can be used to infer about the behavior of new cases.

Schwab (2016) pointed to the changes in the digital economy brought about by artificial intelligence (AI) (machine learning being one of the types of AI) that would be transforming the physical economy, in addition to predicting that, in the future, it would be used to manage global challenges systems that would exceed the human capacity for achievement.

Despite the distance between machines and humans, in the real sense of the word learning, machine learning presents the ability to quickly adapt behaviors, which makes it useful, as Corrêa (2019) also highlights, in supply chain activities, such as high accuracy in demand forecasts based on a large mass of data, reduction of freight costs with improvements in transport performance and minimization of exposure to operational risks, improvement in the recognition of visual patterns in the quality inspection of incoming cargo, process improvement through combination with advanced analytics and sensors, with real-time monitoring, among others.

In turn, Smith (2018) defined machine learning as the art of programming computers that allows them to automatically learn and adjust their functions to improve the way they perform their tasks, with the computer having the ability to improve its performance with based on one’s own experience without there being an explicit program that indicates exactly what to do. Mohri, Rostamizadeh and Talwalkar (2018) defined that this experience would refer to past information available to learn, obtained in the form of electronic data that could be analyzed.

The learning process involves observing the collected data and comparing it with previously collected data in search of patterns and results and adjusting accordingly. Domingos (2012) and Smith (2018) defined that machine learning is the sum of representation, evaluation and optimization, as follows:

- **Representation**: a classifier should be represented in some formal language that the computer can manipulate, which would be equivalent

DOI: https://doi.org/10.29327/2384439.2.4-3

to choosing the learner's hypothesis space set of classifiers that the machine can learn.

- **Evaluation**: an evaluation function would be needed to distinguish good classifiers from bad classifiers. The evaluation function used internally by the algorithm may differ from the external function that one wants the classifier to optimize to facilitate optimization.
- **Optimization**: a method is needed to search for the highest scoring classifier among the classifiers. The choice of optimization technique is essential for learner efficiency and helps determine the classifier produced if the evaluation function has more than one optimum.

Domingos (2012) reinforced that the main objective of machine learning is generalization beyond the examples in the training set.

According to Smith (2018) and Finlay (2017), machine learning is used in several areas such as health, economics, administration, engineering, and it aims to:

- Solve problems involving long lists of rules.
- Solve very complex problems that have no apparent solution.
- Adopt for new data in non-stable environments.

The style of machine learning can be supervised or unsupervised, and the form of function can be any type of classification, regression, decision tree, clustering, or deep learning.

Smith (2018) indicated that types of machine learning could be categorized based on:

- supervised, semi-supervised and unsupervised training.
- how they learn;
- how simple or complex they are.
- in relation to necessary human interaction; Systems can be classified:
- supervised learning: machine learning would already be programmed to wait for a certain output from an algorithm in one's system before it begins its work. The system knows the type of answer it would be trying to achieve and simply needs to sort out the different steps to find it. The algorithm would be learned by a specialized set of training data that guides the machine learning to the correct conclusion.

Russell and Norvig (2022) presented another type of learning, reinforcement learning. In this type, learning would take place through a series of reinforcements, characterized by rewards and punishments, in order to guide their decisions seeking to achieve a greater number of rewards.

Faceli et al. (2022) presented, in this context, two learning hierarchies: classical and modern. In the classic way, based on inductive machine learning, there is supervised learning, linked to predictive tasks (discrete in nature for classifications and continuous for regressions), and unsupervised learning, linked to descriptive tasks (grouping, which performs meetings according to data similarity; summarization, which describes a set of data; and association, which searches for frequent patterns of connection between data attributes).

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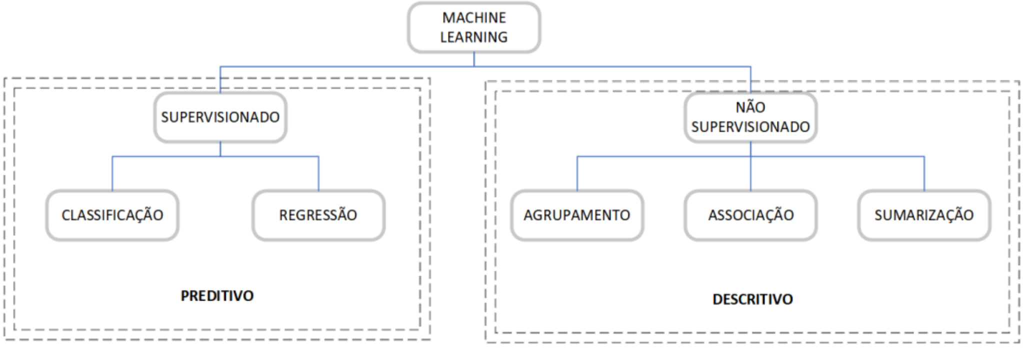
Figure 1: *Classic Learning Hierarchy*

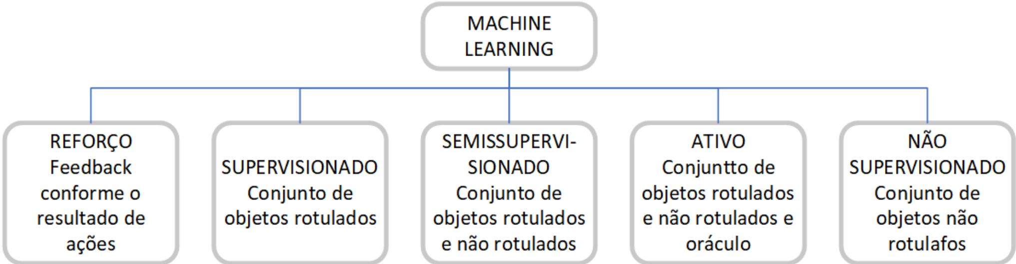


Source: Faceli et al (2022).

Due to the difficulty of fitting some types of machine learning into the classic hierarchy, Faceli et al. (2022) presented an extended hierarchy to include semi-supervised learning, active learning and reinforcement learning.

Many authors have dedicated themselves to studying new applications of machine learning. Carbonneau, Laframboise and Vahidov (2008) addressed the collaborative forecasting and replenishment environment (CFAR) using machine learning, as several factors hinder the progress of this collaboration along the supply chain. Therefore, it would be necessary to forecast demand by participants in the absence of complete information about demand from other participants to support supply chain management.

Figure 2: *Extended learning hierarchy*.



Source: Faceli et al (2022).

Zhu et al., on the other hand, proposed a new integrated ensemble machine learning method to predict the credit risk of China's small and medium enterprises (SMEs) in supply chain financing (SCF). Baryannis, Dani and Antoniu (2019) studied the use of machine learning in risk analysis in supply chains in order to provide predictive analyzes that are both interpretable and have a high standard of performance.

2.4 Value Addition (Performance)

In this topic, the concepts of the supply chain performance and organizational performance constructs were developed, which served as the basis for the subsequent analysis of the relationship between them.

DOI: https://doi.org/10.29327/2384439.2.4-3

2.4.1 Supply Chain Performance

Sriyakul, Prianto and Jermsittiparsert (2019) indicated that the supply chain network is a complex and dynamic phenomenon and it is difficult to identify appropriate indicators of supply chain performance. The authors highlighted that effectiveness and efficiency are two common dimensions found in the supply chain performance literature. In supply chain, determination problems may exist, as those variables that are normally employed as a basis for estimating supply chain performance may fail to cover all resulting dimensions.

Ellinger et al. (2012) highlighted that the relationship between supply chain competencies and company performance would not be well established empirically, due to the scarcity of metrics to quantify the effects of the supply chain. The authors defined the notion of supply chain competence as a means of creating competitive advantage, being a function of integration between and within the links of the chain, integration that would aim to facilitate the sharing of information that connects manufacturing sources and operations with market needs to adjust it to demand.

Collaborative integration between internal and external supply chain participants would focus, according to the authors, on better aligning participant incentives and reward systems to reduce duplication and non-value creation activities. The ability to leverage information technology and process innovation to accelerate the supply chain, reduce overall system inventory and resource utilization, and sustain cash flow have been recognized as significant sources of competitive advantage (RAHIMI et al., 2020).

In this sense, he pointed out that researchers have been trying to introduce new management approaches, such as supply chain agility to provide these resources (CRUZ, 2011). Azevedo et al. (2010), in a conceptual model, examined the impact of supply chain agility on the operational and economic performance of the supply chain and its competitiveness. The authors showed that applying an agile supply chain approach would lead to customer satisfaction through more flexibility, greater accountability, better quality products, and faster delivery times.

2.4.2 Organization Performance

Qrunfleh and Tarafdar (2014) conceptualized that the organization's performance refers to the way in which financial and market goals are achieved. The authors measured company performance through perceived reports of its market share, sales, and overall competitive position. According to their results, the integration of the supply chain would increase the efficiency with which information would be transmitted, improving the company's performance, by reducing stock levels and costs and increasing the number of on-time deliveries, as well as identifying a high correlation between supply chain flexibility and company performance due to the chain's ability to adapt to changes.

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2.5 Relationship between constructs

The relationship between supply chain performance and organizational performance has been discussed in the literature with some frequency. Whitten, Green Jr, and Zelbst (2012) concluded in their research that implementing an appropriate supply chain strategy would lead to improved supply chain performance.

Organizational performance would, in turn, be a function of supply chain performance. The performance of the supply chain, according to the authors, would simultaneously depend on agility, adaptability and alignment (which is why it is called the triple-A chain). The hypotheses raised by the authors were strongly supported that better chain performance would lead to better marketing performance and marketing performance leads to better financial performance.

Sawangwong and Chaopaisarn (2021) presented that the supply chain strategy, aligned with the introduction of new technologies, leads to obtaining a commercial advantage. The application of these technologies would support better supply chain performance in terms of delivery reliability, resource efficiency, supply chain costs and delivery time. These results would improve organizational performance in profitability, return on investment (ROI) and sales growth.

Iansiti and Lakhani (2020) concluded that the systematic conversion of internal and external data into predictions, understandings and choices would guide and automate the organization's operations. The authors also compared, through feedback, what they called traditional operational models with models driven by artificial intelligence (AI).

Karami et al. (2015) highlighted the importance of trust and commitment developed from interaction and collaboration in improving supply chain performance, mainly by sharing information, knowledge and assets.

According to the authors, trust, chain innovation and collaboration would play mediating roles in the relationship between market orientation and supply chain performance.

3. METHODOLOGICAL PROCEDURES

This paper has been based on qualitative and quantitative methodologies used in la linked manner as to achieve the proposed objectives. Below are descriptions of each procedure used.

3.1 Research Phases

This research consisted of three phases, with an initial phase in which the conceptual model was defined based on the relationships between the strategic orientation of the supply chain, supply chain performance and the firm's performance, from an operational point of view, to identify the role of using machine learning in the context of transaction cost.

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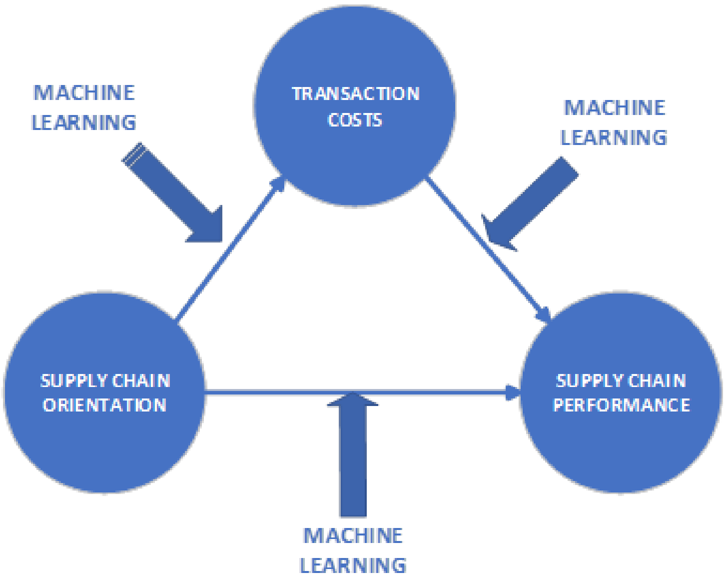
In Phase I, a bibliographic survey of the constructs of this work was carried out in the bibliographic databases Scopus, Science Direct and Web of Science. In Phase II, corresponding to qualitative research, the content of the proposed constructs and relationships were tested through ten focused interviews with professionals working in the supply chain or related areas who use machine learning in their activities. The results obtained were applied to Phase III, using quantitative research, using a questionnaire on Google Docs, to test the strength of the relationship between the constructs that make up the model. Initially, a pre-test was carried out and then the necessary corrections will be made to the questionnaire.

To demonstrate how the collected data responded to the research problem, exploratory factor analysis (EFA) was applied. Consistency was tested through convergent, discriminant and sample reliability validation.

3.2 Conceptual Model

The thesis of this paper was that machine learning moderation generates positive impacts on the relationship between supply chain orientation and supply chain performance, between supply chain orientation and transaction costs, and between transaction costs and supply chain performance, leading to a definition of company performance, according to the model presented in Figure 3, with the respective hypotheses, with the constructs of this work being supply chain orientation and supply chain performance, transaction costs and company performance. The moderating variable is the use of machine learning.
Figure 3: Theoretical model.

Figure 3: Theoretical model.



Source: the author.

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The hypotheses are as follow:

- H1: The use of machine learning positively moderates the relationship between supply chain orientation and the reduction of transaction costs.
- H2: The use of machine learning positively moderates the relationship between supply chain orientation and supply chain performance.
- H3: The use of machine learning positively moderates the relationship between transaction cost reduction and supply chain performance.
- H4: supply chain performance positively influences company performance.

3.3 Characteristics of the qualitative stage

The nature of this phase was exploratory, with the objective of seeking confirmations or changes in the model, since the researched environment would be dynamic due to the advancement of technologies and relationships between organizations.

As disadvantages and precautions to be taken, the authors listed the following:

- limited time to conduct the interview.
- lack or excess of relationships, which depends on the researcher.
- excessive directness of the interviewer.
- lack of direct observation of the scenarios.

Regarding these points, there were difficulties in finding suitable times for the interviewees, but the time consumed varied between 50 minutes and 1 hour and 10 minutes, which proved to be sufficient to cover the topics listed. There was no previous relationship between the interviewees and the interviewer, and contacts were obtained through common contacts. As for directness, we sought to balance it with questions inserted throughout the interview that aimed to explore points presented by the interviewees. It was not possible to directly observe the scenarios, considering the interviewees' statements as sufficient to outline the panorama of the use of machine learning in their organizations.

The interviews were conducted using remote resources, such as Google Meets, Skype, Teams etc., due to the difficulty in scheduling face-to-face meetings due to the pandemic and/or the distance at which the interviewees were located. The interviews were recorded and transcribed. The protocols required for this type of research were followed, such as explanation of the topic and objectives of the research, request to proceed with recording, maintaining confidentiality regarding the interviewee, as well as the company.

The study universe encompasses professionals in management positions who work in organizations that use machine learning as a tool to automate tasks or to assist in decision-making in the areas of logistics and supply chain, regardless of their segment of activity. Sampling was for convenience, based on this described environment and the interviewee's availability to assist the researcher.

The profiles of the interviewees are presented in Table 1. The sizes of the companies vary between medium and large.

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Table 1: Profile of interviewees

Code of interviewee	Job title	Company segment
E1	Industrial consultant	Management platforms
E2	Supply chain manager	Automobile
E3	Supply chain coordinator	Logistics
E4	Director	Technology Start-Up
E5	Marketing Director	Automobile
E6	Operations Vice President	Automobile
E7	Operations Coordinator	Paper and cellulose
E8	Supply chain manager	Industrial automation
E9	Customer success manager	IT
E10	Coordinator	Foreign Commerce
E11	Analyst	Software

Source: the author.

The interviewees were duly informed of the academic nature of the interviews and that their identities, as well as the companies they work for, would not be disclosed and that no confidential data would be requested during the process.

3.4 Quantitative research stage

The questionnaire used in this stage was the result of bibliographical research, with the aim of identifying the variables of each construct as indicated in the tables presented at the end of each topic in the theoretical framework and adjusted based on the results of the interviews in the qualitative stage. The universe was made up of professionals from organizations inserted in supply chains that use machine learning in their activities.

This questionnaire included demographic information about the company and the respondent, and statements about the constructs Transaction Cost Economics Theory (TECT), Supply Chain Strategy Orientation (SSCO), Supply Chain Performance (SCP), Company Performance Organization (PO) and the moderating variable machine learning (ML).

As a pre-test, the questionnaire was applied to 10 professionals. The final questionnaire was sent to 1181 professionals, identified on Linkedin, anamid which 121 valid responses were obtained. The results of this questionnaire were analyzed, identifying and removing outliers (they gave the same answer to all questions or claimed to have no experience with machine learning), 5 in total. The remaining data underwent correlation studies and exploratory factor analysis with SPSS software. And, finally, the analysis of structural equations, with the SmartPLS-4 software.

4. RESULTS AND ANALYZES

This part presents the results and analyzes of the qualitative phases (interviews), with the profile of the interviewees, the matrix for tying the interview script and

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analysis of the responses obtained, as well as of the quantitative phase (exploratory factor analysis and structural equations), with the profile of respondents, areas of activity, market segments, applications of machine learning and analysis of answers to questions.

4.1 Interviews

According to the presented profile, the interviewees work in companies in different segments and the other data in their profiles can be grouped as follows:

- Regarding education, 1 interviewee has a higher education degree, 10 have a postgraduate degree;
- 3 interviewees have degrees in Business Administration, 6 in Engineering, 1 in Statistics, 1 in Economics.
- 1 interviewee has been in the role for less than 2 years, 4 between 2 and 5 years, 6 for over 5 years.
- 1 interviewee has been with the company for less than 2 years, 2 between 2 and 5 years, 8 for over 5 years.
- 1 interviewee works in a company with up to 99 employees, 2 with between 100 and 499 employees and 8 with over 500 employees.
- 8 interviewees work in a multinational company, 2 in a national company with private capital, 1 in a national company with public capital.
- The interviews followed a script, as presented in the tie-in matrix (Chart 2):

Frame 2: lashing matrix

Construct	QUESTIONS	AUTHORS
Transaction cost theory	What attributes do you consider important for transactions? Expected answer: Identify the main elements of transaction cost theory such as: opportunism, bounded rationality, specific assets, uncertainty and frequency How often do adjustments need to be made to contracts? Expected answer: ex-ante costs, es-post costs.	WILLIANSOM (1985); FARINA, AZEVEDO, SAES (1997)
Supply chain performance	What is the main strategic objective of your supply chain? Expected response: Reduction of inventories; reduction of the order cycle; relationship with suppliers (lean). Quick answer; customization (agile).	QI, BOYER E ZHAO (2009)
Chain performance	What are the main performance indicators used in your supply chain? Expected answer: (agility and cost-oriented supply chain). Thus, identifying strategies related to quality, speed, flexibility, costs or reliability.	SRIYAKUL, PRIANTO AND JERMSITTIPARSERT (2019)

DOI: https://doi.org/10.29327/2384439.2.4-3

Company performance	What company performance indicators does supply chain performance influence? Expected answer: percentage of market share, ROI, Variation in percentage of share, Variation in ROI, profit – revenue ratio, performance comparison with competitors.	QRUNFLEH; TARAFDAR (2014)
Machine learning	What are the applications of machine learning tools in your supply chain? Expected response: demand forecast, process improvements.	DOMINGOS (2012); SMITH (2018)
	What type of results are expected/achieved from the interaction between the use of machine learning and the performance of your supply chain and company? Expected response: greater forecast accuracy, better perception of variable correlation. greater market share; higher profit margin; better return on investments; better global competitive position.	DOMINGOS (2012); SMITH (2018); SRIYAKUL, PRIANTO AND JERMSITTIPARSERT (2019); QRUNFLEH, TARAFDAR (2014)

Source: the authors.

4.1.1 Transaction Costs

The interviewees presented elements of transaction costs in their responses in a partial manner, although consistent with the theory. Interviewee E8 highlighted the importance of his analysts (specificity of human assets) in the process of building scenarios for forecasting demand (ex ante costs). As for contracts, the interviewee pointed to strong initial negotiations, mainly due to technical characteristics, but with a smooth relationship after order confirmation, with rare revisions (contracts with strong rationalization).

Interviewee E7 placed uncertainty as an important factor in transaction costs, since his operation is just beginning and depends heavily on the behavior of the international market and economic issues, which have proven to be unstable, in addition to the financial health of his clients. These uncertainties have led the interviewee to frequently renegotiate contracts.

Interviewee E4 considered that the risk of system failures are the main factor in transaction costs in his company, as they can have a major impact on results.

In turn, interviewee E6 sought rational contracts, with the support of a strong legal department, so that the possibility of renegotiating an order became remote, including fluctuations in demand and prices, defined within parameters acceptable to both parties. , as well as payment methods and late fees. Another point highlighted by the interviewee was the long term of these contracts. This interviewee also cited problems related to the distance of suppliers, some of which are in the Far East (location specificity).

Interviewee E5 also showed a strong concern with building contracts that avoid later renegotiations, as did interviewee E3, who maintains long-term contracts with their main customers.

DOI: https://doi.org/10.29327/2384439.2.4-3

Interviewee E2 indicated the product development phase as transaction costs in his chain due to the risks in sizing product volumes and defining savings points.

4.1.2 Supply Chain Strategic Guidance

Interviewee E4 expressed concern about costs, especially logistical costs, which had a major impact on his operation, in addition to the existence of a technological gap between the links in the chain, which, according to his view, did not allow him to achieve better results. The interviewee highlighted that this technological delay in organizations, which still use tools from the 1990s, required a lot of investment to update.

Interviewee E2 follows a similar line, also choosing costs and quality as his strategic objectives.

Interviewee E7 pointed out that the main strategic focus is on meeting demand, since almost all of its production is already committed, using stocks to adjust any fluctuation in demand, with interviewee E3 having a similar practice.

Interviewee E8 expressed his concern about the changes that are in motion:

> “I would say that considering the scenario we live in today, which is an exponential rate of change in technology, I would say, using a term, it is the ability to adapt. Having a supply chain that reacts very quickly to these variations that we have today and, above all, that is capable of absorbing these technologies that will precisely give us the ability to deal with this.”

Interviewee E6, on his turn, pointed to the difficulty of making predictions:

> “We have increasingly been using the system for the following aim: you repeat the history of what happened, both from the point of view of seasonality and from the point of view of volume, capacity, etc. What you could say is that the past does not reflect the future. Thus, I think machine learning will play a strong role.”

Interviewee E5 considered that his chain's strategy encompasses the search for profit, inventory reduction, a good relationship with suppliers, fitting in with a lean chain.

4.1.3 Supply Chain Performance Indicators

For interviewee E8, the main indicator was OTIF (on time, in full), which considers delivery on the date and quantity requested: “it is an indicator that, in a way, shows the end of the chain, but it has a huge input to the entire order fulfillment flow”.

E7 considered indicators related to service times as important for its operation: “Lead time, import time, we have been operating with very interesting time, 25 to 30 days in a maritime process is very fast”. Interviewee E6 also raised the issue of international waiting times as a strong indicator of performance in his chain, in addition to the supplier's ability to meet production, quality and transport costs.

Interviewees E2 and E4 placed the level of customer service (SLA) as their main indicator, mainly linked to the quality of delivery, somewhat in line with previous

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respondents, while interviewee E5 had indicators linked to costs as his main concern.

4.1.4 Organizational Performance

The general view of respondents was that supply chain performance affects company performance. A significant number of interviewees indicated the impact on revenue and profit or results (E2, E3, E6, E8). Interviewee E2 pointed out the direct impact on the company's EBITDA. Interviewee E4 considered that the main impact is on the price of the product.

Interviewee E7, in addition to financial issues (cash flow), pointed out that the chain's performance impacts the relationship with customers, quality and level of service and interviewee E3 indicated market share as being a consequence of the chain's performance. supplies.

4.1.5 Machine Learning

The use of machine learning in the companies studied brought, according to the interviewees, benefits to the results of their processes. The research explored two questions about machine learning: its applications and the results obtained.

4.1.6 Applications

Machine learning applications have focused on expected responses such as demand forecasting (E2, E5, E6, E9)

Other interviewees, such as E8, used machine learning for customer service through chatbots, which also fits into the expected responses such as process improvement, in addition to serving as a source of data for prediction.

Interviewee E7 used process mapping to understand how each step relates to the others and which points are subject to improvement. Interviewee E6 indicated that there is a project to connect the sales area and the supply chain area to control the entire order cycle, identifying minimum production batches and demand behavior of subcomponents. Other applications presented by this interviewee were in planning, programming and production control (PPCP), in the creation of market scenarios and choice of transport modes.

Interviewee E4 used machine learning to recognize images in logistics processes, identifying loads and containers to improve the flow of information.

4.1.7 Acquired Results

The accuracy of the tool was highlighted by interviewee E8 as a great benefit for the company:

> "This is how we do it: once I'd keep the current planning process I would have an X level of accuracy, which is the standard for companies, that is, no more than 70%. However, when we start using this [other] model, it tells us the following: if you were to apply the method used by the intelligent model, your accuracy would be a bit higher than an X level." And what you've been showing us over the last 3 months

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is that there is something more."

Still in the field of accuracy, E6 also considered it a great benefit for planning imported components, reducing waiting times for customers, interviewee E1 used it in forecasting consumer market demand and interviewee E4 considered the quality of information by reading images is one's big gain.

Interviewee E2 pointed to financial gains, such as a greater profit margin.

4.2 Questionnaire

In Tables 3 to 7, related measures of the constructs are presented.

Table 3: measures on the strategic orientation of the supply chain

Code	Measure	Guidance	Author
SSCO_1	Reduction of inventories.	Lean	QI, BOYER AND ZHAO (2009)
SSCO_2	Reduction of the order cycle.	Lean	QI, BOYERAND ZHAO (2009)
SSCO_3	Long-term relationship with suppliers	Lean	QI, BOYER AND ZHAO (2009)
SSCO_4	Quick response to changes in the environment.	Lean	QI, BOYER AND ZHAO (2009); RAHIMI *et al.* (2020)
SSCO_5	Reduction in total operating cost	Lean	RAHIMI *et al.* (2020)
SSCO_6	Differentiation to serve various customer profiles.	Agile	RAHIMI *et al.* (2020)
SSCO_7	IT supply chain integration	Agile	RAHIMI *et al.* (2020)
SSCO_8	Project coordination	Agile	RAHIMI *et al.* (2020)
SSCO_9	Production coordination	Agile	RAHIMI *et al.* (2020)
SSCO_10	Development of new products	Agile	RAHIMI *et al.* (2020)
SSCO_11	Trust-based relationships with suppliers	Agile	RAHIMI *et al.* (2020)
SSCO_12	Trust-based relationships with customers		
SSCO_13	Information flow along the chain	Agile	RAHIMI *et al.* (2020)
SSCO_14	Customization according to customer needs	Agile	RAHIMI *et al.* (2020)
SSCO_15	Increased delivery speed	Agile	RAHIMI *et al.* (2020)
SSCO_16	Degree of customization	Lean+Agile	QI, BOYER AND ZHAO (2009); RAHIMI *et al.* (2020)
SSCO_17	Planning based on demand forecasts in contracts already signed	Lean+Agile	QI, BOYER AND ZHAO (2009); RAHIMI *et al.* (2020)
SSCO_18	Planning based on demand forecasts in orders already signed	Lean+Agile	QI, BOYER AND ZHAO (2009); RAHIMI *et al.* (2020)

Source: The author.

Table 4: measures on transaction cost theory.

Code	Measure	Keyword	Author
TECT_1	Cost of document elaboration	Assumption/Opportunism/*Ex ante* cost	WILLIANSOM (1985)
TECT_2	Cost to correct subsequent misalignments	Assumption/Opportunism/*Ex post* costs	WILLIANSOM (1985)
TECT_3	Maximization of results	Assumption/Opportunism/Strong rationality	WILLIANSOM (1985); FARINA, AZEVEDO, SAES (1997)

DOI: https://doi.org/10.29327/2384439.2.4-3

TECT_4	Later adaptations of the contract	Assumption/Opportunism/Bounded rationality	WILLIANSOM (1985); FARINA, AZEVEDO, SAES (1997)
TECT_5	Lack of rational response	Assumption/Opportunism/Weak Rationality	WILLIANSOM (1985); FARINA, AZEVEDO, SAES (1997)
TECT_6	Frequency in which partners seek to have advantages in negotiations over one's company.	Assumption/Opportunism	FARINA, AZEVEDO, SAES (1997)
TECT_7	Reliability in transaction retry	Assumption/Bounded Rationality	FARINA, AZEVEDO, SAES (1997)
TECT_8	Variance of possible results	Assumption/Bounded Rationality	FARINA, AZEVEDO, SAES (1997)
TECT_9	Safeguarding inclusion	Assumption/Bounded Rationality	FARINA, AZEVEDO, SAES (1997)
TECT_10	Long-term contracts.	Transaction dimensions/Frequency	WILLIANSOM (1985); FARINA, AZEVEDO, SAES (1997)
TECT_11	Knowledge about one's partners	Transaction dimensions/Frequency	WILLIANSOM (1985); FARINA, AZEVEDO, SAES (1997)
TECT_12	Environment variability	Transaction dimensions/Uncertainty	WILLIANSOM (1985); FARINA, AZEVEDO, SAES (1997)
TECT_13	Lack of knowledge of future scenarios	Transaction dimensions/Uncertainty	WILLIANSOM (1985); FARINA, AZEVEDO, SAES (1997)
TECT_14	Difficulty with measuring supply chain performance	Transaction dimensions/Uncertainty	WILLIANSOM (1985); FARINA, AZEVEDO, SAES (1997)
TECT_15	Physical proximity to partners	Transaction Dimensions/ Asset Specificity/ Location Specificity	WILLIANSOM (1985); FARINA, AZEVEDO, SAES (1997); DYER (1997)
TECT_16	Ease of access to partner facilities	Transaction Dimensions/ Asset Specificity/ Location Specificity	WILLIANSOM (1985); FARINA, AZEVEDO, SAES (1997); DYER (1997)
TECT_17	Regional logistics infrastructure conditions at the factory location	Transaction Dimensions/ Asset Specificity/ Location Specificity	WILLIANSOM (1985); FARINA, AZEVEDO, SAES (1997); DYER (1997)
TECT_18	Regional logistics infrastructure	Transaction Dimensions/ Asset Specificity/ Location Specificity	WILLIANSOM (1985); FARINA,

DOI: https://doi.org/10.29327/2384439.2.4-3

	conditions at the location of the distribution center		AZEVEDO, SAES (1997) ; DYER (1997)
TECT_19	Loss of value when reusing assets acquired to serve a specific customer	Transaction Dimensions/ Asset Specificity/ Fixed Assets	WILLIANSOM (1985); FARINA, AZEVEDO, SAES (1997); DYER (1997)
TECT_20	Lag in the applied technology	Transaction Dimensions/ Asset Specificity/ Fixed Assets	WILLIANSOM (1985); FARINA, AZEVEDO, SAES (1997)
TECT_21	Mastery of new knowledge	Transaction Dimensions/ Asset Specificity/ Fixed Assets	WILLIANSOM (1985); FARINA, AZEVEDO, SAES (1997)
TECT_22	Employee training due to a new contract	Transaction Dimensions/ Asset Specificity/ Human Assets	WILLIANSOM (1985); FARINA, AZEVEDO, SAES (1997)
TECT_23	Employee hire due to a new contract	Transaction Dimensions/ Asset Specificity/ Human Assets	WILLIANSOM (1985); FARINA, AZEVEDO, SAES (1997); DYER (1997)
TECT_24	Return on investments made to fulfill a specific contract	Transaction Dimensions/ Asset Specificity/ Dedicated Assets	WILLIANSOM (1985); FARINA, AZEVEDO, SAES (1997); DYER (1997)
TECT_25	Value of one's brand when producing a contract	Transaction Dimensions/ Asset Specificity/ Brand Specificity	WILLIANSOM (1985); FARINA, AZEVEDO, SAES (1997)
TECT_26	Brand strength in the market	Transaction Dimensions/ Asset Specificity/ Brand Specificity	WILLIANSOM (1985); FARINA, AZEVEDO, SAES (1997)
TECT_27	Delivery time of products to customers	Transaction Dimensions/ Asset Specificity/ Time Specificity	WILLIANSOM (1985); FARINA, AZEVEDO, SAES (1997)
TECT_28	Product obsolescence	Transaction Dimensions/ Asset Specificity/ Time Specificity	WILLIANSOM (1985); FARINA, AZEVEDO, SAES (1997)
TECT_29	Perishability of the product	Temporal specificity	WILLIANSOM (1985); FARINA, AZEVEDO, SAES (1997)
TECT_30	Product obsolescence	Temporal specificity	WILLIANSOM (1985); FARINA, AZEVEDO, SAES (1997)

Source: the author.

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Table 5: Measures on *machine learning*

Code	Measure	Keyword	Author
ML_1	Sorting ability	Representation	DOMINGOS (2012); SMITH (2018)
ML_2	Error rate	Assessment	DOMINGOS (2012); SMITH (2018)
ML_3	Optimal response	Optimization	DOMINGOS (2012); SMITH (2018)
ML_4	Lack of human interface	Unsupervised	DOMINGOS (2012); SMITH (2018)
ML_5	Human interface degree	Supervised	DOMINGOS (2012); SMITH (2018)
ML_6	Correlations between variables	Supervised	DOMINGOS (2012); SMITH (2018)
ML_7	Data mass classification	Supervised	DOMINGOS (2012); SMITH (2018)
ML_8	Pattern recognition	Supervised	DOMINGOS (2012); SMITH (2018)

Source: the author.

Table 6: assertions on supply chain performance

Code	Measure	Keyword	Author
SCP_1	Correct delivery of the product	Quality	SRIYAKUL, PRIANTO E JERMSITTIPARSERT (2019)
SCP_2	Compliance with the request	Quality	SRIYAKUL, PRIANTO E JERMSITTIPARSERT (2019)
SCP_3	Product cycle time	Speed	SRIYAKUL, PRIANTO E JERMSITTIPARSERT (2019)
SCP_4	Degree of customization	Flexibility	SRIYAKUL, PRIANTO E JERMSITTIPARSERT (2019)
SCP_5	Reduction of logistics costs	Costs	SRIYAKUL, PRIANTO E JERMSITTIPARSERT (2019)
SCP_6	Delivery to agreed location	Reliability	SRIYAKUL, PRIANTO E JERMSITTIPARSERT (2019)
SCP_7	Service in the correct quantity	Reliability	SRIYAKUL, PRIANTO E JERMSITTIPARSERT (2019)
SCP_8	Deliver products on the promised date	Reliability	SRIYAKUL, PRIANTO E JERMSITTIPARSERT (2019)

Source: the author.

Table 7: assertions on company performance

Code	Measure	Keyword	Author
PO_1	Market share	Market share	QRUNFLEH; TARAFDAR (2014)
PO_2	Level of return on investments in structure	ROI	QRUNFLEH; TARAFDAR (2014)
PO_3	Level of return on equipment investments	ROI	QRUNFLEH; TARAFDAR (2014)
PO_4	Present growth in the percentage of market share in which it operates	Market share growth	QRUNFLEH; TARAFDAR (2014)
PO_5	Increase the level of return on investments in structure	Investment return growth	QRUNFLEH; TARAFDAR (2014)
PO_6	Increase the level of return on investments in equipment	Investment return growth	QRUNFLEH; TARAFDAR (2014)
PO_7	Increase the company's profit margin	Profit margin on sales	QRUNFLEH; TARAFDAR (2014)
PO_8	Better results compared to competitors' performance.	Global competitive position	QRUNFLEH; TARAFDAR (2014)

Source: the author.

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4.3 Profile Of Questionnaire Respondents

The roles of the 121 respondents are distributed as follows: analysts (35.9%) and supervisors (16.3%); directors (15.2%), managers (12.0%) and CEOs (5.4%), ensuring a balance between tactical-operational and strategic views.

Regarding the training of managers, there was a predominance of professionals from technical areas, such as engineering, logistics and information technology.

Other points questioned referred to time in the role and time in the company. Both presented high proportions for periods over 5 years: 41.3% in the company and 55.4% in the function. Between 2 and 5 years in the role represented 25% of respondents and in the company 28.3%. Those who responded that they had been with the company for less than 2 years represented 30.4% and 19.6% in the role.

Regarding the source of the company's capital, 53.3% are multinationals and 46.7% are national. The segments in which they operate are diverse, the three main ones being: Logistics, Consulting and projects/civil construction.

The question about the characteristics of the company's product accepted more than one answer. Thus, the results were:

- 58 respondents indicated demand for each type of final product varies quickly.
- 14 respondents indicated that the time to launch the new product on the market is very short.
- 77 respondents indicated that the volume of each type of final product is very high.
- 5 respondents indicated that the process technology has a very short life cycle.
- 34 respondents indicated that the range for introducing new products is too short.

Regarding market time, 87% of respondents indicated that companies have been operating for more than 5 years, 4.3% between 2 and 5 years and 8.7% of companies have been operating for less than 2 years. Large companies predominated, both in terms of size (number of employees) and revenue (Figures 15 and 16).

Regarding the use of machine learning, 35.9% of respondents indicated that companies have been using it for more than 3 years, while 35.9% between 1 and 3 years and 28.3% of companies have been using it for less than 1 year. Regarding the type of machine learning, 85.9% of responses indicated that companies use the supervised type, 7.6% reinforcement and 6.5% unsupervised. The most used platform is Microsoft, followed by Google.

Regarding the question about the use of machine learning, there could be multiple answers, and the main ones were:

- Supplier evaluation was mentioned 11 times.
- Customer rating, 20 times.
- Classification of materials, 15 times.

DOI: https://doi.org/10.29327/2384439.2.4-3

- Production scheduling, 36 times.
- Transport management, 29 times.
- Load optimization, 35.
- Inventory optimization, 47.
- Distribution planning, 42.
- Demand forecast, 84 times.
- Production scheduling, 58.

The applications standing out in the use of machine learning are those of an operational nature, such as load and inventory optimization, production scheduling and transport management. Aspects linked to the company's external environment, such as supplier evaluation, customer classification and customer support appear in smaller numbers, indicating a predominance of the use of machine learning aimed at the company's internal operations.

4.1 Exploratory Factor Analysis (EFA)

Exploratory factor analysis (EFA) was carried out on the completed questionnaires. The authors add that factor analysis is a statistical approach used to analyze interrelationships between many variables and explain them according to their common inherent dimensions, called factors or main components, so that there is a minimum loss of information. In this principal components analysis, the scores were saved so that in the second stage they could be used to measure the second-order latent variables, using the SmartPLS 4.0 software.

Therefore, an exploratory factor analysis (EFA) was carried out to identify the formation of factors for each construct. There was no unfilled data in the responses, so there was no need to use any technique to fill in the blanks. The extraction method used was that of the main components.

Engevalues or eigenvalues that present results greater than 1 indicate that the variables are significant. 'Commonalities' is the total amount of variance that an original variable shares with all other variables included in the analysis (HAIR et al, 2015).

4.4.1 EFA of the SSCO Construct

When performing the EFA of the supply chain strategic orientation construct, the result of the KMO/MAS coefficient (measure of sample adequacy) was 0.686, above 0.5, indicating that the sample is adequate. (HAIR et al., 2005). The variables were grouped into 5 factors, which have an average extracted variance of 71.87%.

- The factors grouped the variables as follows:
- SSCO_Flexibility: SSCO_4, SSCO_6, SSCO_12, SSCO_14 and SSCO_16;
- SSCO_IT Use: SSCO_7, SSCO_8, SSCO_9 and SSCO_10;
- SSCO_Long-term_Relationship: SSCO_3, SSCO_11, SSCO_17 and SSCO_18;
- Factor 4 (removed): SSCO_5, SSCO_13, SSCO_15;

DOI: https://doi.org/10.29327/2384439.2.4-3

- Factor 5 (removed): SSCO_1 and SSCO_2

Factor 4 was removed because the loadings of SSCO_15 and SSCO_13 were below 0.6. Factor 5 was removed because it is made up of only 2 variables (SSCO_1 and SSCO_2) and has a concentration of responses 4 and 5 (Figure 20). Cronbach's alpha values are greater than 0.7, which, according to Hair et al. (2005), is the minimum acceptable value.

The SSCO_Flexibility score presented a KMO of 0.822, therefore it is an adequate sample. The total variance extracted was 70.3%, forming a single factor, with all loadings greater than 0.6. Cronbach's alpha is 0.892, a high reliability.

The SSCO_Uso_de_TI score is formed by the variables SSCO_9, SSCO_7, SSCO_8 and SSCO_10. It was also consistent, with KMO of 0.705, average variance extracted of 62.058%, all loadings greater than 0.6 and Cronbach's alpha equal to 0.792 (Appendix G).

The third factor (Long-term relationship) is formed by the variables SSCO_17, SSCO_3, SSCO_18 and SSCO_11, with KMO of 0.710, average variance extracted of 67.861%, all loadings greater than 0.6, Cronbach's alpha equal to 0.840 (Appendix G).

4.4.2 EFA of the TECT Construct

For the construct of transaction cost economics theory, the KMO found was 0.635, indicating that the sample is adequate. The average responses for the 30 variables presented values above 3, indicating a tendency to agree with the statements.

The average variance extracted was 75.622%, with 8 components, with Cronbach's alpha of 0.916. The scores formed were:

- TECT_Post_Costs: TECT_10, TECT_12, TECT_4, TECT_20, TECT_11;
- TECT_Uncertainty: TECT_14, TECT_13 and TECT_30;
- TECT_Location: TECT_18, TECT_17, TECT_7;
- TECT_Opportunism: TECT_6, TECT_9 and TECT_26;
- Factor 5 (disregarded due to the low TECT_16 and TECT_25 loads): TECT_27, TECT_16 and TECT_25;
- TECT_Knowledge: TECT_3, TECT_22, TECT_28, TECT_23;
- Factors 7 and 8: disregarded due to the low loads found.

For the TECT_Costs_post score, the results were: KMO of 0.809, average variance extracted of 57.717%, all loadings above 0.6, Cronbach's alpha equal to 0.812. The TECT_Uncertainty score presented a KMO of 0.610, average variance extracted of 73.899%, all loadings above 0.6 and Cronbach's alpha equal to 0.710. The TECT_Location score presented a KMO of 0.674, average variance extracted of 79.460%, all loadings above 0.6 and Cronbach's alpha equal to 0.736. For the TECT_Opportunism score, the KMO value was 0.668, average variance extracted was 67.341%, all loadings greater than 0.6 and Cronbach's alpha of 0.757. The TECT_Knowledge score had a KMO of 0.767, average variance extracted of 64.080%, loadings greater than 0.6 and Cronbach's alpha of 0.804.

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4.4.3 EFA of the ML Construct

The avarage of the variables that make up the machine learning construct are all above 3, indicating a tendency to agree with the statements. The KMO sample adequacy measure is 0.862, they were grouped into one factor, with an average variance extracted of 63.432%. All variables had loads greater than 0.6, therefore, no variables were discarded. Cronbach's alpha was 0.912.

4.4.4 SCP EFA

In the case of the supply chain performance construct, the averages also presented values greater than 3, with a KMO of 0.820, according to the results presented in appendix G, with 2 factors with an average variance extracted of 75.542%. Cronbach's alpha is 0.899 and the groupings (scores) of the variables were as follows:

- SCP_Reliability: SCP_6, SCP_5, SCP_7 and SCP_8;
- SCP_Customization: SCP_1, SCP_2, SCP_3 and SCP_4.

The SCP_Reliability score presented a KMO of 0.774, average extracted variance of 75.165%, loadings above 0.6 and Cronbach's alpha of 0.883. The SCP_Customization score had a KMO equal to 0.730, the load of the SCP_4 variable, when running the EFA with all variables, was slightly below 0.6 (0.520), but it was decided to maintain it due to the small difference. The average variance extracted was 72.699%, with all loadings above 0.6. Cronbach's alpha remained high, at 0.858.

4.4.5 PO EFA

The organization performance construct presented variable average above 3, KMO of 0.790, total variance extracted of 73.264%, in two factors and Cronbach's Alpha of 0.885.

The scores were constituted as follows:

- PO_Growth: PO_8, PO_2, PO_4, PO_7 and PO_1;
- PO_Return: PO_5, PO_6 and PO_3.

The PO_Growth score had a KMO of 0.768, average variance extracted of 64.821%, loadings above 0.7 and Cronbach's alpha of 0.861. The PO_Return score presented a KMO of 0.738, average variance extracted of 86.535%, loadings above 0.9 and Cronbach's alpha of 0.922.

4.5 Hypothesis Testing

From exploratory research, through processing in the SmartPLS 4.0 software, the direct relationships between the constructs strategic supply chain orientation (SSCO), transaction cost economics (TECT), supply chain performance (SCP) and organization performance (PO) were analyzed. In such model, TECT is a mediating variable between SSCO and SCP.

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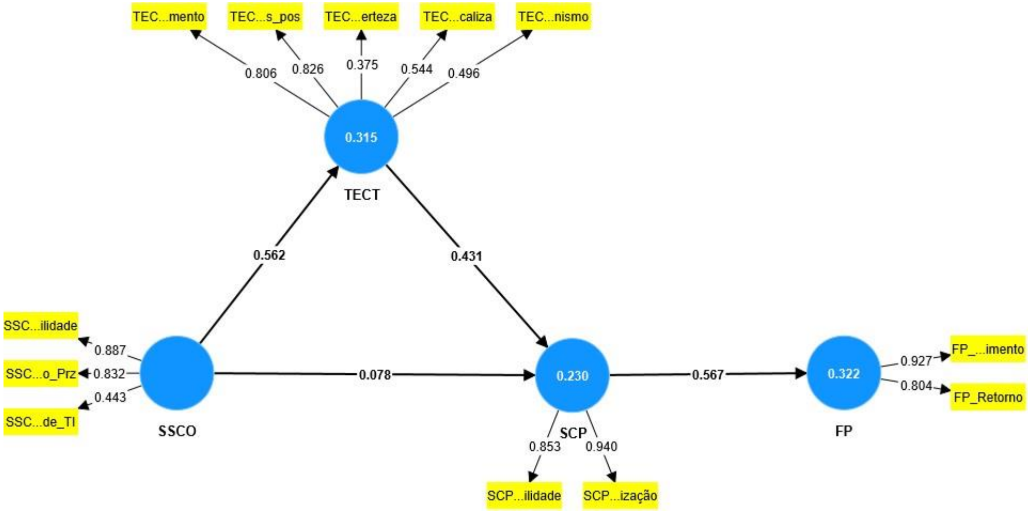
The result with the correlation coefficients for Model 1 was presented in Figure 4.

Figure 4: Correlations between the constructs



Source: the author.

Model 1 indicators are factor scores, as described in the EFA. The correlation between TECT and the TECT_opportunism, TECT_Location and TECT_Uncertainty scores presented values below 0.6, but these were maintained because the variables that compose them presented high loadings. The latent variables presented values above 0.6 in the measurement evaluation and greater than the values of the correlations between the dimensions, according to the Fornell-Larcker criterion.

Cronbach's alphas presented the following values: 0.686 for the PO construct, 0.767 for SCP, 0.583 for SSCO and 0.616 for TECT. Despite the value for SSCO being below 0.6, it was accepted due to proximity and acceptance by the Fornell-Larcker criterion, previously described. The adjusted R^2 coefficients were 0.316 for PO, 0.217 for SCP and 0.310 for TECT.

Figure 5 shows the result of the bootstrap calculation for Model 1. With the exception of the connection between SSCO and SCP (p-value=0.509), all were significant. Likewise, the specific indirect effects on PO, with the exception of SSCO and SCP, were significant.

In Figure 6, Model 2 is presented with the inclusion of the moderating variable ML (machine learning) between the relationships between SSCO and TECT, SSCO and SCP, and TECT and SCP.
Cronbach's alphas presented values above 0.6, with the exception of SSCO, with a value slightly below (0.583), accepted due to the proximity and high loadings of its variables. In the same way as model 1, the latent variables presented values above 0.6 in the measurement evaluation and greater than the values of the correlations between the dimensions, according to the Fornell-Larcker criterion. The VIF (collinearity) values were below 2 for the scores.

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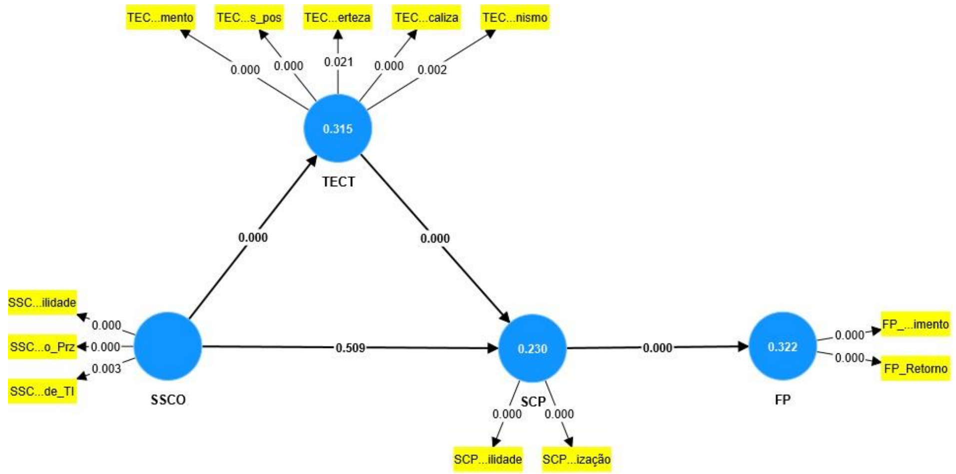
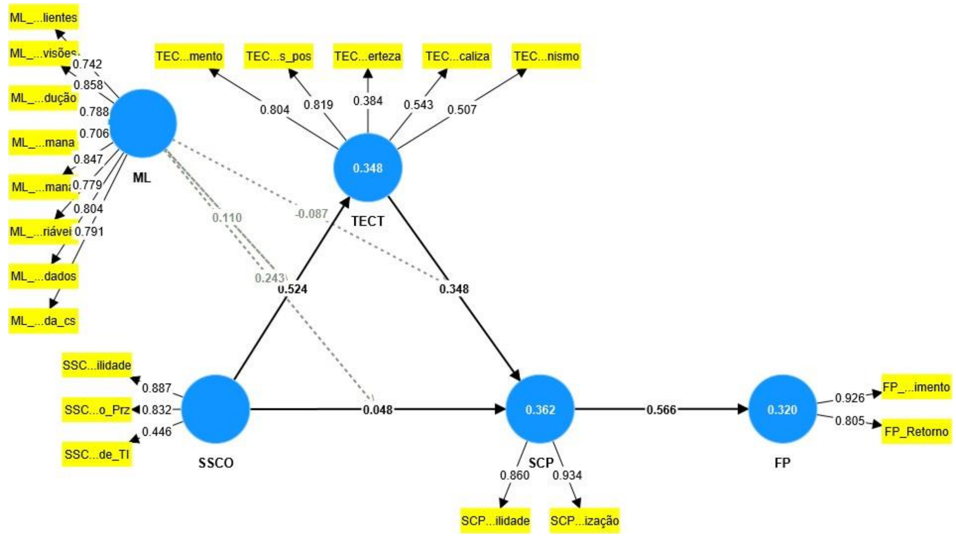
Figure 5: Model 1 Bootstrap



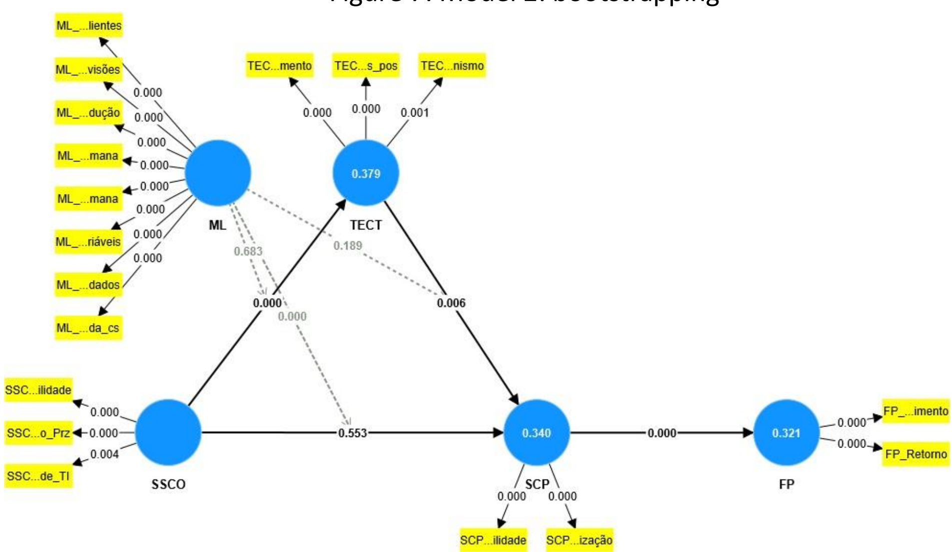
Source: the author.

Figure 6: Model 2: inclusion of the ML moderating variable



Source: the author.

Figure 7: Model 2: bootstrapping



Source: the author.

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The Model 2 bootstrap (Figure 7) was run 10,000 times, with p-value<0.01. Analysis of the specific indirect effects on PF which, with the exception of the SSCO-SCP relationship (p-value=0.517), present a significant relationship (p-value<0.05). The discriminant validity according to the Fornell-Larcker criterion for the ML construct was 0.791, whereas the others remained unchanged. Comparing the two models, based on the adjusted R^2 results, we obtained:

- For the TECT construct: an increase of 6.77% (from 0.31 to 0.331);
- For the SCP construct: an increase of 54.38% (from 0.217 to 0.335)
- For the PO construct: no change. (0.316).

It was noticed that with a strong use of machine learning, aligned with the strategic direction of the supply chain, the chain performance increases, while it decreases with the reduction of its use. The impact of using machine learning on reducing transaction costs based on the chain's strategic orientation showed similar behavior regardless of the level of use, as shown in Figure 30. The impact of using machine learning on chain performance based on Transaction costs also showed similar behavior regardless of the level of use, that is, it increases the chain's performance.

Responding to the hypotheses of this study:

- H1: The use of machine learning positively moderated the relationship between supply chain orientation and the reduction of transaction costs. Regardless of the degree of use of machine learning, transaction costs were reduced. The increase in the adjusted R^2 coefficient also corroborates the hypothesis.
- H2: The use of machine learning positively moderated the relationship between supply chain orientation and supply chain performance. The results showed that, although the relationship is not significant, chain performance increases with more intense use of machine learning. The hypothesis was accepted.
- H3: The use of machine learning positively moderated the relationship between transaction cost reduction and supply chain performance. Similarly to H1, the hypothesis was accepted, regardless of the level of machine learning use.
- H4: Supply chain performance positively influenced company performance. The models showed that the connection between chain performance and company performance was significant and that there was a correlation between the constructs. The hypothesis was accepted.

Therefore, the hypotheses were accepted, for they demonstrate the impact of machine learning on the constructs and their relationships, bringing gains to the company.

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5. CONCLUSION

Technological advances bring changes to companies in terms of their processes, strategies, relationships with their supply chain partners, and market share. This paper proposed to study the impact of supply chain performance on organizational performance based on the application of machine learning in the relationships between the existing links in this chain, considering the economy of transaction costs as a mediating variable between the chain's orientation supply chain performance. The construct scales, created as a result of bibliographic and qualitative research (interviews with managers), proved to be suitable for the quantitative stage. It has been demonstrated that there is a relationship between these performances, and that the use of machine learning affects this relationship.

As for the specific objectives, they were achieved, as follows:

- The characteristics of the types of machine learning were identified from the answers obtained through the questionnaires.
- In the same way, machine learning applications in the supply chain were identified.
- Study of the use of machine learning according to the strategic alignment of the supply chain.
- It was identified that the results in supply chain performance management from the use of machine learning are more of an internal nature, since the applications refer to planning and scheduling activities of internal activities.

Hypotheses H1, H2, H3 and H4 were confirmed, as the use of machine learning presents positive moderating effects on the relationship between the constructs. Despite the non-significant relationship between supply chain strategic orientation and supply chain performance, performance has been shown to be impacted by the use of machine learning.

The original questionnaire variables linked to the transaction costs of opportunism and uncertainty, which were grouped into scores, presented low loadings, but were maintained due to the original variables presenting high loadings. Issues linked to opportunism (costs of correcting subsequent misalignment, lack of rational response), fixed assets (technological lag, loss of value when reusing assets), time specificities (product obsolescence), rationality (variance of possible results) and locational specificity (physical proximity to partners) were retained because they present low loads. This result aligns with the statements of interviewees who indicated that these issues do not occur in their relationships with supply chain partners, since contracts are meticulously constructed by lawyers, who pursue rationality without using machine learning. , there is no room for this type of behavior. Regarding location specificity, its removal can be explained by the fact that the companies in which the interviewees work participate in global chains and, therefore, distances and response times are already factors considered in their planning.

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5.1 Implications of the Study

The proposed model helps managers understand the impacts of using machine learning on supply chain processes. The identified variables demonstrate the concern to serve customers mainly through internal activities, such as product customization, cost reduction and extended activities such as product delivery, aiming for a return on investments made.

In relation to the supply chain, both in relation to strategic orientation and performance, there was no clear division between the assertions related to the agile chain and the lean chain. In the SSCO_Flexibility score, the variable SSCO_4 (speed of response to changes in the environment) appears, as well as the mixed variable SSCO_16 (certain degree of product customization according to customer needs) together with the agile chain variables SSCO_14 (Customizes products), SSCO_6 (Offers differentiated products) and SSCO_12 (Establishes a relationship based on trust with the customer).

The SSCO_Use_of_TI score remained with variables belonging to the agile orientation: SSCO_9 (Uses IT to coordinate production), SSCO_7 (Uses IT to integrate and coordinate the supply chain), SSCO_8 (Uses IT to coordinate projects) and SSCO_10 (Uses IT for the development of new products).

The SSCO_Long-Term_Relationship score again presents a mixed composition: the mixed variables SSCO_17 (Planning based on demand forecasts and contracts already signed) and SSCO_18 (Planning based on demand forecasts and orders already signed); the lean variable SSCO_3 (Seeks to maintain a long-term relationship with suppliers); and the agile variable SSCO_11 (establishes a relationship based on trust with suppliers).

Another issue was the length of time using machine learning, with 64.1% of respondents using it for a maximum of 3 years. This short period means that companies are still starting applications in their processes, not extending to other areas or not yet realizing the full potential of the tool.

5.2 Study Limitations

The number of respondents obtained reflected the difficulty of finding professionals who use machine learning in the management of supply chain activities or, as claimed by 3 professionals contacted, who would not respond for EFAr of exposing their companies' confidential information, even with the guarantee of confidentiality in the dissemination of data and analyses.

The number of professionals contacted and who did not return was large, even with repeated sending of response requests. This also reflected the difficulty in studying a specific segment, opting to make the cut in professionals who work in areas of operations linked to supply chains.

5.3 Future Study Proposals

As a continuation of this study, a machine learning model will be developed that represents the theoretical model resulting from quantitative research and that

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serves for didactic use to demonstrate to students the relationships between these constructs. To this end, Microsoft's Azure software or DataRobots can be used, whichever is more viable in terms of availability and user-friendliness.

The second proposal is to write articles that explore the data obtained by the research and with bibliographical updating, with different crossings from those presented in this thesis, such as separating by company size, segment, type of machine learning used, which will be produced for presentation at conferences and possible publications in journals.

The third proposal is to deepen the research, focusing on the variables that did not make up the model, seeking to understand their relationships with the other variables and what their impacts are on the result of organizational performance.

The fourth line of future research is to understand the technological advancement of machine learning and its impact on the performance of supply chains, given the rapid advances that this and other tools have been presenting.

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