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SÃO CARLOS SCHOOL OF ENGINEERING
DEPARTMENT OF PRODUCTION ENGINEERING**

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**The relationship between supply chain performance and organizational
culture: a fuzzy grey cognitive maps based decision model**

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The relationship between supply chain performance and organizational culture: a fuzzy grey cognitive maps based decision model

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“Não chores, meu filho;

Não chores, que a vida

É luta renhida:

Viver é lutar.

A vida é combate,

Que os fracos abate,

Que os fortes, os bravos

Só pode exaltar.”

Canção do Tamoio – Gonçalves Dias

RESUMO

ZANON, L. G. **Relacionamento entre o desempenho da cadeia de suprimentos e cultura organizacional: modelo decisório baseado em *fuzzy grey cognitive maps***. 2020. 179 f. Dissertação (Mestrado) – Escola de Engenharia de São Carlos, Universidade de São Paulo, São Carlos, 2020.

Compreender a relação entre o desempenho da cadeia de suprimentos e cultura organizacional pode ajudar a prever cenários e melhorar o processo decisório. No entanto, essa relação é raramente explorada devido à complexidade de se abordar quantitativamente sua inerente subjetividade. Embora a utilização de técnicas de *soft computing* tenha o potencial de contornar essa dificuldade, elas raramente são aplicadas a esse contexto. Portanto, este estudo tem como objetivo desenvolver um modelo de decisão em grupo para analisar e quantificar a relação causal entre cultura organizacional e desempenho da cadeia de suprimentos com base na combinação de *fuzzy grey cognitive maps*, *grey clustering* e múltiplos sistemas de inferência *fuzzy*. Esta aplicação não é encontrada na literatura e, por isso, pode prover novas perspectivas teóricas e práticas. O desenvolvimento desta pesquisa é baseado nos atributos de desempenho do modelo SCOR® (*Supply Chain Operations Reference*) (SCC, 2017) e nas práticas organizacionais de Hofstede (2001). A principal contribuição é a introdução de um modelo de tomada de decisão em grupo multicritério que promove o alinhamento entre cultura organizacional e a gestão de cadeias de suprimentos, internalizando a cultura como um direcionador para os esforços de melhoria de desempenho. Outra contribuição é a integração das técnicas *fuzzy grey cognitive maps* e *grey clustering*, também inédita na literatura, aumentando a confiabilidade dos resultados e a velocidade de execução por meio da redução das entradas necessárias ao usuário e do nível de dados imprecisos no modelo computacional. Com a realização de duas aplicações reais em empresas de diferentes setores industriais, os resultados mostram que o modelo é capaz de identificar elementos cruciais em relação ao perfil cultural e ao desempenho de ambas as organizações, auxiliando na priorização, antecipação e viabilizando o desenvolvimento de diretrizes para planos de ação.

Palavras-chave: gestão de desempenho da cadeia de suprimentos; cultura organizacional; tomada de decisão em grupo; *fuzzy grey cognitive maps*; *grey clustering*; inferência *fuzzy*.

ABSTRACT

ZANON, L. G. **The relationship between supply chain performance and organizational culture: a fuzzy grey cognitive maps based decision model.** 2020. 179 p. Dissertation (Master's Degree) –Sao Carlos School of Engineering, University of Sao Paulo, Sao Carlos, 2020.

Assessing the relationship between supply chain performance and organizational culture can help to predict scenarios and improve decision-making. However, this relationship is rarely explored due to the complexity of quantitatively addressing its natural subjectivity. Although soft computing techniques would have the potential to overcome this limitation, they have been rarely applied to this context. Therefore, this study aims to introduce a group decision model to analyze and quantify the causal relationship between organizational culture and supply chain performance based on the combination of fuzzy grey cognitive maps, grey clustering and multiple fuzzy inference systems. Such model is novel in the literature and can provide new theoretical and practical perspectives. The development of this research is based on the SCOR[®] (Supply Chain Operations Reference) model attributes (SCC, 2017) and Hofstede's (2001) organizational practices. The main contribution is the introduction of a multicriteria group decision-making model that promotes the alignment between organizational culture and supply chain management, internalizing culture as a driver for performance improvement efforts. Another contribution is the integration of the fuzzy grey cognitive maps and grey clustering techniques, also not found in the literature, which increased results reliability by reducing the required inputs to the user and the level of imprecise data in the computational model, enhancing speed of execution. With the conduction of two real application cases in companies from different industrial sectors, results show that the model is able to identify crucial elements regarding the cultural profile and performance of both organizations, aiding prioritization, anticipation and enabling the development of guidelines for action plans.

Keywords: supply chain performance management; organizational culture; group decision-making; grey clustering; fuzzy grey cognitive maps; fuzzy inference.

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LIST OF ABBREVIATIONS AND ACRONYMS

AE - Academic Expert
 AC - Active Customers
 AHP - Analytic Hierarchy Process
 AI - Alignment Index
 CTWF - Center-Point Triangular Whitenization Weight Functions
 CTO - Chief Technical Officer
 CM - Cognitive Maps
 CVF - Competing Values Framework
 DEMATEL - Decision-Making Trial and Evaluation Laboratory
 DM - Decision-Maker
 ERM - Enterprise Relationship Matrix
 FCM - Fuzzy Cognitive Map
 FGCM - Fuzzy Grey Cognitive Map
 FGMAGDM - Fuzzy Grey Multi-Attribute Group Decision-Making
 FIS - Fuzzy Inference Systems
 GRM - General Relationship Matrix
 GRA - Grey Relational Analysis
 GC - Grey Clustering
 GST - Grey Systems Theory
 IEEE - Institute of Electrical and Electronics Engineers
 IGRA - Improved Relational Analysis
 IT - Information Technology
 KPI - Key Performance Indicator
 MOORA - Multi-Objective Optimization on The Basis of Ratio Analysis
 MCDM - Multi Criteria Decision-Making
 MCGDM - Multi-Criteria Group Decision-Making
 NPS - Net Promoter Score
 OCP - Organizational Culture Profile
 OP - Organizational Practice
 PVT - Price/Volume Tendency
 SCC - Supply Chain Council
 SCOR® - Supply Chain Operations Reference
 SCM - Supply Chain Management
 TOPSIS - Technique for Order of Preference by Similarity to Ideal Solution

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1. INTRODUCTION

This chapter presents a contextualization of the research theme and the research gaps (section 1.1), the research questions and objectives (section 1.2), contributions (section 1.3), the research procedure (1.4), the dissertation structure (section 1.5) and the cited references (section 1.6).

1.1 CONTEXTUALIZATION AND RESEARCH GAPS

In an era where competition occurs not between firms but between supply chains, companies need to be able to manage and understand organizational culture, as well as its role in supply chain performance (PORTER, 2019). This is justified since several studies sustain that organizational culture significantly influences operational results (CADDEN; MARSHALL; CAO, 2013). In fact, leaders with a vision of their firm's cultural orientation proofed to have more success, creating customer value and improving performance by efficiently aligning intra-and inter-firm activities (MELLO; STANK, 2005). Moreover, Whitfield and Landeros (2006) suggested that cultural consistency and cultural understanding within the supply chain added to the implementation of successful strategies.

A supply chain can be defined as an integrated process network in which several business entities (for example, suppliers, manufacturers, distributors and retailers) work together around a focus company to acquire raw materials, convert those raw materials into products and deliver these products to retailers or end customers, with materials flowing from suppliers to customers and information from customers to suppliers (BEAMON, 1998).

Supply chain management (SCM) involves the integration of managerial practices, definition of common goals and sharing of both risks and results to create and maintain long-term cooperative relationships (SWEENEY, 2011). The SCM main objective is to maximize global value, meeting customer needs by implementing a coherent competitive strategy, producing and distributing goods in the correct quantity and delivering them in the specified location, agreed conditions, in a sustainable manner (CHOPRA; MEINDL, 2003). However, when there is a misalignment between SCM practices and organizational culture, companies may not achieve their integration goals and desired performance improvements (CAO et al., 2015).

Therefore, performance management is vital in supply chains to ensure agility and assertiveness in decision-making as there is often a misconnection between the strategies of the component organizations in the chain (BALFAQIH et al., 2016). According to Porter (2019), culture impacts supply chain performance since it is determinant for organizational alignment and for the establishment of lasting supply relationships. In this direction, Roh et al. (2008) highlight the importance of aligning organizational culture and strategic practices through the difference in productivity between North American and Japanese companies.

Aiman-Smith (2004) states that only qualitative or quantitative approaches are not sufficient to analyze the role of culture within an organization. According to the author, a combination of methods can contribute more to managers, uniting the ability to capture perceptions and experiences from the qualitative approach with the reliability of weighting numerical data from the quantitative approach. Thus, assessing organizational culture through questionnaires and interviews allow to qualitatively understand it. Moreover, applying a technique to map culture quantitatively has the advantage of allowing managers to analyze it as a manageable component.

In this research, the SCOR[®] (Supply Chain Operations Reference) model, developed by the Supply Chain Council, is used as reference for addressing supply chain performance. This is justified since it provides a systematic method that can be used by any organization (DISSANAYAKE; CROSS, 2018) and enables benchmarking performance (LIMA-JUNIOR; CARPINETTI, 2019). In a comparative study with other supply chain performance assessment models, the SCOR[®] model has met the majority of the considered criteria (ESTAMPE et al., 2013). On the other hand, for analyzing culture in organizations, this research uses the Hofstede's (2001) organizational practices. This is justified since, according to Cadden, Marshall and Cao (2013), it should be possible to deconstruct organizational culture into tangible elements to understand its impact on performance. In this way, each of the organizational practices represents culture deconstructed in determinant aspects.

However, the evaluation of this culture-performance relationship is also affected by the presence of multiple experts, which are required to subjectively assess various aspects with scarce information (HAJEK; FROELICH, 2019). To deal with this matter, the computational processing of human language is highly recommended (ZADEH, 1999). Among the computing with words techniques, according to Lima Junior, Osiro and Carpinetti (2013), soft computing stands out in most applications related to multicriteria decision-making.

In a literature review conducted by Zanon and Carpinetti (2018) in the Scopus, Web of Science, Emerald, IEEE Xplore® databases with the strings “supply chain” AND “performance” AND “organizational culture”, few papers were found that quantitatively analyze the relationship between supply chain performance and culture (HULT; KETCHEN; ARRFELT, 2007; CADDEN; MARSHALL; CAO, 2013; ALTAY et al., 2018; DUBEY et al., 2019). In addition, no study was found applying soft computing techniques in a decision model for analyzing the influence of organizational culture over supply chain performance.

Three soft computing techniques were selected due to their capabilities for addressing this research topics. Fuzzy grey cognitive maps (FGCMs) have been specifically developed to quantify causal relationships as well as to deal with subjectivity, uncertainty, hesitancy and multiple means environments (SALMERON; PAPAGEORGIOU, 2012). Therefore, FGCMs were chosen for analyzing how culture impacts supply chain performance. In addition, the grey clustering (GC) technique, also developed to handle causalities (DELGADO; ROMERO, 2016), was used as a mean to reduce the amount of required judgments by the decision-makers and also to generate more accurate outputs for the FGCM. Finally, the fuzzy inference system (FIS) was applied due to its potential for handling nonlinear relationships between input and output variables (POURJAVAD; SHAHIN, 2018) and also due to its capacity of modeling human reasoning through fuzzy if-then rules (KHAN et al., 2018).

Therefore, regarding the state of the art, four significant gaps were identified that justify the execution of this research. The first one refers to the scarcity of studies that quantitatively analyze the influence of organizational culture over supply chain performance (DUBEY et al., 2019). The second gap refers to the lack of multicriteria decision-making techniques applied to this context, especially considering group decision. The third gap refers to the absence of studies with real application cases of soft computing techniques to map the causal relationship between culture and performance. Finally, can also be considered a research gap the still unexplored potential of combining three of these techniques (GC, FGCM and FIS) to handle experts' subjectivity when assessing multiple criteria under uncertainty.

Figure 1.1 illustrates the four gaps and also their intersections, which consist in novel opportunities addressed by this research. For example, there is no record in the literature of GC, FGCM and FIS use in a single group decision-making model. Considering this scenario and the fact that no study was found considering all the topics in Figure 1.1, this research also provides new perspectives by addressing culture and supply chain performance in an interdisciplinary

and integrative way. In addition, this is the first research to combine the use of SCOR[®] performance attributes (SCC, 2017) and Hofstede's (2001) organizational practices to investigate the culture-performance dynamics in supply chains.

Figure 1.1 - Research gaps.

Source: own authorship.

1.2 RESEARCH QUESTION AND OBJECTIVE

Considering the previously arguments and research gaps, the question that motivates the execution of this study is: “How to map and quantify the causal relationships between organizational culture and supply chain performance?”. To enlighten how this broad question will be addressed, it can be unfolded into three specific questions:

- I. How are soft computing techniques being applied in the supply chain management context and what is the state of the art regarding the interface between supply chain performance and organizational culture?
- II. How to combine soft computing and multicriteria decision-making techniques in a decision model that maps the causal relationships between culture and performance?
- III. How to reduce the burden of excessive judgments by decision-makers?

Therefore, in an attempt to answer these questions, the objective of this research is to propose the combination of GC, FGCM and FIS techniques to map and quantify the causal relationship between organizational culture factors and supply chain performance.

This objective can be divided into the following specific objectives:

- I. To review the state of the art regarding supply chain performance management, organizational culture and soft computing applications to these contexts;
- II. To combine GC and FGCM in a single algorithm as well as to computationally implement it along with the FIS technique;
- III. To develop a group decision-making model for mapping and quantifying the causal relationship between organizational culture and supply chain performance;
- IV. To apply the model in two companies from different industrial sectors;
- V. To analyze the obtained results as well as to evaluate research opportunities and limitations.

It is relevant to note that the pilot applications were carried out on the focus company of supply chains (GANGA, 2010). However, it is still possible to assess supply chain performance through the perspective of a focus company with the use of the SCOR[®] model, since its architecture and indicators are related to supply chain processes and to first tier suppliers and customers (LIMA JUNIOR, 2016).

1.3 CONTRIBUTIONS

This research brings contributions for both academics and practitioners, as follows.

a) For academics:

- The development of a literature review useful for guiding researchers and managers in the application of soft computing techniques to supply chain management.
- The development of a novel group decision-making model based on the SCOR[®] performance attributes (SCC, 2017) and Hofstede's (2001) organizational practices, focusing on the alignment of organizational culture and supply chain performance management.
- The identification of future research opportunities resulting from the pilot application results.

b) For practitioners:

The development of a model capable of identifying crucial elements regarding companies' profile, enabling the development of action plans to align culture and performance improvement efforts. This unfolds considering the time horizon of the model application.

- In the short term: dissemination and practical implementation of the produced academic knowledge to the corporate environment, focusing on the companies where the pilot applications will be executed.
- In the long term: to contribute so that these concepts and techniques are incorporated into the organizational routine and processes, internalizing the proposition as a part of continuous improvement initiatives.

1.4 RESEARCH PROCEDURE

The phases of the research development are illustrated in Figure 1.2. Each phase is associated to a specific objective that, in turn, is related to an expected result. In addition, this dissertation is structured in the paper collection format, which will be detailed in section 1.5. Therefore, as it can also be seen in Figure 1.2, all research phases, specific objectives and expected results are associated to developed papers.

This research is predominantly quantitative, as it will be based on the development of a model described in mathematical and computational language which uses analytical techniques to determine the numerical values of the system in question (CAUCHICK; MORABITO; PUREZA, 2010). Therefore, this research follows the quantitative axiomatic prescriptive model-based research as it discusses a quantitative model that analyzes the behavior of a system variable based on the behavior of other variables (BERTRAND; FRANSOO, 2016). In this particular case, the proposed model aims to analyze the relationship between Hofstede's (2001) organizational practices and the SCOR[®] performance attributes. Hence, it is axiomatic as it proposes a conceptual model based on the gaps identified in the literature and the opinions of experts, proposing an approach that integrates the addressed constructs. In addition, this study is prescriptive since it is focused on the development of strategies and actions to improve the results available in the literature, providing solutions for an innovative problem (BERTRAND; FRANSOO, 2016).

Figure 1.2 - Research procedure.

Source: own authorship.

The first phase consists of conducting out an exploratory literature review to investigate the state of the art regarding supply chain performance management and organizational culture, as well as identifying the recent developments exploring their interface. In addition, this first phase seeks to establish a clear understanding of soft computing techniques application for decision-making, with focus on the fuzzy set and grey system theories. The result associated with this first phase, therefore, is to build the basis for the implementation of the soft computing techniques and to strength the theoretical foundations for the development of the decision-making model by identifying how the organizational practices and the SCOR[®] performance attributes can be connected.

The second phase consists on the process of modeling and computationally implementing the soft computing techniques. This will firstly consist in combining GC and FGCM, which is computationally advantageous, and afterwards implementing the FIS technique in a single computational model. This will be followed by exhaustive execution, testing and corrections. Thus, the expected result associated with this second phase is the development of a MATLAB[®] application over which the group decision-making model will function.

The third phase consists on structuring the decision model and in the conduction of two pilot applications in companies from different industrial sectors and supply chains, with the aim of verifying the model behavior in practice and its robustness. It is expected that the results will also encourage future applications in supply chains of diverse competitive strategies (lean, demand driven, agile). The expected result, therefore, consists on the quantitative assessment of the causal relationships between organizational culture and supply chain performance for both companies as well as on the analysis of the obtained information for leveraging improvement initiatives.

Finally, the fourth phase consists of addressing the results in order to assess the advantages and limitations of the research proposition, as well as identifying future research opportunities.

The materials needed to carry out this research are exclusively computational tools. The MATLAB[®] software was used for computational implementation of the techniques and the Microsoft Excel[®] software was applied for the results analysis.

1.5 DISSERTATION STRUCTURE

Duke and Beck (1999) argue that the traditional form in which dissertations are written has some limitations, such as the lack of accessibility, the limited audience to which they are intended, as well as their structure and extension that require changes for publication. The authors therefore suggest an alternative structure, in which the dissertation is composed by a collection of papers.

In this structure, the papers that compose the collection are associated with the dissertation specific research questions and objectives. Therefore, each paper is sufficient as an independent piece of knowledge and in parallel is connected to a logical line that leads the investigation of the dissertation research theme as a whole. In this dissertation the research question is unfolded into three specific questions, which are associated to one or more papers that seek to answer them. The dissertation objective, originated from the research question, is divided into five specific objectives, which are also associated to the papers, as Figure 1.2 shows.

Barbosa (2015) details some advantages of structuring the dissertation in the form of a paper collection, which justify the choice for this format: the researcher is required to develop important skills, such as the ability to select journals, prepare manuscripts in accordance with the journal rules and, thus, exercise the synthesis ability without losing content consistency. In addition, the author mentions that other important advantage of the paper collection format is the potential of results dissemination, which are more visible and available to the scientific community after publication in relevant journals.

In addition, dissertations in their traditional form are usually restricted to university libraries or databases, are not always written in English and their extensive page number limits their readers to a portion of the academy. The papers, on the other hand, are written with a reduced number of pages and, when published in reputable journals, can serve the academy more broadly as well as possibly also provide interesting contributions to practitioners.

This paper collection format may however present some limitations. The first is that the fact that each article is independent of the others can give a false idea of research fragmentation. In this dissertation, this issue was addressed by writing the present introductory chapter, which describes in detail the context of the research development, the identified gaps, the research

question and objective. In addition, Figure 1.2 was also elaborated in order to illustrate how the three papers are cohesively interconnected and how they complement each other for accomplishing the dissertation purpose. Finally, the three papers results are integrated and jointly discussed in a concluding chapter. A second limitation refers to a possible overlap of content between papers. However, this impression may occur only when reading the dissertation in full, which does not happen when reading the papers individually. It should be noted that in this dissertation an effort was made to minimize content overlap and use it as a way to reinforce important research concepts, in order to increase text didactics.

It is also relevant to note that the papers that compose this dissertation were submitted to high impact journals (the case of the second and third papers) or international conferences (which is the case of the first paper) with peer review process. Therefore, in order to keep up with authorship policies, the version of the papers included in this dissertation consists in the one previous to the contributions of the editorial board and or reviewers (preprint), which modified their content and presentation.

Thus, the present dissertation is structured in five chapters.

- Chapter 1 starts by presenting a contextualization and the research gaps that will be addressed. The importance of this study is then highlighted, followed by the presentation of the research question and objective. Subsequently, the expected contributions for the academy and market are made explicit. Finally, the research procedure and its steps are detailed, along with the dissertation structure.
- Chapter 2 is associated with the first research question and with the first specific objective. It consists in the first paper of the collection, entitled: “*Fuzzy Cognitive Maps and Grey Systems Theory in the Supply Chain Management Context: a literature review and a research proposal*”. The paper presents a literature review of Fuzzy Cognitive Maps, Grey Systems Theory and Fuzzy Grey Cognitive Maps application to supply chain management. It also draws research opportunities and suggestions for further studies, especially regarding the use of FGCMs to map and quantify the causal relationship between organizational culture and supply chain performance.
- Chapter 3 is associated with the second and third research questions and with the second specific objective. It consists in the second paper of the collection, entitled: “*Combining grey clustering and fuzzy grey cognitive maps: an approach for group decision-making on cause and effect relationships*”. The paper presents a novel group decision approach

based on the combination of GC and FGCMs for assessing causal relations between criteria under uncertainty. The proposition makes it feasible to reduce the burden of excessive judgments by decision-makers, to visually represent criteria interactions, to determine the relative criteria weights considering their impact in the system and to aid the process of conducting what-if analysis for scenario simulation.

- Chapter 4 is associated with the first and second research questions and with the first, third, fourth and fifth specific objectives. It consists in the third paper of the collection, entitled: “*Exploring the relations between supply chain performance and organizational culture: a fuzzy grey group decision model*”. The paper proposes a decision model to analyze and quantify the causal relationship between organizational culture and supply chain performance based on the combination of fuzzy grey cognitive maps, grey clustering and multiple fuzzy inference systems. It also brings a literature review regarding the state of the art on the interface between organizational culture and supply chain performance. The paper presents two real application cases of the proposed model in companies from different industrial sectors. The main contribution is the introduction of a decision-making model that promotes the alignment between organizational culture and supply chain management, internalizing culture as a driver for performance improvement efforts
- Chapter 5 is also associated with the fifth specific objective. It concludes the dissertation by relating and assessing all three papers results and contributions as well as bringing the challenges, limitations and identified future research opportunities.

1.6 REFERENCES

AIMAN-SMITH, L. What do we know about developing and sustaining a culture of innovation. **The Journal of Marketing**, v. 57, n. 1, p. 23-27, 2004.

ALTAY, N. et al. Agility and resilience as antecedents of supply chain performance under moderating effects of organizational culture within the humanitarian setting: a dynamic capability view. **Production Planning & Control**, v. 29, n. 14, p. 1158-1174, 2018.

BALFAQIH, H. et al. Review of supply chain performance measurement systems: 1998–2015. **Computers in Industry**, v. 82, p. 135-150, 2016.

BARBOSA, J. C. Formatos insubordinados de dissertações e teses na Educação Matemática. **Vertentes da subversão na produção científica em educação matemática. Campinas, SP: Mercado de Letras**, p. 347-367, 2015.

BEAMON, B. M. Supply chain design and analysis: Models and methods. **International journal of production economics**, v. 55, n. 3, p. 281-294, 1998.

BECK, N. K.; DUKE S. W. Education Should Consider Alternative Formats for the Dissertation. *Educational Researcher*, Washington, v. 28, n. 3. P. 31-36, 1999. Available in <http://scholarpractitionerexus.com/wp-content/uploads/2019/12/Duke-Beck-Dissertation-Formats.pdf>. Accessed in May 18th 2020.

BERTRAND, J. Will M.; FRANSOO, Jan C. Modelling and simulation. In: **Research methods for operations management**. Routledge, 2016. p. 306-346.

CADDEN, T.; MARSHALL, D.; CAO, G. Opposites attract: organisational culture and supply chain performance. **Supply Chain Management: an international journal**, 2013.

CAO, Z. et al. The impact of organizational culture on supply chain integration: a contingency and configuration approach. **Supply Chain Management: An International Journal**, v. 20, n. 1, p. 24-41, 2015.

CAUCHICK, P.; MORABITO, R.; PUREZA, V. **Metodologia de pesquisa em engenharia de produção**. 1. Ed. Brasil: Elsevier, 2010.

CHOPRA, S.; MEINDL, P. **Gerenciamento da Cadeia de Suprimentos: Estratégia, Planejamento e Operação**. Pearson Prentice Hall, 2003.

DELGADO, A.; ROMERO, I. Environmental conflict analysis using an integrated *grey* clustering and entropy-weight method: A case study of a mining project in Peru. **Environmental Modelling & Software**, v. 77, p. 108-121, 2016.

DIAS, A. G. Canção do Tamoio. **Portal Domínio Público: biblioteca**, 2015.

DISSANAYAKE, C. Kalpani; CROSS, Jennifer A. Systematic mechanism for identifying the relative impact of supply chain performance areas on the overall supply chain performance using SCOR[®] model and SEM. **International Journal of Production Economics**, v. 201, p. 102-115, 2018.

DUBEY, R. et al. Big data analytics and organizational culture as complements to swift trust and collaborative performance in the humanitarian supply chain. **International Journal of Production Economics**, v. 210, p. 120-136, 2019.

ESTAMPE, D. et al. A framework for analysing supply chain performance evaluation models. **International Journal of Production Economics**, v. 142, n. 2, p. 247-258, 2013.

GANGA, G. M. D. **Proposta de um modelo de simulação baseado em lógica fuzzy e no SCOR® para prever o desempenho da empresa-foco em cadeias de suprimentos**. Tese (Doutorado). Escola de Engenharia de São Carlos – Universidade de São Paulo, São Carlos, 2010.

HAJEK, P.; FROELICH, W. Integrating TOPSIS with interval-valued intuitionistic fuzzy cognitive maps for effective group decision-making. **Information Sciences**, v. 485, p. 394-412, 2019.

HOFSTEDE, G. **Culture's consequences: comparing values, behaviors, institutions, and organizations across nations**. 2nd ed. Thousand Oaks, CA: Sage Publications, 2001.

HULT, G. T. M.; KETCHEN, D. J.; ARRFELT, M. Strategic supply chain management: Improving performance through a culture of competitiveness and knowledge development. **Strategic management journal**, v. 28, n. 10, p. 1035-1052, 2007.

KHAN, Sharfuddin Ahmed et al. Supplier sustainability performance evaluation and selection: A framework and methodology. **Journal of Cleaner Production**, v. 205, p. 964-979, 2018.

LIMA JUNIOR, Francisco Rodrigues. **Avaliação da adequabilidade de redes neurais artificiais e sistemas neuro-fuzzy no apoio à predição de desempenho de cadeias de suprimento baseada no SCOR®**. Tese (Doutorado). Escola de Engenharia de São Carlos – Universidade de São Paulo, São Carlos, 2016.

LIMA-JUNIOR, F. R.; OSIRO, L.; CARPINETTI, L. C. R. A *fuzzy* inference and categorization approach for supplier selection using compensatory and non-compensatory decision rules. **Applied Soft Computing**, v. 13, n. 10, p. 4133-4147, 2013.

LIMA-JUNIOR, F. R.; CARPINETTI, L. C. R. Predicting supply chain performance based on SCOR® metrics and multilayer perceptron neural networks. **International Journal of Production Economics**, v. 212, p. 19-38, 2019.

MELLO, J. E.; STANK, T. P. Linking firm culture and orientation to supply chain success. **International Journal of Physical Distribution & Logistics Management**, 2005.

PORTER, M. G. Supply Chain Integration: Does Organizational Culture Matter?. **Operations And Supply Chain Management-An International Journal**, v. 12, n. 1, p. 49-59, 2019.

POURJAVAD, E.; SHAHIN, A. Hybrid performance evaluation of sustainable service and manufacturing supply chain management: An integrated approach of fuzzy dematel and fuzzy inference system. **Intelligent Systems in Accounting, Finance and Management**, v. 25, n. 3, p. 134-147, 2018.

ROH, J.; HONG, P.; PARK, Y. Organizational culture and supply chain strategy: a framework for effective information flows. **Journal of Enterprise Information Management**, v. 21, n. 4, p. 361-376, 2008.

SALMERON, J. L.; PAPAGEORGIOU, E. I. A fuzzy grey cognitive maps-based decision support system for radiotherapy treatment planning. **Knowledge-Based Systems**, v. 30, p. 151-160, 2012.

SCC, Supply Chain Council. **Supply Chain Operations Reference Model**, version 12.0. Supply Chain Council, 2017.

SWEENEY, E. Towards a unified definition of supply chain management: the four fundamentals. **International Journal of Applied Logistics (IJAL)**, v. 2, n. 3, p. 30-48, 2011.

WHITFIELD, G.; LANDEROS, R. Supplier diversity effectiveness: does organizational culture really matter?. **Journal of Supply Chain Management**, v. 42, n. 4, p. 16-28, 2006.

ZADEH, L. A. *Fuzzy logic= computing with words*. In: **Computing with Words in Information/Intelligent Systems 1**. Physica, Heidelberg, 1999. p. 3-23.

ZANON, L. G.; CARPINETTI, L. C. R. Fuzzy cognitive maps and grey systems theory in the supply chain management context: A literature review and a research proposal. In: **2018 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)**. IEEE, 2018. p. 1-8.

2. FUZZY COGNITIVE MAPS AND GREY SYSTEMS THEORY IN THE SUPPLY CHAIN MANAGEMENT CONTEXT: A LITERATURE REVIEW AND A RESEARCH PROPOSAL

ABSTRACT

This paper presents a review of 71 studies published in the literature from 2004 onwards that apply Fuzzy Cognitive Maps (FCMs), Grey Systems Theory (GST) and Fuzzy Grey Cognitive Maps (FGCMs) to supply chain management. A conceptual framework is proposed to characterize the studies according to several factors such as journal and year of publication, geographic region, purpose, technique, association with other techniques, data source, type and sector of application. The reviewed papers were selected from Science Direct, Scopus, Emerald Insight and IEEE Xplore® databases. The results show that: the number of publications is increasing towards the years; the number of publications that uses FGCMs is significantly lower when compared to FCMs and GST; the main purpose of application is in Multi Criteria Decision-Making (MCDM) support; and that although FGCMs derive from the union of FCMs and GST and both these theories have been applied to the supply chain management, there is no publication proposing the use of FGCMs to this end. Finally, based on the reviewed body of knowledge, this paper also discusses research opportunities and suggestions of further studies, especially the use of FGCM to map and quantify the causal relationships between organizational culture and supply chain performance.

Keywords: fuzzy cognitive maps; grey systems theory; fuzzy grey cognitive maps; supply chain; artificial intelligence; systematic literature review.

2.1 INTRODUCTION

Cognitive maps (CMs) were proposed for decision-making for the first time in 1976 and can be viewed as a simplified mathematical model of a belief system, consisting in the combination of two basic types of elements: concepts and the causal relationships between them (AXELROD, 2015).

Fuzzy Cognitive Maps (FCMs) are typically signed fuzzy weighted graphs, usually involving feedbacks, consisting of nodes and directed links connecting them (BAYKASOĞLU; GÖLCÜK, 2015). The nodes represent descriptive behavioral concepts of the system and the links represent cause-effect relations between the concepts (PAPAGEORGIOU; SALMERON, 2013). In the context of FCM theory, the fuzzy value of a concept denotes the degree in which the specific concept is active in the general system, usually bounded in a normalized range of $[0,1]$ (BAYKASOĞLU; GÖLCÜK, 2015). Furthermore, the weights of the system's interrelations reflect the degree of causal influence between two concepts and they are usually assigned linguistically by experts (PAPAGEORGIOU, 2013).

Grey Systems Theory (GST) has become a very effective theory for solving problems when there is high uncertainty and when dealing with discrete, small and incomplete data sets (SALMERON, 2010). GST has been designed to analyze small data samples with poor information, with successful applications in a wide range of fields (PAPAGEORGIOU; SALMERON, 2012). According to the degree of known information, if the system information is fully known (whole understanding), the system is called a white system, while if the system information is completely unknown it is called a black system (SALMERON, 2010). A system with information partially known and partially unknown is a grey system (JULONG, 1989).

One stronger advantage of GST over fuzzy approach is that GST fits better with multiple meaning environments, since grey uncertainty emerges due to the lack of precise values (SALMERON; PAPAGEORGIOU, 2012). Fuzzy mathematics holds previous information, usually based on experience, while grey systems deal with objective data and do not need any previous information other than the data sets that need to be disposed (SALMERON, 2010). GST also contemplates the data fuzziness, because it can flexibly deal with it. Moreover, fuzzy theory has its strength in the study of environments with cognitive uncertainties (SALMERON; PAPAGEORGIOU, 2012).

Fuzzy Grey Cognitive Map (FGCM) is an innovative soft computing technique, mixing FCMs and GST, which represents unstructured knowledge through causalities expressed in

imprecise terms and grey relationships between them (SALMERON, 2010). FGCMs, as FCMs, represent human tacit knowledge and consist in dynamical systems involving feedback, where the effect of change in a node may affect other nodes, which in turn can affect the node initiating the change (PAPAGEORGIOU; SALMERON, 2012). FGCM nodes represent concepts with grey variables, where the causal influence of the causal grey variable over the effect one is modeled by an edge linking both nodes (SALMERON; PAPAGEORGIOU, 2012). The intensity of each edge is measured by its grey intensity (weight) (KANG; YANG, 2013).

As an overview, FGCM shows several advantages over the classical FCM: it is a generalization and can be applied to closer approximate decision-making; it handles the uncertainty inherent in complex domains by assessing the nodes and edges' greyness; it allows modeling of the uncertainty and experts hesitancy related to the description of the causal relations between the concepts and its states' description; FGCMs are able to represent more kinds of relationships than FCM; the reasoning process would consider a degree of uncertainty (greyness) expressed in grey values (SALMERON, 2010). In addition, a FGCM-based Decision Support System can adapt its knowledge from available raw data and/or other knowledge sources and it can also assess its associated uncertainty (SALMERON; PAPAGEORGIOU, 2012).

Supply chains include different organizations, such as suppliers, manufacturers, transporters, warehouses and retailers. Supply chain management (SCM) is the integration of planning, implementing and controlling of all business processes associated with material and information flow and the transformation of goods from the raw material stage to the end user. The main objective of supply chain management is to minimize overall costs while delivering value to customers and other stakeholders, by producing and distributing goods in the right quantity, to the right place, at the right time and in a sustainable way (LIMA-JUNIOR; CARPINETTI, 2017). A wide variety of decision support techniques have been proposed in the literature to aid supply chain management. FCMs, GST and FGCM are particularly useful to this purpose since they can model uncertainty and causal relationships among other benefits (SALMERON, 2010).

Therefore, the objective of this paper is to present a literature review of FCMs, GST and FGCMs in the supply chain management context so as to answer some questions such as how these techniques are being used, whether they are being applied in combination with others or individually, what are the most common purposes of application, if the majority of studies are

theoretical or practical, in which industries are the majority of applications, directions pointed out by the results of the studies, among others.

To guide the analysis of the reviewed papers and to answer the research questions, a framework is proposed to classify the studies according to several factors. This study analyzed 71 papers in a time span of 14 years, from 2004 onwards. The paper is organized as follows: Section 2.2 provides details of the searching and classification procedures. Section 2.3 presents and comments the searching results. Finally, conclusions are drawn in Section 2.4.

2.2 SEARCHING AND CLASSIFICATION PROCEDURES

Figure 2.1 presents a broad view of the steps carried out to select the papers as well as the criteria used to classify the studies and the publications related to FCMs, GST and FGCMs in the context of supply chain management. The papers were searched for on the following academic databases: Science Direct, Scopus, Emerald Insight and IEEE Xplore®.

The searching procedure consisted of the following steps (LIMA-JUNIOR; CARPINETTI, 2017):

- Step 1: Define and insert the string into the database search field. For FCMs, the string “Fuzzy Cognitive Map” linked with the string “Supply Chain” was used to search for papers in the databases. For GST, the string “Grey Theory” linked with the string “Supply Chain” was used to search for papers in the databases. For FGCMs, only the string “Fuzzy Grey Cognitive Map” was used to search for papers in the databases, since there is no application yet of this technique in the supply chain context.
- Step 2: Refine the search results by year of publication, from 2004 onwards. This time window was chosen since most of the developments on this subject have taken place over the past decade;
- Step 3: Filter the search a second time to select only papers published in academic journals;
- Step 4: Order the papers by relevance according to the criteria defined by each database;
- Step 5: Select the first thousand results;
- Step 6: Select papers dealing with the supply chain context directly. The selection was based on the analysis of the title, abstract and keywords of each paper;
- Step 7: Eliminate duplicated results.

After the application of this searching procedure, the resulting set of papers was classified according to the criteria illustrated in Figure 2.1. The criteria applied to classify the studies were based on a review about quantitative models for supply chain performance evaluation (LIMA-JUNIOR; CARPINETTI, 2017). The set is grouped according to paper classification factors and content stratification factors related to application and validation. The connections shown by the arrows mean the interdependence between the factors. The issues implicit in each of the factors are commented on next.

Figure 2.1 - Framework to analyze FCMs, GST and FGCMs in the supply chain context.

Source: own authorship.

- **Purpose:** The main purposes identified for FCMs, GST and FGCMs in the supply chain context were causal inference, multi criteria decision-making (MCDM) support, performance evaluation, prediction (forecasting) and sensitivity evaluation. The papers were allocated in each category according to the objective described in the abstract and keywords. Thus, overlaps between categories were avoided. For example, if a paper was classified as a prediction paper but included sensitivity analysis, this is justified by the main purpose of application of the techniques.
- **Technique:** it classifies the studies according to the main technique deployed (FCM, GST or FGCM).
- **Check for combination:** it analyses whether the techniques were utilized individually or combined with others (e.g. FCM or FCM-AHP).
- **Data Source and Type of Application:** it considers whether the study uses real data based on a case study or numerical examples based on theoretical scenarios.
- **Sector of Application:** it considers the industry or economic sector in which the study was developed.

2.3 SEARCH RESULTS

Table 2.1 presents the papers distribution by technique and database. It becomes clear that FCM presents a slightly larger number of papers than GST, although their distribution in both total and between databases is balanced. Considering that FGCM are more recent, the results obtained were still relevant and can be considered promising.

Table 2.1 - Distribution of papers by database and technique.

Papers by Database	FCM	Grey Theory	FGCM	Total
ScienceDirect	21	15	6	42
IEEE Xplore®	5	4	2	11
Scopus	4	4	3	11
Emerald	1	6	0	7
Total	31	29	11	71

Source: own authorship.

In the following section, the papers are commented considering the factors of the framework presented in Figure 2.1.

2.3.1. *Journal and Year of Publication*

The journals of the papers and their year of publication are stratified in two groups: FCMs and GSTs in the first group and FGCMs alone in the second group. This is because FGCMs have few publications so far which, if not separated, would get lost in the vast group of the other two.

Table 2.2 describes the journal and year of publication of the papers of the first group and Table 2.3 of the second. It becomes evident that the number of publications is growing towards the years. Although the publications are spread in more than forty different journals there are some main vehicles such as Expert systems with applications, Journal of cleaner production and Industrial engineering and engineering management.

Table 2.2 - Journal and year – group 1

Journal	2004	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Total
Expert Systems with Applications	1		2		1		1	1					6
Journal of Cleaner Production										1	1	2	4
Grey Systems: Theory and Application								1	1	1			3
Industrial Engineering and Engineering Management		1				1				1			3
Applied Soft Computing						1			1				2
Computers and Industrial Engineering				1						1			2
Industrial Management and Data Systems										1	1		2
Int. J. Production Economics									1	1			2
Applied Energy												1	1

Continues.

Continuation.

Journal	2004	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Total
Applied Mathematical Modelling							1						1
Applied Mathematics and Computation			1										1
Business Informatics									1				1
Computational Sciences and Optimization									1				1
Computers and Operations Research												1	1
Computers in Industry						1							1
Egyptian Informatics Journal								1					1
Electronic Commerce Research and Applications											1		1
Engineering Applications of Artificial Intelligence								1					1
Food Control										1			1
Futures						1							1
Grey Systems and Intelligent Services								1					1
IFAC papers online											1		1
Industrial Marketing Management								1					1
Information Management and Engineering					1								1
Information Sciences										1			1
Information Systems for Crisis Response and Management						1							1
Information, Intelligence, Systems and Applications (IISA)										1			1

Continues.

Conclusion.

Journal	2004	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Total
Intelligent Computation Technology and Automation			1										1
international journal of hydrogen energy								1					1
Journal of Business Research												1	1
Journal of Rural Studies										1			1
Journal of Strategic Information Systems						1							1
Kybernetes							1						1
Management and Service Science				1									1
Materials Today												1	1
Mathematical and Computer Modelling		1											1
Measuring Business Excellence												1	1
Neurocomputing												1	1
Performance measurement scenarios with fuzzy cognitive strategic maps							1						1
Procedia Economics and Finance											1		1
Resources, Conservation and Recycling												1	1
Service Systems and Service Management		1											1
Toward Sustainable Operations of Supply Chain and Logistics Systems										1			1
Working Conference on Virtual Enterprises										1			1
Total	1	3	4	2	2	6	4	7	5	12	5	9	60

Source: own authorship.

Table 2.3 - Journal and year – group 2

Journal	2010	2011	2012	2013	2014	2015	2016	2017	Total
International Journal of Approximate Reasoning		1			1				2
Applied intelligence					1				1
Applied Soft Computing			1						1
Control and Decision Conference				1					1
Emergent Trends in Robotics and Intelligent Systems								1	1
Expert Systems with Applications	1								1
Grey Systems and Intelligent Services (GSIS)						1			1
IEEE Transactions on Cybernetics								1	1
Journal of Grey System							1		1
Knowledge-Based Systems			1						1
Total	1	1	2	1	2	1	1	2	11

Source: own authorship.

2.3.2. Country

Figure 2.2 illustrates the distribution of publications by technique by country. It is clear that China and Spain concentrate the largest number of publications. China and Turkey have the largest number of publications on FCMs, China has the largest number of publications on GST and Spain has the highest number of publications on FGCMs.

Figure 2.2 - Stratification by geographic region.

Source: own authorship.

2.3.3. *Technique and check for association*

Figure 2.3 shows how the FCM technique appears in the supply chain related literature. It can be observed that FCM is most commonly applied individually. When it appears combined, it is more likely to be with Fuzzy TOPSIS.

Figure 2.3 - FCMs and check for association.

Source: own authorship.

Figure 2.4 shows how the GST technique appears in the supply chain related literature. It can be observed that GST is most commonly applied individually. When it appears combined, it is more likely to be with Grey DEMATEL.

Figure 2.4 - GST and check for association.

Source: own authorship.

2.3.4. Purpose

The categorization defined for purpose analysis was obtained based on the combination of two previous methodologies. The typical problems solved by FCMs identified by Papageorgiou and Salmeron (2013) provided the categories “causal inference”, “MCDM support” and “prediction”. The stratification of types of application defined by Lima-Junior and Carpinetti, (2017) in their study about quantitative models for supply chain performance evaluation provided the “performance evaluation” and “sensitivity evaluation” categories.

Causal inference consists in determining and quantifying causal relationships between factors. MCDM support is to support decision-making when multiple criteria are present, with different degrees of importance and multiple decision-makers. Performance evaluation consists in measuring performance taking into consideration all the relevant factors that impact it. Prediction is to predict the behavior of lag indicators based on lead indicators or the projection of performance stability over time. Sensitivity evaluation consists in the sensitivity analysis of the output variables by varying the values of the input variables. Figure 2.5 shows that the techniques in general are mostly applied to MCDM support. FCMs are mostly applied to causal inference, GST to MCDM support and FGCM also to MCDM support.

Figure 2.5 - Purposes of application by technique.

Source: own authorship.

Table 2.4 lists the 71 papers with an indication of purpose and context. It shows that although FGCMs derive from the union of FCMs and GST and both these theories have been applied to the context of the supply chain, there is no paper scope that indicates the use of FGCMs (more efficient than their techniques originating alone, as already mentioned) in that context.

Table 2.4 - Papers, purpose and context.

Author	Title	Technique
Asad, Mohammadi and Shirani (2016)	Modeling Flexibility Capabilities of IT-based Supply Chain, Using a Grey-based DEMATEL Method	Grey Theory
Baykasoğlu and Gölcük (2015)	Development of a novel multiple-attribute decision-making model via fuzzy cognitive maps and hierarchical fuzzy TOPSIS	FCM
Baykasoglu, Durmusoglu and Kaplanoglu (2011)	Training Fuzzy Cognitive Maps via Extended Great Deluge Algorithm with applications	FCM
Bouzon, Govindan and Rodriguez (2017)	Evaluating barriers for reverse logistics implementation under a multiple stakeholders' perspective analysis using grey decision-making approach	Grey Theory
Buyukozkan and Vardaloglu (2009)	Analyzing of collaborative planning, forecasting and replenishment approach using fuzzy cognitive map.	FCM
Büyüközkan and Vardaloğlu (2012)	Analyzing of CPFR success factors using fuzzy cognitive maps in retail industry	FCM
Chen (2015)	Autonomous tracing system for backward design in food supply chain	FCM
Du, Qiu and Zhao (2011)	Risk assessment study of manufacturing green supply chain based on Grey Theory	Grey Theory

Continues.

Continuation.

Author	Title	Technique
Elomda, Hefny and Hassan (2013)	An extension of fuzzy decision maps for multi-criteria decision-making	FCM
Feyzioglu, Buyukozkan and Ersoy (2007)	Supply Chain Risk Analysis with Fuzzy Cognitive Maps	FCM
Froelich and Salmeron (2014)	Evolutionary learning of fuzzy grey cognitive maps for the forecasting of multivariate, interval-valued time series	FGCM
Glykas (2012)	Performance measurement scenarios with fuzzy cognitive strategic maps	FCM
Govindan, Khodaverdi and Vafadarnikjoo (2016)	A grey DEMATEL approach to develop third-party logistics provider selection criteria	Grey Theory
Hashemi et al. (2013)	A Grey-Based Carbon Management Model For Green Supplier Selection	Grey Theory
Hashemi, Karimi and Tavana (2015)	An integrated green supplier selection approach with analytic network process and improved Grey relational analysis	Grey Theory
Hashemi, Karimi and Tavana (2015)	An integrated green supplier selection approach with analytic network process and improved Grey relational analysis	Grey Theory
Jamshidi et al. (2015)	A New Decision Support Tool for Dynamic Risks Analysis in Collaborative Networks	FCM
Jamshidi et al. (2016)	Application of FCM for advanced risk assessment of complex and dynamic systems	FCM
Jetter and Schweinfert (2011)	Building scenarios with Fuzzy Cognitive Maps: An exploratory study of solar energy	FCM
Jianhu (2010)	On Prediction Application of Small Enterprise Supply Chain Demand Based on Grey System Theory	Grey Theory
Kang and Yang (2013)	A fuzzy grey cognitive maps-based decision support system for maintaining water quality	FGCM

Continues.

Continuation.

Author	Title	Technique
Kar, Chatterjee and Kar (2014)	A Network-TOPSIS based fuzzy decision support system for supplier selection in risky supply chain	FCM
Kayikci and Stix (2014)	Causal mechanism in transport collaboration	FCM
Kim et al. (2008)	Forward backward analysis of RFID-enabled supply chain using fuzzy cognitive map and genetic algorithm	FCM
Kontogianni, Tourkolias and Papageorgiou (2013)	Revealing market adaptation to a low carbon transport economy: Tales of hydrogen futures as perceived by fuzzy cognitive mapping	FCM
Kumar, Datta and Mahapatra (2014)	Supply chain performance benchmarking using grey-MOORA approach: An empirical research	Grey Theory
Lee et al. (2013)	An agent-based fuzzy cognitive map approach to the strategic marketing planning for industrial firms	FCM
Lee, Kim and Lee (2004)	Fuzzy cognitive map-based approach to evaluate EDI performance: a test of causal model	FCM
Li and Chen (2013)	Supply chain optimization modeling in uncertain environment with prediction mechanism	Grey Theory
Li, Yamaguchi and Nagai (2007)	A grey-based decision-making approach to the supplier selection problem	Grey Theory
Liche and Campean (2014)	The Influence of Changes in Customer's Technology Portfolio on Supplier's Organization	FCM
Liu, Fangqiu and Lin (2017)	Site selection of photovoltaic power plants in a value chain based on grey cumulative prospect theory for sustainability: A case study in Northwest China	Grey Theory
Lopez and Ishizaka (2017)	A hybrid FCM-AHP approach to predict impacts of offshore outsourcing location decisions on supply chain resilience	FCM

Continues.

Continuation.

Author	Title	Technique
Lopolito et al. (2015)	Translating local stakeholders' perception in rural development strategies under uncertainty conditions: An application to the case of the bio-based economy in the area of Foggia (South Italy)	FCM
Martin et al. (2017)	An Analysis of the Associated Implications of Green Manufacturing Using Fuzzy Cognitive Maps	FCM
Mathivathanan, Govindan and Haq (2017)	Exploring the impact of dynamic capabilities on sustainable supply chain firm's performance using Grey-Analytical Hierarchy Process	Grey Theory
Mehrjerdi (2014)	Strategic system selection with linguistic preferences and grey information using MCDM	Grey Theory
Memon, Lee and Mari (2015)	A Combined Grey System Theory and Uncertainty Theory-Based Approach for Supplier Selection in Supply Chain Management	Grey Theory
Papageorgiou and Salmeron (2012)	Learning Fuzzy Grey Cognitive Maps using Nonlinear Hebbian-based approach	FGCM
Prakash, Soni and Rathore (2015)	A grey based approach for assessment of risk associated with facility location in global supply chain	Grey Theory
Rajesh (2016)	Forecasting supply chain resilience performance using grey prediction	Grey Theory
Rajesh and Ravi (2015)	Modeling enablers of supply chain risk mitigation in electronic supply chains: A Grey DEMATEL approach	Grey Theory
Rajesh and Ravi (2015)	Supplier selection in resilient supply chains: a grey relational analysis approach	Grey Theory
Rezaee, Yousefi and Babaei (2017)	Multi-stage cognitive map for failures assessment of production processes: An extension in structure and algorithm	FCM

Continues.

Continuation.

Author	Title	Technique
Rezaei and Azar (2017)	A fuzzy cognitive mapping model for service supply chains performance	FCM
Salmeron (2010)	Modelling grey uncertainty with Fuzzy Grey Cognitive Maps	FGCM
Salmeron (2015)	A Fuzzy Grey Cognitive Maps-based intelligent security system	FGCM
Salmeron (2015)	Simulating Synthetic Emotions with Fuzzy Grey Cognitive Maps.	FGCM
Salmeron (2016)	An Autonomous FGCM-based System for Surveillance Assets Coordination	FGCM
Salmeron and Gutierrez (2012)	Fuzzy Grey Cognitive Maps in reliability engineering	FGCM
Salmeron and Palos-Sanchez (2017)	Uncertainty Propagation in Fuzzy Grey Cognitive Maps With Hebbian-Like Learning Algorithms	FGCM
Salmeron and Papageorgiou (2012)	A Fuzzy Grey Cognitive Maps-based Decision Support System for radiotherapy treatment planning	FGCM
Salmeron and Papageorgiou (2014)	Fuzzy grey cognitive maps and nonlinear Hebbian learning in process control	FGCM
Samvedi and Jain (2013)	A grey approach for forecasting in a supply chain during intermittent disruptions	Grey Theory
Shi et al. (2007)	Research on Supply Chain Information Classification Based on Information Value and Information Sensitivity	Grey Theory
Su et al. (2016)	Improving sustainable supply chain management using a novel hierarchical grey-DEMATEL approach	Grey Theory
Trappey, Trappey and Wu (2010)	Genetic algorithm dynamic performance evaluation for RFID reverse logistic management	FCM

Continues.

Conclusion.

Author	Title	Technique
Trucco and Ward (2011)	A Clustering approach to the Operational Resilience analysis of Key Resource Supply Chains (KRSC): the case of Fast Moving Consumer Goods	FCM
Tseng (2011)	Green supply chain management with linguistic preferences and incomplete information	Grey Theory
Vlahakis and Aposotlou (2015)	A FCM Analysis for Supply Chain Management	FCM
Wang and Hsu (2008)	Using genetic algorithms grey theory to forecast high technology industrial output	Grey Theory
Wang et al. (2011)	Improving inventory effectiveness in RFID-enabled global supply chain with Grey forecasting model	Grey Theory
Wei, Lu and Yanchun (2008)	Using fuzzy cognitive time maps for modeling and evaluating trust dynamics in the virtual enterprises	FCM
Wu, et al. (2016)	Multi-attribute approach to sustainable supply chain management under uncertainty	Grey Theory
Xiao, Chen and Li (2012)	An integrated FCM and fuzzy soft set for supplier selection problem based on risk evaluation	FCM
Xu and Jia (2009)	Forecasting Moral Hazards in Supply Chain	Grey Theory
Yang et al. (2015)	Risk Assessment of Supply Chain Based on Combination Weighting Method and Grey Theory	Grey Theory
Zahir et al (2017)	Managing food security through food waste and loss: Small data to big data	FCM
Zhang (2008)	Supply Chain Overall Risk Evaluation Based on Grey Theory and Modified TOPSIS in Fuzzy Environment	FCM
Zhang, Wang and Liu (2012)	4-stage distribution network optimization of supply chain with grey demands	Grey Theory
Ziv et al. (2018)	The potential impact of Brexit on the energy, water and food nexus in the UK: A fuzzy cognitive mapping approach	FCM

Source: own authorship.

2.3.5. Data source, type and sector of application

From the 71 analyzed papers, 41 of them, 58%, use the case study as the data source. The other 42% consists of theoretical studies based on the development of numerical models, which at some point must be validated with an application to a real problem.

Table 2.5 shows that Electronics and Logistics are the fields with most of the applications of the techniques in general. FCMs are more applied to Food, Logistics, Manufacturing and Transport; GST to Electronics; FGCMs to Chemical, Health and Security.

It is worth to note that again there are no applications of FGCM to the real aspects and challenges of the supply chain management context in the stratified fields.

Table 2.5 - Application fields of the techniques

Application field	FCM	Grey Theory	FGCM	Total
Electronics	1	5	0	6
Logistics	2	4	0	6
Energy	1	1	1	3
Automotive	0	2	0	2
Chemical	0	0	2	2
Food	2	0	0	2
Health	0	0	2	2
Manufacturing	2	0	0	2
Safety	0	0	2	2
Transport	2	0	0	2
Agriculture	1	0	0	1
Fast moving consumer goods	1	0	0	1
Financial	1	0	0	1
Information technology	0	1	0	1
Meteorology	0	0	1	1
Outsourcing	1	0	0	1
Politics	1	0	0	1
Retail	1	0	0	1
Small business	0	1	0	1
Software	1	0	0	1
Virtual enterprises	1	0	0	1
Water treatment	0	0	1	1

Source: own authorship.

2.4 CONCLUSION

This paper presented a literature review of 71 studies that apply FCMs, GST and FGCMs to the supply chain context. A conceptual framework was proposed to analyze and characterize them according to journal and year of publication, geographic region, purpose, technique, association with other techniques, data source, type and sector of application.

The number of publications is growing towards the years, mostly from 2010 onwards and the journals interest in the application of these techniques in SCM is also increasing. 58% of the papers consisted of practical applications in a major proportion in the fields of electronics and logistics. The main purpose of application is MCDM support and, although FGCMs derives from the union of FCMs and GST and both these theories have been applied to the supply chain context, there is no indication of use of FGCMs in this context.

The review of these papers identified the current body of knowledge on FCMs, GST and FGCMs in the supply chain context and, therefore, helped to bring light to research opportunities. The results suggest the application of FGCMs in SCM, to MCDM support, performance evaluation and forecasting. FGCMs can also be applied to green and lean supply chains. Also, regarding performance evaluation, further studies could include developing new models based on the SCOR[®] metrics. This paper enlightens several other research possibilities that could be made feasible based on the scope of all the 71 analyzed papers. As a highly relevant topic, the use of FGCM to map and quantify the causal relationships between organizational culture and supply chain performance is proposed as a further research by these authors. In addition, the search procedure presented in this paper, based on the proposition of Lima-Junior and Carpinetti (2017) can be used as reference for future literature reviews.

Finally, a limitation of this study is that, although the literature search was carried out on the main databases considering a wide time window, it may be the case that some studies available on other databases were missed. Therefore, this study is not exhaustive and can be complemented.

2.5 REFERENCES

ASAD, M. M.; MOHAMMADI, V.; SHIRANI, M. Modeling flexibility capabilities of IT-based supply chain, using a grey-based DEMATEL method. **Procedia Economics and Finance**, v. 36, p. 220-231, 2016.

AXELROD, R. (Ed.). **Structure of decision: The cognitive maps of political elites**. Princeton university press, 2015.

BAYKASOGLU, A.; GÖLCÜK, I. Development of a novel multiple-attribute decision-making model via fuzzy cognitive maps and hierarchical fuzzy TOPSIS. **Information Sciences**, v. 301, p. 75-98, 2015.

BAYKASOGLU, A.; DURMUSOGLU, Z. D.; KAPLANOGLU, V. Training fuzzy cognitive maps via extended great deluge algorithm with applications. **Computers in Industry**, v. 62, n. 2, p. 187-195, 2011.

BOUZON, M.; GOVINDAN, K.; RODRIGUEZ, C. M. T. Evaluating barriers for reverse logistics implementation under a multiple stakeholders' perspective analysis using grey decision-making approach. **Resources, conservation and recycling**, v. 128, p. 315-335, 2018.

BÜYÜKÖZKAN, G.; VARDALOGLU, Z. Analyzing of CPFR success factors using fuzzy cognitive maps in retail industry. **Expert Systems with Applications**, v. 39, n. 12, p. 10438-10455, 2012.

BUYUKOZKAN, G.; VARDALOGLU, Z. Analyzing of collaborative planning, forecasting and replenishment approach using fuzzy cognitive map. In: **2009 International Conference on Computers & Industrial Engineering**. IEEE, 2009. p. 1751-1756.

CHEN, R. Autonomous tracing system for backward design in food supply chain. **Food Control**, v. 51, p. 70-84, 2015.

DU, D.; QIU, J.; ZHAO, H. Risk assessment study of manufacturing green supply chain based on grey theory. In: **Proceedings of International Conference on Information Systems for Crisis Response and Management (ISCRAM)**. IEEE, 2011. p. 234-240.

ELOMDA, B. M.; HEFNY, H. A.; HASSAN, H. A. An extension of fuzzy decision maps for multi-criteria decision-making. **Egyptian Informatics Journal**, v. 14, n. 2, p. 147-155, 2013.

FEYZIOGLU, O.; BUYUKOZKAN, G.; ERSOY, M. S. Supply chain risk analysis with fuzzy cognitive maps. In: **2007 IEEE international conference on industrial engineering and engineering management**. IEEE, 2007. p. 1447-1451.

FROELICH, W.; SALMERON, J. L. Evolutionary learning of fuzzy grey cognitive maps for the forecasting of multivariate, interval-valued time series. **International Journal of Approximate Reasoning**, v. 55, n. 6, p. 1319-1335, 2014.

GLYKAS, M. Performance measurement scenarios with fuzzy cognitive strategic maps. **International Journal of Information Management**, v. 32, n. 2, p. 182-195, 2012.

GOVINDAN, K.; KHODAVERDI, R.; VAFADARNIKJOO, A. A grey DEMATEL approach to develop third-party logistics provider selection criteria. **Industrial Management & Data Systems**, 2016.

HASHEMI, S. H. et al. A grey-based carbon management model for green supplier selection. In: **Proceedings of 2013 IEEE International Conference on Grey systems and Intelligent Services (GSIS)**. IEEE, 2013. p. 402-405.

HASHEMI, S. H.; KARIMI, A.; TAVANA, M. An integrated green supplier selection approach with analytic network process and improved Grey relational analysis. **International Journal of Production Economics**, v. 159, p. 178-191, 2015.

HASHEMI, S. H.; KARIMI, A.; TAVANA, M. An integrated green supplier selection approach with analytic network process and improved Grey relational analysis. **International Journal of Production Economics**, v. 159, p. 178-191, 2015.

IRANI, Z. et al. Managing food security through food waste and loss: Small data to big data. **Computers & Operations Research**, v. 98, p. 367-383, 2018.

JAMSHIDI, A. et al. A new decision support tool for dynamic risks analysis in collaborative networks. In: **Working Conference on Virtual Enterprises**. Springer, Cham, 2015. p. 53-62.

JAMSHIDI, A. et al. Application of FCM for advanced risk assessment of complex and dynamic systems. **IFAC-PapersOnLine**, v. 49, n. 12, p. 1910-1915, 2016.

JETTER, A.; SCHWEINFORT, W. Building scenarios with Fuzzy Cognitive Maps: An exploratory study of solar energy. **Futures**, v. 43, n. 1, p. 52-66, 2011.

JIANHU, Z. On prediction application of small enterprise supply chain demand based on Grey System theory. In: **2010 2nd IEEE International Conference on Information Management and Engineering**. IEEE, 2010. p. 356-360.

JULONG, D. Introduction to grey system theory. **The Journal of grey system**, v. 1, n. 1, p. 1-24, 1989.

KANG, B.; DENG, Y. A fuzzy grey cognitive maps-based decision support system for maintaining water quality. In: **2013 25th Chinese Control and Decision Conference (CCDC)**. IEEE, 2013. p. 4154-4158.

KAR, M. B.; CHATTERJEE, K.; KAR, S. A network-TOPSIS based fuzzy decision support system for supplier selection in risky supply chain. In: **2014 Seventh International Joint Conference on Computational Sciences and Optimization**. IEEE, 2014. p. 288-293.

KAYIKCI, Y.; STIX, V. Causal mechanism in transport collaboration. **Expert systems with applications**, v. 41, n. 4, p. 1561-1575, 2014.

KIM, M. et al. Forward-backward analysis of RFID-enabled supply chain using fuzzy cognitive map and genetic algorithm. **Expert Systems with Applications**, v. 35, n. 3, p. 1166-1176, 2008.

KONTOGIANNI, A.; TOURKOLIAS, C.; PAPAGEORGIOU, E. I. Revealing market adaptation to a low carbon transport economy: Tales of hydrogen futures as perceived by fuzzy cognitive mapping. **International journal of hydrogen energy**, v. 38, n. 2, p. 709-722, 2013.

LEE, K. C. et al. An agent-based fuzzy cognitive map approach to the strategic marketing planning for industrial firms. **Industrial Marketing Management**, v. 42, n. 4, p. 552-563, 2013.

LEE, S.; KIM, B. G.; LEE, K. Fuzzy cognitive map-based approach to evaluate EDI performance: a test of causal model. **Expert Systems with Applications**, v. 27, n. 2, p. 287-299, 2004.

LI, C.; CHEN, K. Supply chain optimization modeling in uncertain environment with prediction mechanism. **Grey Systems: Theory and Application**, 2013.

LI, G.; YAMAGUCHI, D.; NAGAI, M. A grey-based decision-making approach to the supplier selection problem. **Mathematical and computer modelling**, v. 46, n. 3-4, p. 573-581, 2007.

LICHE, C. A.; MORAR, L.; CAMPEAN, E. The Influence of Changes in Customer's Technology Portfolio on Supplier's Organization. In: **2014 IEEE 16th Conference on Business Informatics**. IEEE, 2014. p. 124-132.

LIMA-JUNIOR, F. R.; CARPINETTI, L. C. R. Quantitative models for supply chain performance evaluation: a literature review. **Computers & Industrial Engineering**, v. 113, p. 333-346, 2017.

LIU, J.; XU, F.; LIN, S. Site selection of photovoltaic power plants in a value chain based on grey cumulative prospect theory for sustainability: A case study in Northwest China. **Journal of Cleaner Production**, v. 148, p. 386-397, 2017.

LÓPEZ, C.; ISHIZAKA, A. A hybrid FCM-AHP approach to predict impacts of offshore outsourcing location decisions on supply chain resilience. **Journal of Business Research**, v. 103, p. 495-507, 2019.

LOPOLITO, A. et al. Translating local stakeholders' perception in rural development strategies under uncertainty conditions: An application to the case of the bio-based economy in the area of Foggia (South Italy). **Journal of Rural Studies**, v. 37, p. 61-74, 2015.

MARTIN, N. et al. An analysis of the associated implications of green manufacturing using fuzzy cognitive maps. **Materials Today: Proceedings**, v. 4, n. 2, p. 4219-4227, 2017.

MATHIVATHANAN, D.; GOVINDAN, K.; HAQ, A. N. Exploring the impact of dynamic capabilities on sustainable supply chain firm's performance using Grey-Analytical Hierarchy Process. **Journal of cleaner production**, v. 147, p. 637-653, 2017.

MEHRJERDI, Y. Z. Strategic system selection with linguistic preferences and grey information using MCDM. **Applied Soft Computing**, v. 18, p. 323-337, 2014.

MEMON, M. S.; LEE, Y. H.; MARI, S. I. A combined grey system theory and uncertainty theory-based approach for supplier selection in supply chain management. In: **Toward Sustainable Operations of Supply Chain and Logistics Systems**. Springer, Cham, 2015. p. 461-473.

PANDARI, A. R.; AZAR, A. A fuzzy cognitive mapping model for service supply chains performance. **Measuring Business Excellence**, 2017.

PAPAGEORGIOU, E. I. Review study on fuzzy cognitive maps and their applications during the last decade. In: **Business Process Management**. Springer, Berlin, Heidelberg, 2013. p. 281-298.

PAPAGEORGIOU, E. I.; SALMERON, J. L. A review of fuzzy cognitive maps research during the last decade. **IEEE Transactions on Fuzzy Systems**, v. 21, n. 1, p. 66-79, 2012.

PAPAGEORGIOU, E. I.; SALMERON, J. L. Learning fuzzy grey cognitive maps using nonlinear hebbian-based approach. **International Journal of Approximate Reasoning**, v. 53, n. 1, p. 54-65, 2012.

PRAKASH, S.; SONI, G.; RATHORE, A. P. S. A grey based approach for assessment of risk associated with facility location in global supply chain. **Grey Systems: Theory and Application**, 2015.

RAJESH, R. Forecasting supply chain resilience performance using grey prediction. **Electronic Commerce Research and Applications**, v. 20, p. 42-58, 2016.

RAJESH, R.; RAVI, V. Modeling enablers of supply chain risk mitigation in electronic supply chains: A Grey-DEMATEL approach. **Computers & Industrial Engineering**, v. 87, p. 126-139, 2015.

RAJESH, R.; RAVI, V. Supplier selection in resilient supply chains: a grey relational analysis approach. **Journal of Cleaner Production**, v. 86, p. 343-359, 2015.

REZAEE, M. J.; YOUSEFI, S.; BABAEI, M. Multi-stage cognitive map for failures assessment of production processes: An extension in structure and algorithm. **Neurocomputing**, v. 232, p. 69-82, 2017.

SAHU, A. K.; DATTA, S.; MAHAPATRA, S. S. Supply chain performance benchmarking using grey-MOORA approach. **Grey Systems: Theory and Application**, 2014.

SALMERON, J. L. A Fuzzy Grey Cognitive Maps-based intelligent security system. In: **2015 IEEE International Conference on Grey Systems and Intelligent Services (GSIS)**. IEEE, 2015. p. 29-32.

SALMERON, J. L. Modelling grey uncertainty with fuzzy grey cognitive maps. **Expert Systems with Applications**, v. 37, n. 12, p. 7581-7588, 2010.

SALMERON, J. L. Simulating Synthetic Emotions with Fuzzy Grey Cognitive Maps. In: **Emergent Trends in Robotics and Intelligent Systems**. Springer, Cham, 2015. p. 39-46.

SALMERON, J. L.; GUTIERREZ, E. Fuzzy grey cognitive maps in reliability engineering. **Applied Soft Computing**, v. 12, n. 12, p. 3818-3824, 2012.

SALMERON, J. L.; PALOS-SANCHEZ, P. R. Uncertainty propagation in fuzzy grey cognitive maps with Hebbian-like learning algorithms. **IEEE transactions on cybernetics**, v. 49, n. 1, p. 211-220, 2017.

SALMERON, J. L.; PAPAGEORGIOU, E. I. A fuzzy grey cognitive maps-based decision support system for radiotherapy treatment planning. **Knowledge-Based Systems**, v. 30, p. 151-160, 2012.

SALMERON, J. L.; PAPAGEORGIOU, E. I. Fuzzy grey cognitive maps and nonlinear Hebbian learning in process control. **Applied intelligence**, v. 41, n. 1, p. 223-234, 2014.

SALMERON, J. L. An Autonomous FGCM-based System for Surveillance Assets Coordination. **Journal of Grey System**, v. 28, n. 1, 2016.

SAMVEDI, A.; JAIN, V. A grey approach for forecasting in a supply chain during intermittent disruptions. **Engineering Applications of Artificial Intelligence**, v. 26, n. 3, p. 1044-1051, 2013.

SHI, X. et al. Research on Supply Chain Information Classification Based on Information Value and Information Sensitivity. In: **2007 International Conference on Service Systems and Service Management**. IEEE, 2007. p. 1-7.

SU, C. et al. Improving sustainable supply chain management using a novel hierarchical grey-DEMATEL approach. **Journal of Cleaner Production**, v. 134, p. 469-481, 2016.

TRAPPEY, A. JC; TRAPPEY, C. V.; WU, C. Genetic algorithm dynamic performance evaluation for RFID reverse logistic management. **Expert Systems with Applications**, v. 37, n. 11, p. 7329-7335, 2010.

TRUCCO, P.; WARD, D. A clustering approach to the operational resilience analysis of key resource supply chains (KRSC): The case of fast Moving Consumer Goods. In: **2011 IEEE International Conference on Industrial Engineering and Engineering Management**. IEEE, 2011. p. 990-994.

TSENG, M. Green supply chain management with linguistic preferences and incomplete information. **Applied Soft Computing**, v. 11, n. 8, p. 4894-4903, 2011.

VLAHAKIS, G.; APOSOTLOU, D. A FCM analysis for supply chain management. In: **2015 6th International Conference on Information, Intelligence, Systems and Applications (IISA)**. IEEE, 2015. p. 1-6.

WANG, C.; HSU, L. Using genetic algorithms grey theory to forecast high technology industrial output. **Applied mathematics and computation**, v. 195, n. 1, p. 256-263, 2008.

WANG, S.-J. et al. Improving inventory effectiveness in RFID-enabled global supply chain with Grey forecasting model. **The Journal of Strategic Information Systems**, v. 20, n. 3, p. 307-322, 2011.

WEI, Z.; LU, L.; YANCHUN, Z. Using fuzzy cognitive time maps for modeling and evaluating trust dynamics in the virtual enterprises. **Expert Systems with Applications**, v. 35, n. 4, p. 1583-1592, 2008.

WU, K. et al. Multi-attribute approach to sustainable supply chain management under uncertainty. **Industrial Management & Data Systems**, 2016.

XIAO, Z.; CHEN, W.; LI, L. An integrated FCM and fuzzy soft set for supplier selection problem based on risk evaluation. **Applied Mathematical Modelling**, v. 36, n. 4, p. 1444-1454, 2012.

XU, X.; JIA, L. Forecasting Moral Hazards in Supply Chain. In: **2009 International Conference on Management and Service Science**. IEEE, 2009. p. 1-4.

YANG, L. et al. Risk assessment of supply chain based on combination weighting method and grey theory. In: **2015 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)**. IEEE, 2015. p. 895-899.

ZHANG, H. Supply chain overall risk evaluation based on grey theory and modified TOPSIS in fuzzy environment. In: **2008 International Conference on Intelligent Computation Technology and Automation (ICICTA)**. IEEE, 2008. p. 706-711.

ZHANG, Q.; WANG, H.; LIU, H. 4-stage distribution network optimization of supply chain with grey demands. **Kybernetes**, v. 41.5/6, p. 633-642. 2012.

ZIV, G. et al. The potential impact of Brexit on the energy, water and food nexus in the UK: A fuzzy cognitive mapping approach. **Applied energy**, v. 210, p. 487-498, 2018.

3. COMBINING GREY CLUSTERING AND FUZZY GREY COGNITIVE MAPS: AN APPROACH FOR GROUP DECISION-MAKING ON CAUSE AND EFFECT RELATIONSHIPS

ABSTRACT

Fuzzy Grey Cognitive Maps (FGCMs) have been widely adopted to support cause and effect decision-making under uncertainty. However, capturing the information for the initial state vector and the relationship matrix from multiple specialists can be cumbersome, which may affect the convergence of FGCMs or cause them to reach a chaotic state. To address this issue, this paper presents a novel group decision approach based on the combination of Grey Clustering (GC) and Fuzzy Grey Cognitive Maps for assessing causal relationships in uncertain environments. GC is applied as a mean to obtain the initial state vector from the relationship matrix data, composed by experts' judgments. The proposed approach is able to classify the relational criteria for building the initial state vector, to visually represent their interactions, to determine the relative criteria weights considering their impact in the system and to aid the process of conducting what-if analysis for scenario simulation. The main benefit of the GC-FGCM association is the reduction of required inputs and uncertainty in the computational model, improving group decision on causal relationships. A real application was conducted in a technology start-up to test the approach for practical implications. Results allowed the identification of important elements regarding the company's profile and performance, aiding prioritization and enabling the development of action plans. Results were also more precise in a similar comparison with the traditional FGCM. Hence, this study addresses the need for new alternatives to improve the reliability and convergence of FGCM-based systems. Finally, suggestions for future applications are proposed.

Keywords: grey clustering; fuzzy grey cognitive maps; group decision-making; grey systems theory; organizational culture; start-up.

3.1 INTRODUCTION

Real-life situations require complex decision-making, with various experts having to assess multiple criteria and deal with imprecise information (HAJEK; FROELICH, 2019). Indeed, Multi-Criteria Group Decision-Making (MCGDM) approaches that are capable of considering uncertainty are more likely to provide realistic results (HAERI; REZAEI, 2019). The complementary skills of each group member allow the team to perceive the implications of their decisions from different perspectives (MAZZUTO et al., 2018). This is of particular interest for organizations, which are intricate social systems, guided by human behaviour, where subjects interact in a manner that is quantitative, qualitative, or both (NAIR; RECKIEN; VAN MAARSEVEEN, 2019). In this direction, Tseng (2010) highlights that there is a need for the development of cause and effect decision-making models, especially considering group decision.

In the literature that concerns the modelling of causal relationships, the cognitive map stands out for its flexibility and efficiency in handling systems where complex interactions occur (FURNARI, 2015). In this direction, Fuzzy Cognitive Maps (FCMs) are neuro-fuzzy systems capable of incorporating experts' knowledge, uncertainty and of providing a graphical representation easily interpreted by humans (SALMERON; PAPAGEORGIOU, 2012; KONAR; CHAKRABORTY, 2005). They are structured by nodes, which indicate the most relevant factors of a decisional situation, and links between these nodes, which model their relationship (KOSKO, 1986). However, FCMs have a number of drawbacks, such as the incompleteness in considering the semantics of causality, the simulation of causal dynamics and the representation of fuzziness (NAIR; RECKIEN; VAN MAARSEVEEN, 2019; CARVALHO, 2013). To overcome this, a FCM extension was proposed by Salmeron (2010), named fuzzy grey cognitive map (FGCM). Based on the Grey Systems Theory (GST) and fuzzy cognitive maps, FGCMs can be adapted to a wide range of problems and have been specifically developed to deal with subjectivity, uncertainty and grey environments. The FGCM is also able to quantify causal relationships, even with scarce data (SALMERON, 2010). The main difference between FGCMs and FCMs refers to the weights design: while FCMs use weights with discrete numerical values, FGCMs consider weights with grey intensity including grey uncertainty and fuzziness (SALMERON; GUTIERREZ, 2012).

FGCMs handle the inherent uncertainty in complex domains by assessing the nodes and edges' greyness and allow modelling experts' hesitancy related to the description of the causal relationships between concepts (SALMERON; PAPAGEORGIOU, 2012). FGCMs are able to

represent more kinds of relationships than FCMs, since the reasoning process considers a degree of uncertainty (greyness) expressed in grey values (SALMERON; GUTIERREZ, 2012). Finally, a FGCM-based decision support approach can adapt its knowledge from available raw data and other inherently uncertain data sources (SALMERON; PAPAGEORGIOU, 2012).

As in FCMs, two inputs are required for the FGCM technique: the initial state vector and the relationship matrix (SALMERON, 2010). Both inputs are obtained from the specialists' tacit knowledge (SALMERON; GUTIERREZ, 2012). However, as pointed out by Boutalis, Kottas and Christodoulou (2009), the process of capturing the information for these inputs from multiple specialists can affect the convergence speed of FCMs and FGCMs, as well as causing them to enter into a chaotic state. This occurs since the system activation is dependent on the initial input data. Hence, if the initial state vector and relationship matrix are inconsistent, which is likely to occur when dealing with multiple criteria and multiple decision-makers, convergence may be affected (FROELICH et al., 2012).

To address this issue, the grey clustering (GC) technique can be applied to obtain the initial state vector from the relationship matrix information. It does that by extracting conclusions from the matrix judgmental data, categorizing these data in importance classes (RAJESH, 2018). To the best of the authors' knowledge, the literature does not present a similar proposition. In addition, according to Nápoles et al. (2016), more efficient strategies to improve the convergence of FCM-based systems are still required. Hence, the research question that motivates the execution of this study regards how to robustly support group cause and effect decision-making by using GC as a mean to improve FGCMs' process.

Considering the previous arguments, this paper proposes a group decision-making model for assessing cause and effect relationships by combining the grey clustering and fuzzy grey cognitive maps techniques. The main benefit of the association of both techniques is the reduction of required inputs and uncertainties regarding data collection, which therefore increases model reliability. The main practical implication is the improvement of the process of mapping, identification and quantification of causal relationships under high uncertainty and multiple decision-makers. In this proposal, imprecision is also assessed by the use of computational processing of human language or computing with words (ZADEH, 1999). This is justified since linguistic approaches have the advantage of reducing distortion and information lost, which leverages results reliability and potentializes convergence (TSENG, 2010).

The study has followed the quantitative axiomatic prescriptive model-based research. It is axiomatic because it aims to develop a quantitative model to produce knowledge concerning the behaviour of a system variable based on the behaviour of other variables (BETRAND; FRANSOO, 2016). In this particular case, the proposed model aims to classify and rank relational data. Moreover, this study is prescriptive since it is primarily interested in developing policies, strategies and actions to improve the available results in the existing literature to find a solution for a newly defined problem (BETRAND; FRANSOO, 2016). The GC and FGCM techniques were implemented in MATLAB® and a real pilot application is presented to illustrate the model behaviour in practice. The application was conducted on a technology start-up that develops management systems to small businesses and which has recently received venture capital investments.

This paper is organized as follows: section 3.2 presents a review regarding the main aspects of the grey systems theory and its recent applications to group decision-making; section 3.3 discusses fuzzy grey cognitive maps; section 3.4 addresses the grey clustering technique; section 3.5 details the proposed GC-FGCM decision-making model; section 3.6 illustrates the use of the proposal through a real application case; section 3.7 addresses discussions; finally, section 3.8 draws conclusions and suggestions for further research.

3.2 GREY SYSTEMS THEORY

The Grey Systems Theory (GST) is an effective method for handling problems where high uncertainty, small and incomplete data sets are present (SALMERON, 2010). In comparison with conventional statistical models, grey models require fewer data to estimate the behaviour of unknown systems (DENG, 1989). GST has been widely and successfully applied in the analysis of various systems such as social, financial, technological, agricultural, industrial, medical and military (KAYACAN; ULUTAS; KAYNAK, 2010).

Regarding GST applications to group decision-making, some examples of recent developments are as follows. Liu, Du and Wang (2019) propose a grey group approach for managing behaviour, negotiation and consensus in decision-making. Song et al. (2018) apply grey group decision-making for health management. Hashemi et al. (2018) integrate GST to a group decision-making approach for the contractor assessment problem. Zhu et al. (2016) investigate the application of grey relational analysis for dealing with double information and multiple decision-makers. Zhao, Jian and Liu (2015) have developed a grey clustering group

decision model that classifies multiple attributes based on their interactions into China regional innovation. However, they do not address how to deal with cause and effect relationships in group decision-making situations, neither the process of classifying and ranking this relational data.

GST avoids the disadvantages of conventional statistical methods and only needs a small amount of information to estimate systems' behaviour by dividing them into three types according to the degree of known information (SALMERON; PAPAGEORGIOU, 2012). If structures and internal characteristics of a system are fully known the system is a white system, whereas if the internal structures and characteristics are completely unknown it is called a black system (SALMERON; GUTIERREZ, 2012). Therefore, one system with both known partial information and unknown partial information is a grey system.

Let U be the universal set. The grey set $G \in U$ is defined by $G = \begin{cases} \overline{\mu}_G(x): x \rightarrow [0,1] \\ \underline{\mu}_G(x): x \rightarrow [0,1] \end{cases}$

where $\overline{\mu}_G(x)$ and $\underline{\mu}_G(x)$ respectively are the lower and upper membership functions and $\underline{\mu}_G(x) \leq \overline{\mu}_G(x)$ (SALMERON; PAPAGEORGIOU, 2012). Therefore, a grey set G can become a fuzzy set when $\underline{\mu}_G(x) = \overline{\mu}_G(x)$, since in this specific case only one function determines the membership degree of an element to the G set, as with fuzzy sets (SALMERON, 2010).

A grey number is one whose exact value is unknown, but the range in which it is included is not (SALMERON; GUTIERREZ, 2012). Thus, a grey number with known lower and upper limits is called an interval grey number and it is represented as $\otimes G \in [\underline{G}, \overline{G}]$, $\underline{G} \leq \overline{G}$ (SALMERON, 2010). If the grey number $\otimes G$ has only a lower limit, it is denoted as $\otimes G \in [\underline{G}, +\infty)$ and if it has only an upper limit, it is denoted as $\otimes G \in (-\infty, \overline{G}]$ (SALMERON; PAPAGEORGIOU, 2012). In this sense, a black number would be a number of which no information is known, $\otimes G \in (-\infty, +\infty)$, and a white number is a number of which all information is known, $\otimes G \in [\underline{G}, \overline{G}]$, $\underline{G} = \overline{G}$ (SALMERON, 2010). The length of a grey number can be calculated as $l(\otimes G) = |\overline{G} - \underline{G}|$, where when $l(\otimes G) = 0$, $\otimes G$ corresponds to a white number and when $l(\otimes G) = \infty$, nothing can be concluded because $\otimes G$ can be either a grey number with an unknown limit or a black number (SALMERON; PAPAGEORGIOU, 2012).

Let $\otimes G_1 \in [\underline{G}_1, \overline{G}_1]$, $\underline{G}_1 \leq \overline{G}_1$, and $\otimes G_2 \in [\underline{G}_2, \overline{G}_2]$, $\underline{G}_2 \leq \overline{G}_2$, be two grey numbers and be λ a positive real number. Then, the following operations are defined according to Equations (3.1) to (3.5) (SALMERON, 2010).

$$\otimes G_1 + \otimes G_2 \in [\underline{G}_1 + \underline{G}_2, \overline{G}_1 + \overline{G}_2] \quad (3.1)$$

$$\otimes G_1 - \otimes G_2 \in [\underline{G}_1 - \overline{G}_2, \overline{G}_1 - \underline{G}_2] \quad (3.2)$$

$$\begin{aligned} & \otimes G_1 \times \otimes G_2 \in \\ & \left[\min(\underline{G}_1 \cdot \underline{G}_2, \underline{G}_1 \cdot \overline{G}_2, \overline{G}_1 \cdot \underline{G}_2, \overline{G}_1 \cdot \overline{G}_2), \max(\underline{G}_1 \cdot \underline{G}_2, \underline{G}_1 \cdot \overline{G}_2, \overline{G}_1 \cdot \underline{G}_2, \overline{G}_1 \cdot \overline{G}_2) \right] \end{aligned} \quad (3.3)$$

$$\begin{aligned} \otimes G_1 \div \otimes G_2 & \in [\underline{G}_1, \overline{G}_1] \times [1/\overline{G}_2, 1/\underline{G}_2] \\ & \in \left[\min(\underline{G}_1 \cdot 1/\overline{G}_2, \underline{G}_1 \cdot 1/\underline{G}_2, \overline{G}_1 \cdot 1/\overline{G}_2, \overline{G}_1 \cdot 1/\underline{G}_2), \right. \\ & \quad \left. \max(\underline{G}_1 \cdot 1/\overline{G}_2, \underline{G}_1 \cdot 1/\underline{G}_2, \overline{G}_1 \cdot 1/\overline{G}_2, \overline{G}_1 \cdot 1/\underline{G}_2) \right] \end{aligned} \quad (3.4)$$

$$\lambda \cdot \otimes G_1 \in [\lambda \cdot \underline{G}_1, \lambda \cdot \overline{G}_1] \quad (3.5)$$

In addition, the process of converting a grey number into a white one is defined as whitenization and occurs as shown in Equation (3.6) (SALMERON; PAPAGEORGIOU, 2012). If $\psi = 0.5$, the process is called *equal weight mean whitenization* (LIU; LIN, 2006).

$$\widehat{\otimes} G = \psi \underline{G} + (1 - \psi) \overline{G} \mid \psi \in [0,1] \quad (3.6)$$

For group decision-making, aggregation between grey numbers is done according to Equation (3.7), where $\otimes G^k_{ij}$ corresponds to the judgement of the k th decision-maker regarding the impact of criterion i over criterion j (MEMOM; LEE; MARI, 2015).

$$\otimes G_{ij} = \sqrt[k]{\otimes G^1_{ij} \times \otimes G^2_{ij} \times \dots \times \otimes G^n_{ij}} \quad (3.7)$$

Grey matrices, denoted as $A(\otimes)$, are generically represented as in Equation (3.8) (SALMERON, 2010). The grey matrix elements are denoted as $\otimes a_{ij}$ for the i th row and the j th column (SALMERON; PAPAGEORGIOU, 2012). It is worth to note that unidimensional grey matrices are called n-dimensional grey vectors.

$$A(\otimes) = \begin{pmatrix} \otimes a_{11} & \dots & \otimes a_{1n} \\ \dots & \otimes a_{ij} & \dots \\ \otimes a_{n1} & \dots & \otimes a_{nn} \end{pmatrix} \quad (3.8)$$

Therefore, let Equations (3.9) and (3.10) represent respectively a grey matrix and a grey vector. Then, with the previously defined grey operations, the multiplication of the matrix and the vector occurs as in Equation (3.11) (SALMERON, 2010).

$$B(\otimes) = \begin{pmatrix} \otimes b_{11} & \otimes b_{12} \\ \otimes b_{21} & \otimes b_{22} \end{pmatrix} \quad (3.9)$$

$$\otimes \vec{C} = (\otimes C_1 \quad \otimes C_2) \quad (3.10)$$

$$\begin{aligned} \vec{R}(\otimes) &= \vec{C}(\otimes) \cdot B(\otimes) \\ &= ((\otimes C_1 \cdot \otimes b_{11}) + (\otimes C_2 \cdot \otimes b_{21}) \quad (\otimes C_1 \cdot \otimes b_{12}) + (\otimes C_2 \cdot \otimes b_{22})) \end{aligned} \quad (3.11)$$

3.3 FUZZY GREY COGNITIVE MAPS

The FGCM is an innovative soft computing technique that combines FCMs and GST. It has the property to represent unstructured knowledge of causal relationships in grey systems, thus assessing human tacit knowledge (PAPAGEORGIOU; SALMERON, 2012). FGCMs are dynamic feedback systems where the effect of change on one node can affect the other nodes (SALMERON; PAPAGEORGIOU, 2012). Figure 3.1 presents a general flow chart of the FGCM technique.

Figure 3.1 - The fuzzy grey cognitive map technique.

Source: own authorship.

The FGCM nodes are variables, representing crisp or fuzzy concepts, and the relationships between nodes are represented by directed edges, which assign the influence of the causal variable on the effect variable (SALMERON, 2010). Since FGCMs are hybrid

methods between grey systems and neural networks, each cause is measured by its grey intensity as in Equation (3.12), where i is the pre-synaptic node and j the post-synaptic one (SALMERON; PAPAGEORGIOU, 2012).

$$\otimes w_{i \rightarrow j} \in [\underline{w_{i \rightarrow j}}, \overline{w_{i \rightarrow j}}] \mid \forall i, j \rightarrow \underline{w_{i \rightarrow j}} \leq \overline{w_{i \rightarrow j}}, \{w_{i \rightarrow j}, \overline{w_{i \rightarrow j}}\} \in [-1, +1] \quad (3.12)$$

For the FGCM design, experts identify the criteria and determine the number and type of grey concepts (nodes) that compose the FGCM (SALMERON, 2010). In addition, experts know which nodes influence others and how. With linguistic terms, they are able to pairwise assess the cause and effect relationships between criteria, their intensity and if they are negative or positive. By associating linguistic terms to grey numbers, the grey relationship matrix is obtained, denoted as $A(\otimes)$.

In addition to the determination of the relationship matrix, the initial perception of the importance of each criterion must also be determined. Again, by converting the linguistic terms to their respective grey numbers, the grey initial state vector ($\otimes \vec{C}_0$) is obtained as in Equation (3.13). It is noteworthy that if there are multiple decision-makers, the aggregation of the initial state vector and the relationship matrix of each decision-maker should be performed according to Equation (3.7).

$$\otimes \vec{C}_0 = \left(\otimes \vec{C}_0^{[1]} \quad \otimes \vec{C}_0^{[2]} \quad \dots \quad \otimes \vec{C}_0^{[n]} \right) = \left([\underline{\otimes \vec{C}_0^{[1]}}, \overline{\otimes \vec{C}_0^{[1]}}] \quad [\underline{\otimes \vec{C}_0^{[2]}}, \overline{\otimes \vec{C}_0^{[2]}}] \quad \dots \quad [\underline{\otimes \vec{C}_0^{[n]}}, \overline{\otimes \vec{C}_0^{[n]}}] \right) \quad (3.13)$$

Then, the range of the initial state vector should be evaluated to determine which function is applied to activate the system. There are two main types of activation functions: the unipolar sigmoid function and the hyperbolic tangent function (BUENO; SALMERON, 2009). If the vector values are in the range $[0, 1]$ then the unipolar sigmoid function is the one to be applied; on the other hand, if the values are in the range $[-1, 1]$ then the hyperbolic tangent function should be applied (SALMERON, 2010).

Thus, the nodes' values (i.e., the grey concept values in the cognitive map) are iteratively calculated by multiplying the initial state vector and the relationship matrix within the activation function, used to monotonically map these values in a normalized range. Equation (3.14) shows how the system activation occurs, where $\otimes \vec{C}_t$ is the grey vector at the iteration or state t ; $S(x)$ is the sigmoid activation function and $A(\otimes)$ is the grey relationship matrix (SALMERON; PAPAGEORGIOU, 2012). The component i of the vector state $\otimes C_{(t+1)}^{[i]}$ is expressed as in Equation (3.15).

$$\begin{aligned}
 \otimes \vec{C}_{(t+1)} &= S[\otimes \vec{C}_t \cdot A(\otimes)] = S[\otimes \vec{C}'_t] = S[(\otimes C'_t^{[1]} \quad \otimes C'_t^{[2]} \quad \dots \quad \otimes C'_t^{[n]})] \\
 &= \left(S(\otimes C'_t^{[1]}) \quad S(\otimes C'_t^{[2]}) \quad \dots \quad S(\otimes C'_t^{[n]}) \right) \\
 &= (\otimes C_{(t+1)}^{[1]} \quad \otimes C_{(t+1)}^{[2]} \quad \dots \quad \otimes C_{(t+1)}^{[n]})
 \end{aligned} \tag{3.14}$$

$$\otimes C_{(t+1)}^{[i]} \in \left[\left(1 + e^{-\lambda \cdot \underline{C}'_t^{[i]}} \right)^{-1}, \left(1 + e^{-\lambda \cdot \overline{C}'_t^{[i]}} \right)^{-1} \right] \tag{3.15}$$

In Equation (3.15), λ is a constant value that determines the slope degree of the sigmoid functions. To specify the value of λ , one should consider the system convergence behaviour and expected granularity for the results. According to Bueno and Salmeron (2009), for large values of λ , for example from 5 to 10, the system convergence speed increases (which means fewer iterations are required) but granularity is reduced, compromising the differentiation of final values. For a small value of λ (e.g. 1 or 2), the sigmoid function approximates a linear function. The authors also highlight that the ideal value of λ must be determined by performing tests to verify the convergence values. Mago, Papageorgiou and Mago (2014), for example, tested $\lambda = \{0.8, 0.7, 0.6, 0.5, 0.45, 0.4, 0.3\}$ and concluded that their system outputs were more accurate for $\lambda = 0.7$. Kang et al. (2016) also state that values of λ equal to or close to 1 are ideal, since they provide the possibility of differentiation between the results after convergence, providing better interpretability.

On the other hand, Equation (3.16) shows how the system activation occurs when applying the hyperbolic tangent function and Equation (3.17) express the component i of the vector state $\otimes C_{(t+1)}^{[i]}$ (SALMERON; PAPAGEORGIOU, 2012).

$$\begin{aligned}
 \otimes \overrightarrow{C_{(t+1)}} &= \tanh[\otimes \overrightarrow{C_t} \cdot A(\otimes)] = \tanh[\otimes \overrightarrow{C'_t}] \\
 &= \tanh[(\otimes C'_t^{[1]} \quad \otimes C'_t^{[2]} \quad \dots \quad \otimes C'_t^{[n]})] \\
 &= (\tanh(\otimes C'_t^{[1]}) \quad \tanh(\otimes C'_t^{[2]}) \quad \dots \quad \tanh(\otimes C'_t^{[n]})) \\
 &= (\otimes C_{(t+1)}^{[1]} \quad \otimes C_{(t+1)}^{[2]} \quad \dots \quad \otimes C_{(t+1)}^{[n]})
 \end{aligned} \tag{3.16}$$

$$\otimes C_{(t+1)}^{[i]} \in \left[\left(\frac{e^{\lambda \cdot C'_t^{[i]}} - e^{-\lambda \cdot C'_t^{[i]}}}{e^{\lambda \cdot C'_t^{[i]}} + e^{-\lambda \cdot C'_t^{[i]}}} \right), \left(\frac{e^{\lambda \cdot \overrightarrow{C'_t}^{[i]}} - e^{-\lambda \cdot \overrightarrow{C'_t}^{[i]}}}{e^{\lambda \cdot \overrightarrow{C'_t}^{[i]}} + e^{-\lambda \cdot \overrightarrow{C'_t}^{[i]}}} \right) \right] \tag{3.17}$$

The state of the grey dynamic system then evolves along the process (SALMERON, 2010). In addition, according to Salmeron and Papageorgiou (2012), after the iterative process, the FGCM reaches either one of two states: it settles down to a fixed pattern of node values (convergence) or it can keep cycling between several fixed grey states, being even possible to reach a chaotic state. For the output analysis after convergence, FGCMs allow the calculation of the degree of uncertainty associated with each of the obtained values, called greyness (SALMERON, 2010). High values of this indicator lead to the conclusion that the results have high associated uncertainty. Greyness is calculated as in Equation (3.18), where $|l(\otimes C_i)|$ corresponds to the absolute value of the grey node length of the final state vector and $l(\otimes \psi)$ is determined by Equation (3.19), which depends of the data variation present in the FGCM. Finally, whitenization is performed according to Equation (3.6).

$$\varphi(\otimes C_i) = |l(\otimes C_i)|/l(\otimes \psi) \tag{3.18}$$

$$l(\otimes \psi) = \begin{cases} 1 & \text{if } \{\otimes C_i, \otimes w_i\} \subseteq [0,1] \\ 2 & \text{if } \{\otimes C_i, \otimes w_i\} \subseteq [-1, +1] \end{cases} \quad \begin{matrix} \forall \otimes C_i, \otimes w_i \\ \forall \otimes C_i, \otimes w_i \end{matrix} \quad (3.19)$$

3.4 GREY CLUSTERING

As mentioned in section 3.1, this paper proposes to apply the GC technique to obtain the initial state vector from the FGCM relationship matrix. This reduces the required inputs and other uncertainties regarding data collection, which contributes to improving the convergence speed and model reliability. GC was developed based on the GST for classifying scarce and incomplete data associated with uncertainty and with human judgments. Figure 3.2 illustrates a general flowchart of the GC technique. Grey whitenization functions are used to calculate the criteria membership degree to predefined classes, assigning each criterion to the class with the highest calculated membership (DELGADO; ROMERO, 2016).

Figure 3.2 - The grey clustering technique.

Source: own authorship.

The GC first step refers to the criteria identification. These criteria are inputs for the technique and are classified into each of the given classes. Thus, by associating linguistic terms

with grey numbers, the impacts between criteria can be assessed by pairwise evaluation. It is noteworthy that, according to Rajesh (2018), this procedure not only assesses the impact of criterion x over y , but can also correspond to the relationship between them (e.g. if it is low, medium or strong).

After converting the linguistic judgements to their respective grey numbers, the grey relationship matrix, denoted by $\alpha(\otimes) = [\otimes \dot{a}_{ij}]$, is calculated, which gathers the information about the impacts between criteria. If more than one decision-maker is present, aggregation should be performed according to Equation (3.7). If the grey numbers associated with the linguistic terms are not normalized, the normalization of matrix $\alpha(\otimes) = [\otimes \dot{a}_{ij}]$ should be conducted according to Equations (3.20), (3.21) and (3.22), where $\underline{\otimes} \tilde{a}_{ij}$ corresponds to the normalized lower limit of grey number $\otimes \tilde{a}_{ij}$ and $\overline{\otimes} \tilde{a}_{ij}$ to its normalized upper limit (RAJESH, 2018).

$$\underline{\otimes} \tilde{a}_{ij} = (\underline{\otimes} \dot{a}_{ij} - \min_j \underline{\otimes} \dot{a}_{ij}) / \Delta_{min}^{max} \quad (3.20)$$

$$\overline{\otimes} \tilde{a}_{ij} = (\overline{\otimes} \dot{a}_{ij} - \min_j \overline{\otimes} \dot{a}_{ij}) / \Delta_{min}^{max} \quad (3.21)$$

$$\Delta_{min}^{max} = \max_j \underline{\otimes} \dot{a}_{ij} - \min_j \underline{\otimes} \dot{a}_{ij} \quad (3.22)$$

According to Rajesh (2018), the b_{ij} matrix should store the normalized grey values so they can be converted to white values, which compose the matrix $B = [b_{ij}^*]$ as in Equations (3.23) and (3.24).

$$b_{ij} = \left(\frac{\underline{\otimes} \tilde{a}_{ij}(1 - \underline{\otimes} \tilde{a}_{ij}) + (\overline{\otimes} \tilde{a}_{ij} \times \overline{\otimes} \tilde{a}_{ij})}{(1 - \underline{\otimes} \tilde{a}_{ij} + \overline{\otimes} \tilde{a}_{ij})} \right) \quad (3.23)$$

$$b_{ij}^* = \left(\min \otimes \dot{a}_{ij} + (b_{ij} \times \Delta_{\min}^{\max}) \right) \quad (3.24)$$

Once this is done, the grey classes into which the criteria will be classified should be determined. According to Delgado and Romero (2016), for group decision-making, the center-point triangular whitenization weight functions (CTWF) method is the most recommended for its objectivity and reliability. This is because respondents tend to be more assertive when performing a judgment about the central point of a grey class than to define more parameters. The CTWF method is also better able to handle uncertainties, as it only needs one point for mathematical determination of the grey classes, and it is not necessary for decision-makers to determine their limits, which is often difficult due to the lack of reliable data (CHEN et al., 2019).

The CTWF method consists of the following steps (DELGADO; ROMERO, 2016):

1. The numerical range of the criteria values is divided into the number of grey classes to be obtained. Thus, the central points $(\lambda_1, \lambda_2, \dots, \lambda_s)$ of classes 1, 2, ..., s are also determined.
2. The defined grey classes are then expanded in two directions, with the addition of classes 0 and $(s + 1)$, with the central points λ_0 and λ_{s+1} , respectively. Thus, the CTWF for the k th grey class, regarding the impact of criterion i on criterion j , denoted as x_{ij} , is defined by Equation (3.25), where $f_j^k(x_{ij})$ corresponds to the CTWF of the k th grey class for the j th criterion.

$$f_j^k(x_{ij}) = \begin{cases} 0, & x \notin [\lambda_{k-1}, \lambda_{k+1}] \\ \frac{x - \lambda_{k-1}}{\lambda_k - \lambda_{k-1}}, & x \in [\lambda_{k-1}, \lambda_k] \\ \frac{\lambda_{k+1} - x}{\lambda_{k+1} - \lambda_k}, & x \in [\lambda_k, \lambda_{k+1}] \end{cases} \quad (3.25)$$

3. The clustering coefficient can be calculated as in Equation (3.26).

$$\sigma_i^k = \sum_{j=1}^m f_j^k(x_{ij}) \quad (3.26)$$

4. Finally, the criteria can be classified into the grey classes. If $\sigma_i^{k*} = \max_{i \leq k \leq s} \{\sigma_i^k\}$, then the criterion i belongs to the class k^* . In case many criteria belong to the same grey class k^* , they can be ordered according to the magnitudes of their respective clustering coefficients.

3.5 THE GC-FGCM DECISION-MAKING MODEL

As with FCMs, it is possible to note in Figure 3.1 that FGCMs require two inputs: $\otimes$ $\vec{C}_0$, the initial state vector, and $A(\otimes)$, the relationship matrix. The first correspond to the initial importance of each criterion in the system and the latter to the causal relationships between criteria (SALMERON, 2010). Salmeron and Gutierrez (2012) highlight that both are obtained from the tacit knowledge of specialists. However, Boutalis, Kottas and Christodoulou (2009) state that the information in these inputs may affect the FGCM convergence. As mentioned in section 3.1, this is justified since the collected data may diverge due to the action of subjectivity and uncertainty over multiple decision-makers, as well as due to fatigue when there are a high number of criteria, causing inconsistencies to appear between $\otimes$ $\vec{C}_0$ and $A(\otimes)$.

In Figure 3.2, it is possible to note that GC requires only one input: $\alpha(\otimes)$ which, as in FGCMs, is a relationship matrix. When assessing causal relationships between criteria, the GC matrix $\alpha(\otimes)$ is equivalent to the FGCM matrix $A(\otimes)$, since both are composed by the pairwise evaluations of impacts between criteria. This is a common step to Figure 3.1 and Figure 3.2, as shown by Equation (3.27), where r_{ij} denotes the assessed relation between criterion i and criterion j .

$$\alpha(\otimes) = A(\otimes) = \begin{matrix} & \begin{matrix} \text{Criterion 1} & \text{Criterion 2} & \cdots & \text{Criterion } n \end{matrix} \\ \begin{matrix} \text{Criterion 1} \\ \text{Criterion 2} \\ \vdots \\ \text{Criterion } n \end{matrix} & \begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nn} \end{pmatrix} \end{matrix} \quad (3.27)$$

In Figure 3.2, it is also possible to note that the GC technique classifies the criteria in matrix $\alpha(\otimes)$ into grey classes. Therefore, GC can be used to classify the criteria of the FGCM

relationship matrix. For example, in the study conducted by Rajesh (2018) nine linguistic terms are associated with grey numbers for pairwise evaluation of causal relationships between criteria so as to generate the $\alpha(\otimes)$ relationship matrix (“extremely low”, “very low”, “moderately low”, “medium”, “moderately high”, “high”, “very high”, “extremely high”). The author then uses GC to classify the criteria in the “low importance”, “medium importance” and “high importance” clusters. Proceeding in a similar way, by applying the GC to the $A(\otimes)$ matrix, it is possible to associate each criterion to its own correspondent class of importance, based only on the information provided by the decision-makers to compose the $A(\otimes)$ matrix. Moreover, if grey numbers are associated with the determined classes, as it is commonly done with linguistic terms, the initial state vector is obtained from the relationship matrix, as Equation (3.28) shows, where $GC_{Criterion\ n}$ stands for the grey class assigned to the criterion n . Therefore, the GC output becomes the FGCM input.

$$\begin{array}{c}
 \text{Impact on} \\
 \text{the system}
 \end{array}
 \begin{array}{c}
 \text{Grey numbers associated} \\
 \text{with each grey class}
 \end{array}
 \begin{array}{c}
 \text{Criterion 1} \\
 \text{Criterion 2} \\
 \vdots \\
 \text{Criterion n}
 \end{array}
 \begin{array}{c}
 GC_{Criterion\ 1} \\
 GC_{Criterion\ 2} \\
 \vdots \\
 GC_{Criterion\ n}
 \end{array}
 =
 \begin{array}{c}
 \left[\begin{array}{cc}
 \overline{\otimes \vec{C}_0^{[1]}}, & \overline{\otimes \vec{C}_0^{[1]}} \\
 \overline{\otimes \vec{C}_0^{[2]}}, & \overline{\otimes \vec{C}_0^{[2]}} \\
 \vdots & \vdots \\
 \overline{\otimes \vec{C}_0^{[n]}}, & \overline{\otimes \vec{C}_0^{[n]}}
 \end{array} \right]
 \end{array}
 \quad (3.28)$$

If there are multiple decision-makers ($k = 1, \dots, n$) the aggregation of judgements in matrices $\alpha^{(k)}(\otimes) = A^{(k)}(\otimes)$ should be performed according to Equation (3.7). Figure 3.3 illustrates a general flowchart detailing the step-by-step of the GC-FGCM combination. In this figure, the horizontal flowchart, in grey, corresponds to the steps of the GC technique and the vertical flowchart, in white, is associated with the steps of the FGCM technique. Hence, it is possible to visualize how both techniques are combined in one single model.

This proposition can increase decision-making reliability by reducing the inputs required to the user and the uncertainty associated with the input data, which contributes to improve the system convergence. In this way, the combined GC-FGCM approach is ideal for aiding the process of mapping, identifying and quantifying cause and effect relationships in

environments with high uncertainty, need for cognitive judgments, scarce data and inaccuracy. In a hypothetical example, for the application of an FGCM with the presence of three decision-makers, six inputs would be required, two from each: one being the relationship matrix and the other the initial state vector. With the GC-FGCM combination the number of inputs is halved since only the relationship matrix from each decision-maker is needed.

Figure 3.3 - The combined GC-FGCM approach.

Source: own authorship.

The GC-FGCM process begins with the GC technique, the horizontal piece of the flowchart in Figure 3.3, in grey. Firstly, the criteria related to the modelled problem should be identified, over which the existing causal relationships will be mapped and quantified by multiple experts with linguistic terms associated to grey numbers, defined in a normalized scale. This pairwise evaluation of relationships between criteria is the only required input to the user.

These evaluations are converted to their respective grey numbers and the grey relationship matrix is obtained, $\alpha(\otimes) = A(\otimes)$. With Equations (3.20) to (3.24), the whitenization of $\alpha(\otimes) = A(\otimes)$ is executed, resulting in a weighted white matrix that quantifies the impact of criterion i over criterion j .

Then, grey classes are defined according to the previously set linguistic terms. As they are associated with grey numbers distributed in a normalized scale, we can apply the CTFW method and, with Equation (3.25), obtain the whitenization functions. With Equation (3.26), the grey clustering coefficient is calculated and the criteria are clustered each into their respective grey class. Since each grey class has an associated grey number, the initial state vector is obtained. Thus, the FGCM process automatically begins, which can be seen in the vertical piece of the flowchart in Figure 3.3, in white. Having $\otimes \vec{C}_0$ and $\alpha(\otimes) = A(\otimes)$, as in Equations (3.14) and (3.16), the system activation and posterior convergence occurs. For the analysis of the final results, the uncertainty degree is calculated according to Equation (3.18) and, finally, they are whitened according to Equation (3.6). To exemplify how this proposition works in practice and its potential contributions, a real application was conducted to investigate the causal relationship between organizational culture aspects and operational performance of a Brazilian technology start-up.

3.6 PILOT APPLICATION IN A START-UP

Ripsas and Tröger (2014) define a start-up as a young company, with less than 10 years old, guided by an innovative business model and thriving for significant growth. Blank and Dorf (2012) highlight that these firms explore and organize sustainable and expandable business models, while severely lacking resources in comparison with other companies. Therefore, inconsistent decision-making could lead the start-up to fail (GIARDINO; WANG; ABRAHAMSSON, 2014) and this process is affected by uncertainty (TANRISEVER; ERZURUMLU; JOGLEKAR, 2012).

The particular relevance of leadership in the context of start-ups relates to the strong relationship between the behaviour of the leader with strategic vision and the performance of a new enterprise (CHAMMAS; HERNANDEZ, 2019). Ensley, Hmieleski and Pearce (2006) argue that the individual characteristics and behaviour of leaders can become imprinted into the organizational culture of firms, which becomes institutionalized and difficult to later modify.

Chatterji et al. (2019) state that organizational culture has a profound impact on the behaviour of individuals and is closely linked to leadership.

Generally, performance is assessed in different aspects, such as financial or operational. However, there is still a gap when considering other perspectives on performance, such as customer related ones (ZANON et al., 2020). In this direction, few studies propose models to aid entrepreneurs for improving new businesses performance. Chammas and Hernandez (2019) seek to assess the leadership influence in start-ups results. Chatterji et al. (2019) explore whether advices founders receive influences start-up performance. Seo, Kim and Lee (2018) address the effects of knowledge assets on start-ups outcomes. Rompho (2018) seeks to investigate the use of performance measures in start-up firms. Gelderen, Frese and Thurik (2000) study the relationship between strategy and start-ups results.

However, they do not model the impact of organizational culture on start-ups performance. In addition, they do not address the inherent uncertainty in new business ventures. Moreover, in a conducted literature review, Zanon and Carpinetti (2018) concluded that although FGCMs derive from the union of FCMs and GST and both these theories have been applied to the field of operations management, few studies propose the use of FGCMs in this context.

Therefore, this section presents an application of the proposed GC-FGCM combination for mapping and quantifying the causal relationship between factors related to organizational culture and start-up performance. The results support assertive decision-making in an environment with presence of subjectivity and uncertainty. In addition, assessing these causal relationships can help predicting scenarios and to dynamically outline action plans for performance improvement.

The application was conducted in a Brazilian start-up located in the city of São Paulo, with approximately 2 years old. The company has now more than 4,000 clients and has recently received venture capital investments. It focuses on providing technology management tools for beauty salons, barbershops, spas and other related business establishments. The customers (business owners or managers) receive a credit and debit card payment machine as well as scheduling, financial control and inventory software. Four decision-makers were involved in this application: the start-up founder and Chief Technical Officer (CTO), the human-resources management leader, the account manager and the operations leader. As with other start-ups, the

one of this pilot application also has to survive and compete in an environment with lack of precise data and uncertainty.

Therefore, for the application of the GC-FGCM model, firstly the criteria had to be identified. For assessing organizational culture, the cultural dimensions defined by Hofstede (2011) were considered. This is justified since, according to Cadden, Marshall and Cao (2013), one must be able to deconstruct organizational culture into tangible elements to understand its impact on performance. Thus, each of the Hofstede's dimensions represent the culture deconstructed in determinant aspects. In addition, as they constitute independent factors, cultural dimensions fit the cognitive map model, composed by nodes and the relationships between them. Hofstede (2011) defines each dimension as follows:

- Power distance refers to the degree of power distribution. High power distance indicates hierarchical organizations and low power distance is associated with horizontal ones.
- Uncertainty avoidance refers to the level of organizational tolerance to uncertainty. Low uncertainty avoidance means uncertainty acceptance and high uncertainty avoidance is associated with discomfort and resistance.
- Individualism vs. collectivism refers to the degree in which people in an organization tend to act as a group or as an individual.
- Masculinity vs. femininity refers to the degree of aggressiveness, assertiveness and competitiveness present in the organization. In cultures characterized by masculinity there is the presence of conflict and denial, while in cultures of femininity there is presence of negotiation, consideration and consensus.
- Long vs. short term orientation refers to the connection of the past with current and future actions. Long-term orientation means focus on future accomplishments while short term is associated to appreciation of the past and traditions.
- Indulgence vs. restraint refers to the degree of gratification versus regulation. Indulgence organizations are worried about freedom of leisure and enjoyment while restraint organizations are not.

As Table 3.1 shows, based on Hofstede's definitions, the four decision-makers reached a consensus regarding the start-up organizational profile. Table 3.1 also associates a code to each one of the dimensions in order to facilitate the reader's comprehension when the data is inserted into the computational model.

Table 3.1 - Start-up's cultural profile.

Cultural dimension	Diagnosis	Code
Power distance	Low power distance	c ₁
Uncertainty avoidance	Low uncertainty avoidance	c ₂
Individualism vs. collectivism	Collectivism	c ₃
Masculinity vs. femininity	Femininity	c ₄
Long vs. short term orientation	Short term orientation	c ₅
Indulgence vs. restraint	Indulgence	c ₆

Source: own authorship.

In order to operationalize measurement, performance indicators are established to quantify the efficiency or effectiveness of actions and processes, being verifiable variables that measure and represent the current progress of the organization (ZANON; ULHOA; ESPOSTO, 2020). Hence, the four decision-makers identified the company performance indicators to be inserted in the model, as Table 3.2 shows. As a start-up, the company does not have a structured performance measurement system. However, it has few but well-defined indicators, which guide decision-making and strategy actions. The decision-makers also assessed the current performance of the start-up in each one of the indicators, using linguistic terms.

Table 3.2 - Indicators definition and current performance.

Indicator	Code	Definition	Current performance
Price/Volume Tendency	TPV	Calculates the volume of financial transactions by the debit/credit card machines in the current month in comparison to the previous month.	Low
Net Promoter Score	NPS	Measures customer loyalty and if a customer is advising the company to other customers.	Medium
Active Customers	AC	Indicates the number of active customers in a given period.	High

Source: own authorship.

Therefore, following Figure 3.3, each DM assessed the influence of the cultural dimensions (criteria c1 to c6) over the performance indicators (criteria TPV, NPS and AC)

using the linguistic terms in Table 3.3. Four relationship matrices were obtained, one for each DM, as presented in Tables 3.4 to 3.7.

Table 3.3 - Linguistic terms and associated grey numbers.

Linguistic Term	Code	$\underline{G}$	$\overline{G}$
Null	N	0	0
Very Low	VL	0.1	0.3
Low	L	0.3	0.5
Medium	M	0.5	0.6
High	H	0.6	0.8
Very High	VH	0.8	1

Source: own authorship.

Table 3.4 - DM1 linguistic assessment of impacts between criteria.

DM₁	PVT	NPS	AC
c1	L	H	H
c2	VH	H	VH
c3	M	H	VH
c4	L	L	VL
c5	H	M	VH
c6	L	L	M

Source: own authorship.

Table 3.5 - DM2 linguistic assessment of impacts between criteria.

DM₂	PVT	NPS	AC
c1	M	H	H
c2	L	M	H
c3	VH	H	H
c4	N	L	N
c5	H	L	H
c6	VH	M	H

Source: own authorship.

Table 3.6 - DM3 linguistic assessment of impacts between criteria.

DM ₃	PVT	NPS	AC
c1	VH	H	VH
c2	H	H	VH
c3	H	M	H
c4	L	L	M
c5	L	M	H
c6	L	L	L

Source: own authorship.

Table 3.7 - DM4 linguistic assessment of impacts between criteria.

DM ₄	PVT	NPS	AC
c1	L	L	VL
c2	M	M	H
c3	M	M	H
c4	VL	L	L
c5	H	VH	VH
c6	L	M	M

Source: own authorship.

The linguistic terms in Tables 3.4 to 3.7 were then converted to their respective grey numbers, which were aggregated using Equation (3.7). As a result, Tables 3.8 and 3.9 present the aggregated relationship matrices for respectively the lower and upper grey values.

Table 3.8 - Aggregated relationship matrix, grey lower values.

Grey relationship matrix	<u>G</u>						PVT	NPS	AC
	c1	c2	c3	c4	c5	c6			
c1	0.000	0.000	0.000	0.000	0.000	0.000	0.436	0.505	0.412
c2	0.000	0.000	0.000	0.000	0.000	0.000	0.518	0.548	0.693
c3	0.000	0.000	0.000	0.000	0.000	0.000	0.589	0.548	0.645
c4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.300	0.000
c5	0.000	0.000	0.000	0.000	0.000	0.000	0.505	0.495	0.693
c6	0.000	0.000	0.000	0.000	0.000	0.000	0.383	0.387	0.461

Continues.

Conclusion.

Grey relationship matrix	$\underline{G}$						PVT	NPS	AC
	c1	c2	c3	c4	c5	c6			
PVT	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
NPS	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AC	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Source: own authorship.

Table 3.9 - Aggregated relationship matrix, grey upper values.

Grey relationship matrix	$\overline{G}$						PVT	NPS	AC
	c1	c2	c3	c4	c5	c6			
c1	0.000	0.000	0.000	0.000	0.000	0.000	0.622	0.711	0.662
c2	0.000	0.000	0.000	0.000	0.000	0.000	0.700	0.693	0.894
c3	0.000	0.000	0.000	0.000	0.000	0.000	0.733	0.693	0.846
c4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.500	0.000
c5	0.000	0.000	0.000	0.000	0.000	0.000	0.711	0.651	0.894
c6	0.000	0.000	0.000	0.000	0.000	0.000	0.595	0.548	0.616
PVT	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
NPS	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AC	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Source: own authorship.

Table 3.10 presents the Δ max-min calculation based on Equations (3.20) to (3.24) for the whitenization of the aggregated grey relationship matrix, which results in a weighted white matrix (b_{ij}^*) that quantifies the impact of criterion i over criterion j (Table 3.11).

Table 3.10 - Δ max-min calculation.

Δ_{min}^{max}	c1	c2	c3	c4	c5	c6	PVT	NPS	AC
	0.000	0.000	0.000	0.000	0.000	0.000	0.733	0.711	0.894

Source: own authorship.

Table 3.11 - Whitenization of the aggregated grey relationship matrix.

b_{ij}^*	c1	c2	c3	c4	c5	c6	c7	c8	c9
c1	0.00	0.00	0.00	0.00	0.00	0.00	0.39	0.45	0.49
c2	0.00	0.00	0.00	0.00	0.00	0.00	0.46	0.45	0.75
c3	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.45	0.70
c4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.27	0.00
c5	0.00	0.00	0.00	0.00	0.00	0.00	0.46	0.41	0.75
c6	0.00	0.00	0.00	0.00	0.00	0.00	0.36	0.33	0.49
PVT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NPS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Source: own authorship.

Table 3.12 illustrates the grey class determination procedure. The classes are defined analogously to the set of linguistic terms in Table 3.3 since they should reflect the criteria importance in the system. As the grey classes are associated with grey numbers distributed in a normalized scale, we can apply the CTFW method and, based on Equation (3.25), obtain the whitenization functions. These functions will calculate the membership degree of each criterion to each grey class. Therefore, $f_1(x)$ calculates the membership degree of each criterion to the grey class VL and so on, as in Equations (3.29) to (3.33).

Table 3.12 - Grey classes determination.

<i>Grey Classes</i>	$\underline{G}$	$\overline{G}$	<i>Center Point</i>	λ
VL	0	0.2	0.1	1
L	0.2	0.4	0.3	2
M	0.4	0.6	0.5	3
H	0.6	0.8	0.7	4
VH	0.8	1	0.9	5

Source: own authorship.

$$f_1(x) = \begin{cases} 0, & x \notin [0; 0.3] \\ \frac{x}{0.1}, & x \in [0; 0.1] \\ \frac{0.3-x}{0.2}, & x \in [0.1; 0.3] \end{cases} \quad (3.29)$$

$$f_2(x) = \begin{cases} 0, & x \notin [0.1; 0.5] \\ \frac{x-0.1}{0.2}, & x \in [0.1; 0.3] \\ \frac{0.5-x}{0.2}, & x \in [0.3; 0.5] \end{cases} \quad (3.30)$$

$$f_3(x) = \begin{cases} 0, & x \notin [0.5; 0.7] \\ \frac{x-0.3}{0.2}, & x \in [0.3; 0.5] \\ \frac{0.7-x}{0.2}, & x \in [0.5; 0.7] \end{cases} \quad (3.31)$$

$$f_4(x) = \begin{cases} 0, & x \notin [0.5; 0.9] \\ \frac{x-0.5}{0.2}, & x \in [0.5; 0.7] \\ \frac{0.9-x}{0.2}, & x \in [0.7; 0.9] \end{cases} \quad (3.32)$$

$$f_5(x) = \begin{cases} 0, & x \notin [0.7; 1] \\ \frac{x-0.7}{0.2}, & x \in [0.7; 0.9] \\ \frac{1-x}{0.1}, & x \in [0.9; 1] \end{cases} \quad (3.33)$$

Applying Equation (3.26), the grey clustering coefficient is calculated and the criteria can be classified into the grey classes (“very low”, “low”, “medium”, “high” and “very high”), as Table 3.13 shows. To exemplify how the classification process occurs, we have $\sigma_{c1}^{k*} = \max_{1 \leq k \leq 5} \{0; 0.88; 2.12; 0; 0\} = 2.12 \rightarrow k^* = M$.

Table 3.13 - Clustering.

σ_i^k	GC-VL	GC-L	GC-M	GC-H	GC-VH	σ_i^{k*}	AGC
c1	0.00	0.88	2.12	0.00	0.00	2.12	M
c2	0.00	0.45	1.55	0.73	0.27	1.55	M
c3	0.00	0.25	1.75	0.98	0.02	1.75	M
c4	0.14	0.86	0.00	0.00	0.00	0.86	L
c5	0.00	0.63	1.37	0.73	0.27	1.37	M
c6	0.00	1.64	1.36	0.00	0.00	1.64	L
PVT	0.00	0.00	0.00	0.00	0.00	0.00	N
NPS	0.00	0.00	0.00	0.00	0.00	0.00	N
AC	0.00	0.00	0.00	0.00	0.00	0.00	N

Source: own authorship.

Therefore, since each grey class has an associated grey number, as Table 3.12 shows, we can obtain the FGCM initial state vector as in Table 3.14.

Table 3.14 - The FGCM initial state vector.

Initial state vector	Importance in the system	$\underline{G}$	$\overline{G}$	Whitenization
c1	M	0.5	0.6	0.55
c2	M	0.5	0.6	0.55
c3	M	0.5	0.6	0.55
c4	L	0.3	0.5	0.4
c5	M	0.5	0.6	0.55
c6	L	0.3	0.5	0.4
PVT	N	0	0	0
NPS	N	0	0	0
AC	N	0	0	0

Source: own authorship.

As it can be observed in columns 3 and 4 of Table 3.14, the grey initial state vector range is [0,1]. Therefore, the system activation function should be the sigmoid function. With this, we can activate the system according to Equations (3.14) and (3.15). The evolution of the initial state values until convergence can be observed in Figure 3.4 (for the lower grey values) and Figure 3.5 (for the upper grey values).

Figure 3.4 - Convergence for the system lower grey values.

Source: own authorship.

Figure 3.5 - Convergence for the system upper grey values.

Source: own authorship.

After convergence, the final vector is obtained, as in Table 3.15. The uncertainty degree is calculated according to Equation (3.18) and, finally, the results are whitened according to Equation (3.6).

Table 3.15 - The FGCM steady state vector.

Final vector	$\underline{G}$	$\overline{G}$	Lenght	Greyness	Whitenization
c1	0.604	0.604	0.00	0.00	0.604
c2	0.604	0.604	0.00	0.00	0.604
c3	0.604	0.604	0.00	0.00	0.604
c4	0.604	0.604	0.00	0.00	0.604
c5	0.604	0.604	0.00	0.00	0.604
c6	0.604	0.604	0.00	0.00	0.604
PVT	0.834	0.885	0.05	0.05	0.859
NPS	0.855	0.904	0.05	0.05	0.879
AC	0.862	0.908	0.05	0.05	0.885

Source: own authorship.

3.7 DISCUSSIONS

Figure 3.6 illustrates the FGCM considering the final state vector and the relationship matrix. It is a visual yet precise way of expressing concepts and analysing them at their natural level of abstraction. To facilitate visualization of the intensity of these causal relationships, a scale that associates different types of arrows with each of the linguistic terms is proposed, as shown in Figure 3.6. In addition, when building the cognitive map, the criteria are represented by circles of different sizes and associated to colours for differentiation. White circles are associated with cause criteria and grey circles are associated with effect criteria (i.e. the criteria which receive the influence). Regarding their size, for the white circles, the bigger the circle

the greater the influence the criterion has over the system. For grey circles, the bigger the circle, the more influenced the criterion is by others. t

Figure 3.6 - The aggregated and final state values FGCM.

Source: own authorship.

For this pilot application case, it is possible to obtain relevant information by analysing Figure 3.6. Regarding the cultural dimensions, it can be observed that c_1 , c_2 , c_3 and c_5 have a medium influence over performance, while c_4 and c_6 have a low influence. In the context of a start-up, this medium and low influences are possibly justified since the organizational culture could still be under development and also due to the extremely dynamic external environment, which overplays internal aspects. In addition, it is important to note that the model provides information about the most preminent cultural aspects of the organizational profile regarding performance and their interaction. This consists also in a contribution to the operations management body of knowledge, since few studies address this interface.

For this pilot application, it is possible to conclude that the low power distance, low uncertainty avoidance, collectivism and short-term orientation are the key cultural aspects related to performance. It is also possible to note that this influence of culture over performance is positive, since AC is the performance indicator with greater received cultural influence and the only indicator classified as with high performance by the decision-makers. In addition, the indicators that receive less cultural influence have poorer performance, which also supports the hypothesis that, for the start-up, despite its turbulent environment, culture is fostering performance.

This information can be used for the development of guidelines for action plans. Therefore, knowing that low power distance, low uncertainty avoidance, collectivism and short-term orientation foster performance, practices and behaviours aligned with these dimensions could be reinforced at the same time that the ones misaligned with the dimensions could be identified and suppressed. In addition, strategies could be structured for improving positive cultural influence over the NPS and PVT indicators, by changing or establishing new processes for managing activities related to these indicators. Finally, as a feedback for the start-up, it is suggested that the GC-FGCM approach could be executed every time the indicators are reviewed, for scenario simulation by means of what-if analysis. Thus, considering the data and results presented in Table 3.15 as well as Figure 3.6, the GC-FGCM approach was initially validated in a real situation where complex relationships between variables have to be assessed.

Another aspect that reinforces this new proposition validity refers to the system convergence. Granularity and interpretability of the results were achieved for distinct values of λ and the system converged within less than 30 iterations for all performed tests. The fact that the system requires a small number of iterations and does not provide inconsistent outputs indicates that the information obtained from the causal relationship matrix is reliable. Finally, important conclusions can be held by comparing the obtained results in this study with the ones obtained by Salmeron (2010), in the paper where FGCMs were firstly proposed. Salmeron (2010) applied FGCMs in the context of information technology (IT) projects, considering the case of commercial IT projects and open source IT projects, which is similar to the application context presented in this paper. For commercial IT projects, the average greyness level obtained was 0.13 while for the open source projects it was 0.30. In the present paper, which considered the case of the technology start-up, the average greyness was 0.02, which also supports the GC-FGCM proposition. Therefore, results show that the GC-FGCM approach proved to be efficient for classifying and ranking relational data.

3.8 CONCLUSION

This paper presented a group decision-making approach for assessing causal relationships in complex and uncertain environments based on a novel combination of the grey clustering and fuzzy grey cognitive maps techniques. The central idea is to improve the extraction of relevant information from pairwise evaluations of multiple criteria so as decision-makers can gain a better understanding of their role and importance in the analysed system. The GC technique acts as a mean to minimize the level of imprecise data inserted in the model by reducing the required inputs for the FGCM execution. This could lead to more assertive outputs and, therefore, conclusions made by the decision-makers. In addition, the GC technique makes the process of running a FGCM for group decision quicker and easier.

Under uncertainty, even with the support of grey numbers and computing with words, some situations may blur the process of assessing the primal scenario of a system, especially if various decision-makers are involved. Therefore, the GC-FGCM proposition makes possible to obtain the initial state vector from the relationship matrix and to automatically provide relevant information regarding the criteria. Firstly, it is able to classify the criteria based on their initial role in the system. Secondly, it is able to provide detailed information regarding criteria interaction. Thirdly, it ranks and attributes relative weights to the criteria considering their impact in the system as a whole. Fourthly, it directly enables the development of what-if analysis regarding criteria interaction for testing various grey scenarios and decisions, without requiring modifications in the initial state vector, which could also represent a difficulty. Finally, it is relevant to note that this process takes place with natural human language processing, to provide an intuitive interface for human reasoning, and is also capable of considering hesitation.

The results of the real application case illustrated the expected benefits of the proposition. The model was capable of showing which organizational culture factors were most relevant considering their capability of fostering performance. In addition, it was capable of detailing how each of these cultural factors affected each of the performance indicators. Finally, the model was capable of ranking the indicators by the level of received cultural influence and inferring if this influence was positive or not. Therefore, in general, the proposed approach made feasible the identification of crucial elements regarding the company's profile and

performance, providing the possibility of scenario simulation, prioritization, anticipation and enabling the development of guidelines for action plans.

It is relevant to note that it is difficult to compare the proposition presented in this paper with others since the initial state vectors will necessarily differ. In this proposition it is obtained from the relationship matrix data and in traditional FGCMs it usually comes from experts' evaluations. This may lead to differences in the results. However, by comparing the level of greyness in the final results with the original FGCM proposition by Salmeron (2010) in a similar application case, it was possible to conclude that the results of the GC-FGCM model have less associated uncertainty. Hence, this paper addresses the need for new alternatives to improve the reliability and convergence chances of FCM-based systems (NÁPOLES et al., 2016; FROELICH et al., 2012).

However, it should be emphasized that the conclusions derived from the model execution are dependent of experts' knowledge. In addition, the drawback associated with this proposition refers mostly to the difficulty of defining suitable linguistic terms and corresponding grey numbers. This is justified since the obtained results are dependent of this process. Also, when in the presence of an extensive number of criteria, the pairwise evaluation of causal relationships may be affected by fatigue of the decision-maker. Therefore, the proposed decision model can be further improved. In this regard, consensus techniques could be applied to increase the robustness of the aggregated relationship matrix by minimizing divergence among decision-makers. In addition, the application of learning approaches for obtaining the relationship matrix from data, if available, can exclude the need for expert's knowledge and the use of linguistic terms.

Finally, new applications can be conducted for testing the model in practice. Environments where performance criteria are impacted by external or internal factors can benefit from the proposition. For example, supply chain performance indicators are also impacted by organizational culture. In healthcare management, operating rooms represent one of the most critical structures and their performance could also be assessed considering the influence of other particular aspects such as surgical complexity, size and duration. Another possible application regards risk factors and their impact on product development, project management and other related areas. The possibilities also expand to cybersecurity, regarding the analysis of the relationship between system weaknesses and potential attack factors; industry 4.0, regarding the relationship between total productive maintenance criteria and

failure causes, and so on. Generally, the model is applicable for classifying, ranking and interpreting relational data under uncertainty in dynamic, complex and multi-meanings environments.

3.9 REFERENCES

BERTRAND, J. Will M.; FRANSOO, Jan C. Modelling and simulation. In: **Research methods for operations management**. Routledge, 2016. p. 306-346.

BLANK, S.; DORF, B. **The Start-up Owner's Manual**. Pescadero. 2012.

BOUTALIS, Y.; KOTTAS, T. L.; CHRISTODOULOU, M. Adaptive estimation of fuzzy cognitive maps with proven stability and parameter convergence. **IEEE Transactions on Fuzzy Systems**, v. 17, n. 4, p. 874-889, 2009.

BUENO, S.; SALMERON, J. L. Benchmarking main activation functions in fuzzy cognitive maps. **Expert Systems with Applications**, v. 36, n. 3, p. 5221-5229, 2009.

CADDEN, T.; MARSHALL, D.; CAO, G. Opposites attract: organisational culture and supply chain performance. **Supply Chain Management: an international journal**, 2013.

CARVALHO, J. P. On the semantics and the use of fuzzy cognitive maps and dynamic cognitive maps in social sciences. **Fuzzy Sets and Systems**, v. 214, p. 6-19, 2013.

CHAMMAS, C. B.; DA COSTA HERNANDEZ, J. M. Comparing transformational and instrumental leadership. **Innovation & Management Review**, 2019.

CHATTERJI, A. et al. When does advice impact startup performance?. **Strategic Management Journal**, v. 40, n. 3, p. 331-356, 2019.

CHEN, K. et al. Grey clustering evaluation based on AHP and interval grey number. **International Journal of Intelligent Computing and Cybernetics**, v. 12, p. 127-137, 2019.

DELGADO, A.; ROMERO, I. Environmental conflict analysis using an integrated grey clustering and entropy-weight method: A case study of a mining project in Peru. **Environmental Modelling & Software**, v. 77, p. 108-121, 2016.

DENG, J. Introduction to grey system theory. **The Journal of grey system**, v. 1, n. 1, p. 1-24, 1989.

ENSLEY, M. D.; HMIELESKI, K. M.; PEARCE, C. L. The importance of vertical and shared leadership within new venture top management teams: Implications for the performance of startups. **The leadership quarterly**, v. 17, n. 3, p. 217-231, 2006.

FROELICH, W. et al. Application of evolutionary fuzzy cognitive maps to the long-term prediction of prostate cancer. **Applied Soft Computing**, v. 12, n. 12, p. 3810-3817, 2012.

FURNARI, S. A cognitive mapping approach to business models: Representing causal structures and mechanisms. **Advances in Strategic Management**, v. 33, n. 1, p. 207-239, 2015.

GELDEREN, M.; FRESE, M.; THURIK, R. Strategies, uncertainty and performance of small business startups. **Small Business Economics**, v. 15, n. 3, p. 165-181, 2000.

GIARDINO, C.; WANG, X.; ABRAHAMSSON, P. Why early-stage software startups fail: a behavioral framework. In: **International conference of software business**. Springer, Cham, 2014. p. 27-41.

HAERI, S. A. S.; REZAEI, J. A grey-based green supplier selection model for uncertain environments. **Journal of cleaner production**, v. 221, p. 768-784, 2019.

HAJEK, P.; FROELICH, W. Integrating TOPSIS with interval-valued intuitionistic fuzzy cognitive maps for effective group decision-making. **Information Sciences**, v. 485, p. 394-412, 2019.

HASHEMI, H. et al. A new group decision model based on grey-intuitionistic fuzzy-ELECTRE and VIKOR for contractor assessment problem. **Sustainability**, v. 10, n. 5, p. 1635, 2018.

HOFSTEDE, G. Dimensionalizing cultures: The Hofstede model in context. **Online readings in psychology and culture**, v. 2, n. 1, p. 8, 2011.

KANG, B. et al. Generalized fuzzy cognitive maps: a new extension of fuzzy cognitive maps. **International Journal of System Assurance Engineering and Management**, v. 7, n. 2, p. 156-166, 2016.

KAYACAN, E.; ULUTAS, B.; KAYNAK, O. Grey system theory-based models in time series prediction. **Expert systems with applications**, v. 37, n. 2, p. 1784-1789, 2010.

KONAR, A.; CHAKRABORTY, U. K. Reasoning and unsupervised learning in a fuzzy cognitive map. **Information Sciences**, v. 170, n. 2-4, p. 419-441, 2005.

- KOSKO, B. et al. Fuzzy cognitive maps. **International journal of man-machine studies**, v. 24, n. 1, p. 65-75, 1986.
- LIU, S.; LIN, Y. **Grey information: theory and practical applications**. Springer Science & Business Media, 2006.
- LIU, Y.; DU, J.; WANG, Y. An improved grey group decision-making approach. **Applied Soft Computing**, v. 76, p. 78-88, 2019.
- MAGO, V. K.; PAPAGEORGIOU, E. I.; MAGO, A. Employing fuzzy cognitive map for periodontal disease assessment. In: **Fuzzy Cognitive Maps for Applied Sciences and Engineering**. Springer, Berlin, Heidelberg, 2014. p. 375-389.
- MAZZUTO, G. et al. Aggregate experts knowledge in Fuzzy Cognitive Maps. In: **2018 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)**. IEEE, p. 1-6, 2018.
- MEMON, M. S.; LEE, Y. H.; MARI, S. I. Group multi-criteria supplier selection using combined grey systems theory and uncertainty theory. **Expert Systems with Applications**, v. 42, n. 21, p. 7951-7959, 2015.
- NAIR, A.; RECKIEN, D.; VAN MAARSEVEEN, M. A generalised fuzzy cognitive mapping approach for modelling complex systems. **Applied Soft Computing**, v. 84, p. 105754, 2019.
- NÁPOLES, G. et al. On the convergence of sigmoid fuzzy cognitive maps. **Information Sciences**, v. 349, p. 154-171, 2016.
- PAPAGEORGIOU, E. I.; SALMERON, J. L. Learning fuzzy grey cognitive maps using nonlinear hebbian-based approach. **International Journal of Approximate Reasoning**, v. 53, n. 1, p. 54-65, 2012.
- RAJESH, R. Measuring the barriers to resilience in manufacturing supply chains using Grey Clustering and VIKOR approaches. **Measurement**, v. 126, p. 259-273, 2018.
- RIPSAS, S.; TRÖGER, S. **Deutscher Startup Monitor 2014**. KPMG, Berlin, 2014.
- ROMPHO, N. Operational performance measures for startups. **Measuring Business Excellence**, 2018.
- SALMERON, J. L. Modelling grey uncertainty with fuzzy grey cognitive maps. **Expert Systems with Applications**, v. 37, n. 12, p. 7581-7588, 2010.

SALMERON, J. L.; GUTIERREZ, E. Fuzzy grey cognitive maps in reliability engineering. **Applied Soft Computing**, v. 12, n. 12, p. 3818-3824, 2012.

SALMERON, J. L.; PAPAGEORGIOU, E. I. A fuzzy grey cognitive maps-based decision support system for radiotherapy treatment planning. **Knowledge-Based Systems**, v. 30, p. 151-160, 2012.

SCHEIN, E. H. **Organizational culture and leadership**. John Wiley & Sons, 2010.

SEO, S. Y.; KIM, S. D.; LEE, M. S. The Effects of Knowledge Assets on the Performances of Startup Firms: Moderating Effects of Promotion Focus. **The Journal of Asian Finance, Economics and Business (JAFEB)**, v. 5, n. 4, p. 187-199, 2018.

SONG, K. et al. Health management decision of sensor system based on health reliability degree and grey group decision-making. **Sensors**, v. 18, n. 7, p. 2316, 2018.

TANRISEVER, F.; ERZURUMLU, S. S.; JOGLEKAR, N. Production, process investment, and the survival of debt-financed startup firms. **Production and Operations Management**, v. 21, n. 4, p. 637-652, 2012.

TSENG, M. L. An assessment of cause and effect decision-making model for firm environmental knowledge management capacities in uncertainty. **Environmental monitoring and assessment**, v. 161, n. 1-4, p. 549-564, 2010.

ZADEH, L. A. Fuzzy logic= computing with words. In: **Computing with Words in Information/Intelligent Systems 1**. Physica, Heidelberg, 1999. p. 3-23.

ZANON, L. G. et al. A decision-making model based on fuzzy inference to predict the impact of SCOR[®] indicators on customer perceived value. **International Journal of Production Economics**, p. 107520, 2020.

ZANON, L. G.; CARPINETTI, L. C. R. Fuzzy cognitive maps and grey systems theory in the supply chain management context: A literature review and a research proposal. In: **2018 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)**. IEEE, 2018. p. 1-8.

ZANON, L. G.; ULHOA, T. F.; ESPOSTO, K. F. Performance measurement and lean maturity: congruence for improvement. **Production Planning & Control**, p. 1-15, 2020.

ZHAO, H.; JIAN, L.; LIU, Y. A novel grey clustering group decision-making model and application. In: **2015 IEEE International Conference on Grey Systems and Intelligent Services (GSIS)**. IEEE, 2015. p. 327-332.

ZHU, J. et al. A hierarchical clustering approach based on three-dimensional gray relational analysis for clustering a large group of decision-makers with double information. **Group Decision and Negotiation**, v. 25, n. 2, p. 325-354, 2016.

4. EXPLORING THE RELATIONS BETWEEN SUPPLY CHAIN PERFORMANCE AND ORGANIZATIONAL CULTURE: A FUZZY GREY GROUP DECISION MODEL

ABSTRACT

Assessing the relationship between supply chain performance and organizational culture can help to predict scenarios and improve decision-making. However, this relationship is rarely explored due to the complexity of quantitatively addressing its natural subjectivity. Although soft computing techniques would have the potential to overcome this limitation, they have been rarely applied to this context. This paper aims to introduce a decision model to analyze and quantify the causal relationship between organizational culture and supply chain performance based on the combination of fuzzy grey cognitive maps, grey clustering and multiple fuzzy inference systems. Such model is novel in the literature and can provide new theoretical and practical perspectives. The development of this study is based on the SCOR[®] (Supply Chain Operations Reference) model attributes (SCC, 2017) and Hofstede's (2001) organizational practices. The main contribution is the introduction of a decision-making model that promotes the alignment between organizational culture and supply chain management, internalizing culture as a driver for performance improvement efforts. By conducting two real application cases in companies from different industrial sectors, results show that the model is able to identify crucial elements regarding the cultural profile and performance of both organizations, aiding prioritization, anticipation and enabling the development of guidelines for action plans.

Keywords: supply chain performance management; organizational culture; group decision-making; grey clustering; fuzzy grey cognitive maps; fuzzy inference.

4.1 INTRODUCTION

Supply Chain Management is a key strategic factor for better achieving organizational goals such as competitiveness, customer service and increased profitability (GUNASEKARAN; PATEL; TIRTIROGLU, 2001). It is considered essential for supplier and customer integration with the aim of improving operational effectiveness (CROOM et al., 2007). Therefore, the development of models and approaches that lead to a better understanding of supply chain performance and contribute to its optimization is an important and challenging task (CHAN; HOU; LANGEVIN, 2012).

Organizational culture, in turn, has a profound impact on the behavior of individuals, being closely linked to leadership (HOFSTEDE, 2001). One who is not capable to comprehend the essence of the organizational culture and its influence on daily tasks is bound to be controlled and even to become a victim of the forces that derive from it (SCHEIN, 2010). In an empirical research focused on investigating the relationship between culture, quality management and improvement initiatives, Gambi et al. (2013) highlight that culture is as a key component for organizational performance.

Whitfield and Landeros (2006) state that the relevance of the relationship between organizational culture and supply chain performance has been recognized in the literature. However, few studies address how this relationship occurs in practice (WINKLHOFFER; PRESSEY; TZOKAS, 2006). According to Croom et al. (2007), companies are increasingly establishing strategic alliances along the supply chain to achieve success, with culture being an essential success ingredient. Porter (2019) argues that culture severely impacts supply chain performance, since it is determinant for organizational alignment and the establishment of lasting supply relationships. Cadden, Marshall and Cao (2013) also highlight the significant influence of organizational culture on operational performance.

Thus, it can be inferred that exists a causal relationship between organizational culture and supply chain performance (CADDEN et al., 2015). Mapping and quantifying this relation can help predict scenarios and outline action plans for performance improvement. However, the evaluation of this culture-performance causality is affected by subjectivity. To deal with this matter, the computational processing of human language is highly recommended (ZADEH, 1999). Among the computing with words techniques, according to Lima Junior, Osiro and Carpinetti (2013), fuzzy logic and its variations stand out in most applications related to decision support.

Hajek and Froelich (2019) highlight that real-life situations require complex decision-making. This encompasses multiple experts having to assess multiple criteria with uncertain information. In this way, the development of decision support systems with the ability of processing information in a human-oriented style can enhance problem solving (FERNANDEZ et al., 2019). Multi-Criteria Group Decision-Making (MCGDM) models that are capable of considering this vagueness are more likely to provide realistic results (HAERI; REZAEI, 2019). Indeed, the complementary skills of each group member allows the team to present and assess issues from various viewpoints, which is of particular interest for organizations (MAZZUTO et al., 2018). Complex social systems, such as organizations, include human behavior and can have concepts interacting in a manner that is quantitative and/or qualitative (NAIR; RECKIEN; VAN MAARSEVEEN, 2019).

In this direction, Keshavarz Ghorabae et al. (2017) highlighted that human judgment always contains some uncertainty and ambiguity. According to Congjun, Xinping and Jin (2007), there are two main kinds of uncertainty that affect decision-making: uncertainty brought by subjectivity, which is best handled by the fuzzy set theory; and uncertainty caused by incomplete information, which is addressed by the GST. These authors state that fuzzy grey multi-attribute group decision-making (FGMAGDM) is therefore recommended for enhancing the feasibility and rationality of decision processes in real problems with the presence of these two types of uncertainty and multiple decision-makers, such as the one discussed by the present study. Computing with Words (ZADEH, 1996) operationalizes the fuzzy-grey approach for assessing the influence of culture over supply chain performance.

Reviewing the literature, few papers were found that quantitatively seek to analyze the relationship between supply chain performance and organizational culture (HULT; KETCHEN; ARRFELT, 2007; CADDEN; MARSHALL; CAO, 2013; ALTAY et al., 2018; DUBEY et al., 2019). To the best of the authors' knowledge, no study has been produced so far applying soft computing techniques in a decision model for analyzing the influence of organizational culture over supply chain performance.

Therefore, this paper presents a decision model to analyze and quantify the causal relationship between organizational culture and supply chain performance based on the combination of fuzzy grey cognitive maps (FGCMs), grey clustering (GC) and fuzzy inference systems (FISs). The model uses as reference for both culture and performance the Hofstede's (2001) organizational practices (OPs) and the SCOR® (Supply Chain Operations Reference)

model performance attributes (SCC, 2017). The GC technique is applied to classify the OPs according to their quantified influence on performance. The FGCM then uses this information to rank the SCOR[®] attributes according to their degree of received cultural influence. Finally, the FIS enables the definition of a new indicator to evaluate how culture fosters performance in supply chains.

For modelling cause and effect relationships, cognitive maps stand out for their flexibility and effectiveness in dealing with systems in which complex interactions occur (FURNARI, 2015). Based on the Grey Systems Theory (GST) and fuzzy cognitive maps, FGCMs (SALMERON, 2010) can be adapted to a wide range of problems and have been specifically developed to deal with subjectivity, uncertainty, hesitancy and multiple means environments. FGCMs are also able to quantify causal relationships, even with scarce data (SALMERON; PAPAGEORGIOU, 2012), and therefore were chosen for analyzing how culture impacts supply chain performance. The GC technique, also based on the GST and developed to handle causalities (DELGADO; ROMERO, 2016), was used in this paper as a mean to generate more accurate inputs for the FGCM. FISs have been largely applied in supply chain management problems to overcome the intrinsic vagueness in criteria evaluation (AQLAN; LAM, 2015; GHADIMI; TOOSI; HEAVEY, 2018; KAUSHAL; BASAK, 2018; POURJAVAD; SHAHIN, 2018a; KHAN et al., 2018). The FIS application in the context of this paper is required due both to its potential for handling nonlinear relationships between input and output variables (POURJAVAD; SHAHIN, 2018b), and also to the capacity of modeling human reasoning through fuzzy if-then rules (KHAN et al., 2018). Here, as in Chen, Tsai and Kuo (2005), GST use is justified for processing the incomplete in-company data, to classify and rank the criteria, while the fuzzy set theory is required to assess criteria interactions in the form of inference rules.

This study has followed the quantitative axiomatic prescriptive model-based research as it discusses a quantitative model that analyses the behavior of a system variable based on the behavior of other variables (BERTRAND; FRANSOO, 2016). In this particular case, the proposed model aims to analyze the dynamic between Hofstede's (2001) organizational practices and the SCOR[®] performance attributes. In addition, this study is prescriptive since it is focused on the development of strategies and actions to improve the results available in the literature to provide solutions for an innovative problem (BERTRAND; FRANSOO, 2016). The FGCM, GC and FIS techniques were implemented in MATLAB[®] and two real application

cases in two different industrial sectors were conducted to test the model in practice and to provide the literature with practical results on the subject.

This paper is organized as follows. Section 4.2 presents a literature review addressing organizational culture, supply chain performance and the aforementioned soft computing techniques. Section 4.3 details the proposed decision-making model. Section 4.4 illustrates the use of the model by describing its application to the two real cases. Section 4.5 addresses discussions and compares the results obtained in both companies. Finally, Section 4.6 draws some conclusions and gives suggestions for further research.

4.2 LITERATURE REVIEW

4.2.1. *Supply chain performance*

The historical purely financial focus on operations has changed to a multidimensional perspective due to the relevancy of aspects such as strategy deployment and organizational learning (BITITCI et al., 2011). In order to operationalize measurement, performance indicators are verifiable variables that quantify the efficiency or effectiveness of actions and processes. They are of informative nature, guided by organizational objectives and enable the formulation of action plans for more assertive decision-making (LOHMAN; FORTUIN; WOUTERS, 2004; NEELY; GREGORY; PLATTS, 2005). Therefore, performance management is vital in supply chains to ensure agility and assertiveness in decision-making (BALFAQIH et al., 2016).

Cai et al. (2009) define supply chain performance management as the process of selecting appropriate key performance indicators (KPIs), setting challenging but accomplishable goals, planning their deployment, communicating the strategy, monitoring the results and implementing improvements based on accurate feedback. Different performance management approaches have been developed in the last decades to assess the performance of supply chains from different perspectives (RAMEZANKHANI; TORABI; VAHIDI, 2018).

In a comparative study between 16 supply chain performance assessment models, Estampe et al. (2013) concluded that the SCOR[®] model meets most of the considered criteria. In addition, the SCOR[®] model provides a systematic methodology that can be used by any organization in order to analyze supply chain performance (DISSANAYAKE; CROSS, 2018). Finally, the SCOR[®] metrics provide the possibility for a company to compare its performance with other organizations by using a benchmarking tool named SCORmark, which holds a

historical performance database of over 1000 companies and 2000 supply chains, helping to identify competitive requirements for improvement (LIMA-JUNIOR; CARPINETTI, 2019). For these reasons, the SCOR[®] model was selected in this study. Following the SCOR[®] guidelines, supply chain performance measurement is deployed in performance attributes and indicators: attributes are used to set strategic directions and indicators are used to quantify a supply chain capability to accomplish these strategic attributes (LIMA-JUNIOR; CARPINETTI, 2016, SCC, 2017). The five SCOR[®] Performance Attributes are described in Table 4.1. These performance attributes are divided into two groups: the customer-focused group that involves reliability, responsiveness and agility, and the internal-focused group, which involves cost and assets management efficiency (SCC, 2017).

Table 4.1 - The SCOR[®] Performance Attributes.

Performance attributes	Definition
Reliability	How reliably tasks are executed with focus on the predictability of the outcome of a process. Typical indicators include: the right quantity, the right quality.
Responsiveness	How fast tasks are executed. The focus is on how fast a supply chain responds to the customer. Typical indicators include cycle-time indicators.
Agility	How able a supply chain is to respond to influences, with focus on marketplace changes to gain competitive advantage. Typical indicators include flexibility and adaptability.
Costs	How costly processes are operating, with focus on labor, material, transportation and management costs. A typical indicator is cost of goods sold.
Asset Management Efficiency (Assets)	How efficiently assets are used, with focus on inventory reduction and insourcing vs. outsourcing. Typical indicators include inventory days of supply and capacity utilization.

Source: SCC (2017).

The SCOR[®] is widely used by the industry community as well as in the academic field (AKKAWUTTIWANICH; YENRADEE, 2018). Ntabe et al. (2015) suggest that the SCOR[®] is the main model for strategic decision-making and essential for supply chain performance management. However, Akkawuttiwanich and Yenradee (2018) affirm that a logical method to manage these indicators for supply chain improvement is still unclear. According to

Dissanayake and Cross (2018), several techniques, including fuzzy logic, can be applied successfully to address this issue. In this paper, soft computing techniques such as FCGM, GC and FIS are employed to assess the causal relationship between organizational culture and supply chain performance attributes of the SCOR[®] model.

4.2.2. *Organizational culture*

Three main reasons can be cited regarding why organizational culture should receive attention in the context of supply chain management: first, because culture is more difficult to manage than other factors, such as technology or information; second since culture influences the general behavior of individuals in terms of information sharing, teamwork (therefore, also in organizational learning capacity) and risk tolerance, among others; finally, because culture impacts supply chain performance (CAO et al., 2015). Groysberg et al. (2018) affirm that culture is among the main managerially available factors for improving organizational effectiveness, since it expresses goals through values and beliefs and guides activities through shared premises and norms.

The literature on organizational culture is interdisciplinary and, therefore, several definitions have been proposed. Table 4.2 presents some formalizations of the concept.

Table 4.2 - Organizational culture definitions.

Author	Organizational culture definition
Groysberg et al. (2018)	An organization's tacit social order that in the long-term shapes attitudes and behavior.
Cameron and Quinn (2011)	The organizational values associated with the dominant leadership styles that make an organization unique.
Schein (2010)	Stabilizing forces with multiple layers that differ in visibility and interpretability according to basic assumptions, values, standards and artifacts.
Hofstede (2001)	Collective programming of the mind; shared beliefs, values and practices that distinguish one organization from another.

Continues.

Conclusion.

Author	Organizational culture definition
O'Reilly and Chatman (1996)	System of shared values and norms that defines what is important and which attitudes and behaviors are most appropriate.
Deshpandé and Webster Jr (1989)	Pattern of shared beliefs and values that help individuals understand an organization, providing them with behavioral norms.
Smircich (1983)	Organizations do not have cultures, they are cultures; culture is a kind of social glue that connects the organization within itself.
Wallach (1983)	Set of shared beliefs, values, norms and philosophies that determine how things work; results in patterns of behavior, speech and self-presentation.
Kroeber and Kluckhohn (1952)	Transmitted patterns of values, ideas and other symbol systems that shape behaviors within an organization.

Source: own authorship.

While there is no consensus about an exact definition of organizational culture, most authors agree that culture refers to the underlying values, beliefs and principles expressed in the form of management structure and practices' (CADDEN et al., 2015). According to Hofstede (2001), cultures in organizations differ in the level of practices, which would be the visible and manageable piece of culture.

To analyze how culture manifests itself in organizations, models are developed in order to materialize its main aspects and make it manageable (BORTOLOTTI; BOSCARI; DANESE, 2015). Hofstede et al. (1990) proposed a tool composed by six independent organizational practices (OPs) applicable to any company, which is considered appropriate for use in the supply chain context (CADDEN; MARSHALL; CAO, 2013). This tool is widely used in inter organizational research (CADDEN ET AL., 2015; CADDEN; MARSHALL; CAO, 2013; POTHUKUCHI et al. 2002) and consists of a five-point Likert scale questionnaire with 35 items, capable of assessing organizational culture at this practice level.

Verbeke (2000) updated Hofstede et al. (1990) approach and proposed a more robust and validated measurement tool, suitable for research in production-related and supply chain organizations. Afterwards, Cadden et al. (2015) executed minor adjustments to wording and

scale, as well as acted in order to guarantee content validity for the method, which resulted in the following OPs to analyze culture in supply chains: “results” vs. “process”; “employee” vs. “job”; “open” vs. “closed”; “loose” vs. “tight”; “normative” vs. “pragmatic”; and “market” vs. “internal”. Thus, this tool is presented in full in Appendix A. Verbeke (2000) suggests that a high mean score on each dimension would represent the optimal cultural profile as this would reflect an organization that is results-driven, employee-focused, externally-oriented and where communication is encouraged. Table 4.3 presents the definitions for each OP.

Table 4.3 - Organizational practices definition.

OP	Definition
Process	A high “process” score indicates an organization highly rule-driven, focused on business processes, defined roles and routines. A low “process” score indicates focus on results and flexibility to deviate from rules and responsibilities to ensure that goals will be met.
Employee	A high “employee” score indicates an organizational concern with personal development, events and individual achievements. A low “employee” score indicates more focus on the job than on the person who is executing it.
Open	A high “open” score indicates an opening to criticism and organizational learning. A low “open” score indicates resistance to change and criticism, and defensive behavior.
Tight	A “tight” score indicates an organization who thrives to control its employees and how they behave. A low “tight” score indicates the prevalence of flexibility and autonomy.
Normative	A high “normative” score indicates a pragmatic organization with focus on goals achievement. A low score indicates more concern on following standards.
Market	A high “market” score indicates an organization which values information from consumers and about competition in the formulation and implementation of the strategy. A low “market” score indicates more focus on internal information regarding operational performance in the formulation and implementation of the strategy.

Source: Cadden et al. (2015)

This OPs tool was chosen as the representative of culture in the present study since the OPs are independent factors, which fit the nodes and edges structure that is the basis of FGCMs. This, in turn, makes possible to analyze the causal relation between culture, as OPs, and supply chain performance, quantified by the SCOR® performance attributes.

4.2.3. *Organizational culture and supply chain performance*

The dynamic of this interface is based on the so-called relational theory. It sustains that the creation of competitive advantage and the success of supply chains depend on the presence of an organizational culture profile that supports information sharing, organizational learning, flexibility, joint collaboration and stakeholder development (BRAUNSCHEIDEL; SURESH; BOISNIER, 2010; SAMBASIVAN; YEN, 2010).

Thus, a misaligned view on organizational culture and supply chain management can negatively affect the chain performance (WHITFIELD; LANDEROS, 2006). According to Cadden, Marshall and Cao (2013), managers should be able to assess the culture of their organizations. The authors highlight that the success of this assessment is associated with the ability to deconstruct organizational culture into tangible elements, which make it easier to comprehend how each cultural aspect impacts performance. This justifies the choice of Hofstede's (2001) organizational practices to compose the decision model proposed in this work, since they consist in culture deconstructed in complementary dimensions which describe the profile of a company.

Prajogo and McDermott (2011) state that the analysis of how culture affects supply chain performance is essential to optimize strategic decision-making. Few studies address organizational culture in the supply chain context, although the literature calls for new contributions on the subject (TOMIC et al., 2017). A bibliographic review was conducted in March 2020, in the Web of Science, Scopus, Emerald and IEEE Xplore® databases to investigate what has been published so far. The following strings were used: “organizational culture” and “supply chain”, associated with the “AND” operator. Only the studies that simultaneously mentioned organizational culture and supply chain performance within the stated objective were selected. Table 4.4 summarizes the results.

Table 4.4 - Papers dealing simultaneously with organizational culture and supply chain performance.

Authors	Journal	Year	Proposition	Applied organizational culture model	Data analysis
Dubey et al.	International Journal of Production Economics	2019	To investigate how Big Data Analytics and organizational culture can complement each other with the aim of improving the performance of humanitarian supply chains.	CVF	Quantitative
Jermittiparsert and Wajeetongratana	International Journal of Innovation, Creativity and Change	2019	To examine the relationship between information technology integration, information technology flexibility and the role of organizational culture on supply chain agility.	No model was applied.	Qualitative
Fantazy and Tipu	Journal of Enterprise Information Management	2019	To explore how firm's resources such as culture of competitiveness relate to sustainable supply chain management and organizational performance.	No model was applied.	Quantitative
Sinaga et al.	International Journal of Supply Chain Management	2019	To analyze the effect of organizational culture capability and relationship building on supply chain operational performance	No model was applied.	Quantitative
Porter	Operations and Supply Chain Management- An International Journal	2019	To investigate the relationship between organizational culture, supply chain integration and operational performance.	CVF	Quantitative
Altay et al.	Production Planning & Control	2018	To investigate the relationship between effects of agility and resilience on supply chain performance under the moderation of organizational culture.	CVF	Quantitative

Continues.

Continuation.

Authors	Journal	Year	Proposition	Applied organizational culture model	Data analysis
Tomic et al.	Journal of Engineering Manufacture	2017	To investigate the impact of organizational culture on the use of quality improvement tools and methodologies and how both affect the performance of companies in a supply chain.	The authors combine various models.	Quantitative
Anjum et al.	International Journal of Academic Research in Business and Social Sciences	2016	To investigate the role of organizational culture as a mediator between supply chain integration and operational performance.	CVF	Quantitative
Yunus and Tadisina	Business Process Management Journal	2016	To investigate the role of organizational culture as a mediator between supply chain integration and operational performance in Indonesia.	CVF	Quantitative
Cao et al.	Supply Chain Management: an international journal	2015	To investigate the impact of organizational culture on supply chain integration.	CVF	Quantitative
Cadden et al.	Production Planning & Control	2015	To investigate the impact of organizational culture on the dependency between supply chain links and on performance.	Hofstede	Quantitative
Cadden, Marshall and Cao	Supply Chain Management: an international journal	2013	To investigate the impact of cultural proximity between organizations in a supply chain on their performance.	Hofstede	Quantitative
Braunscheidel, Suresh and Boismier	Human Resource Management	2010	To investigate the impact of organizational culture on supply chain integration.	CVF	Qualitative and quantitative

Continues.

Conclusion.

Authors	Journal	Year	Proposition	Applied organizational culture model	Data analysis
Cadden, Humphreys and McHugh	Journal of General Management	2010	To investigate the impact of organizational culture in forming strategic alliances in supply chains.	Hofstede	Qualitative
Sambasivan and Yen	Journal of Physical Distribution & Logistics Management	2010	To investigate the impact of organizational culture in forming strategic alliances in manufacturing supply chains.	CVF	Quantitative
Dowty and Wallace	International Journal of Production Economics	2010	To investigate the organizational culture's supportive capacity in supply chain disruption.	Douglas GRID GROUP theory	Qualitative
Liu et al.	Journal of Operations Management	2010	To investigate the role of organizational culture in the adoption of digital systems for supply chain management.	CVF	Quantitative
Williams, Ponder and Autry	The International Journal of Logistics Management	2009	To develop a scale capable of measuring the safety culture of a supply chain.	From the authors.	Quantitative

Source: own authorship.

The results presented in Table 4.4 indicate the main directions that the integrative literature on organizational culture and supply chain performance has been taking. Some notable points are:

- Five of the eighteen articles address the impact of organizational culture on supply chain integration (BRAUNSCHEIDEL; SURESH; BOISNIER, 2010; CAO ET AL., 2015; YUNUS; TADISINA, 2016; ANJUM et al., 2016; PORTER, 2019). From this premise, the impact on performance is discussed according to the relational theory.

- The organizational culture models are aligned with the most cited and applied ones in the literature: Quinn and Rohrbaugh (1983), the CVF (competing values framework) model; Douglas (1999), the Grid/Group model; O'Reilly et al. (1991), the OCP model (organizational culture profile); and Hofstede (2001), the cultural dimension model.
- The articles that used the CVF model justified its choice, among other factors, since it makes it possible to deal quantitatively with organizational culture. However, it is important to note that the CVF model does not deconstruct culture into dimensions, which is crucial for understanding its impact on supply chain performance (CADDEN; MARSHALL; CAO, 2013).
- Most articles have applied an analytical and descriptive data analysis, with focus on statistical approaches. No paper applying soft computing techniques was found.
- Supply chain performance is mainly represented by the “flexibility” and “agility” attributes. Braunscheidel, Suresh and Boismier (2010), for example, concluded that cultures encouraging flexibility and innovation benefit delivery performance and that cultures characterized by inflexibility and control were associated with inferior performance. Still, no work was found relating to the SCOR® model attributes with organizational culture aspects.
- Liu et al. (2010) highlight that organizational culture can influence, in addition to performance, the decision-making process in supply chains.

The cause and effect relationship between organizational culture and supply chain performance is a central theme of all articles. However, none of them proposes models to quantify these relationships. Therefore, it is important to develop quantitative decision-making models that allow analyzing the impact of organizational culture on supply chain performance.

4.2.4. *Soft computing techniques*

Tseng et al. (2018) state that uncertainties affect decision-making in supply chains and, therefore, appropriate techniques should be applied to deal with their influence. This aspect acquires even more importance when dealing with a complex concept such as organizational culture. Soft computing consists of a collection of techniques that aim to exploit the tolerance for imprecision and uncertainty in complex systems, to achieve tractability, robustness, and low solution cost (ZADEH, 1996). Among these approaches, fuzzy logic and grey systems theory

stand out for the number of successful applications in several different fields (LIMA JUNIOR; CARPINETTI, 2017; SALMERON; PAPAGEORGIOU, 2012).

A fuzzy set is an extension of a classical set. In classical set theory, the membership of an element to a set is established by a binary relation: the element either belongs or does not belong to the set. In fuzzy set theory, an element belongs to a fuzzy set with different membership degrees, usually from zero to one (ZADEH, 1965), which are determined by a membership function. Formally, let U be the universe of discourse and x be an element in U . The fuzzy set $\tilde{A}$ in U is defined by a membership function $\mu_{\tilde{A}}(x)$ that associates the element x in U to a real value $\in [0,1]$ in order to represent the membership degree of x in $\tilde{A}$ (ZADEH, 1965; POURJAVAD; SHAHIN, 2018b). In other words, if $\mu_{\tilde{A}}(x) = 0$, x does not belong to fuzzy set $\tilde{A}$, if $\mu_{\tilde{A}}(x) = 1$, x has maximum membership to fuzzy set $\tilde{A}$; if $\mu_{\tilde{A}}(x)$ has a value between 0 and 1, x partially belongs to fuzzy set $\tilde{A}$ (POURJAVAD; SHAHIN, 2018b). Therefore, $\forall x \in U$, $\tilde{A} = \{x, \mu_{\tilde{A}}(x)\}$ and the degree of membership of any x can be calculated by the membership function $\mu_{\tilde{A}}(x)$ defined on U (ZADEH, 1965; BELLMAN; ZADEH, 1970; ZIMMERMANN, 2010).

A triangular fuzzy set, described by the membership function in Equation (4.1), is a fuzzy set that meets the properties of normality and convexity (ZADEH, 1965).

$$\mu_{\tilde{A}}(x_i) = \begin{cases} 0 & \text{for } x_i < a, \\ \frac{x_i - a}{m - a} & \text{for } a \leq x_i \leq m, \\ \frac{b - x_i}{b - m} & \text{for } m \leq x_i \leq b, \\ 0 & \text{for } x_i > b. \end{cases} \quad (4.1)$$

The other soft computing tool applied in this study is the grey system theory. According to this theory, if structures and internal characteristics of a system are fully known the system is called a white system; whereas if the internal structures and characteristics of the system are completely unknown it is called a black system (SALMERON; GUTIERREZ, 2012). Therefore, one system with both known partial information and unknown partial information is a grey system.

A grey set $G \in U$ is defined by $G = \begin{cases} \overline{\mu_G}(x): x \rightarrow [0,1] \\ \underline{\mu_G}(x): x \rightarrow [0,1] \end{cases}$, where $\overline{\mu_G}(x)$ and $\underline{\mu_G}(x)$ are respectively the lower and upper membership functions and $\underline{\mu_G}(x) \leq \overline{\mu_G}(x)$. A grey number is one whose exact value is unknown, but the range in which it is included is not. Thus, a grey number with known lower and upper limits is called an interval grey number and it is represented as $\otimes G \in [\underline{G}, \overline{G}]$, $\underline{G} \leq \overline{G}$. If the grey number $\otimes G$ has only a lower limit, it is denoted as $\otimes G \in [\underline{G}, +\infty)$ and if it has only an upper limit, it is denoted as $\otimes G \in (-\infty, \overline{G}]$. It follows that a black number is a number of which no information is known, $\otimes G \in (-\infty, +\infty)$, and a white number is a number about which all information is known, $\otimes G \in [\underline{G}, \overline{G}]$, $\underline{G} = \overline{G}$ (SALMERON, 2010). The length of a grey number can be calculated as $l(\otimes G) = |\overline{G} - \underline{G}|$: if $l(\otimes G) = 0$, then $\otimes G$ corresponds to a white number; if $l(\otimes G) = \infty$, nothing can be concluded because $\otimes G$ can be either a grey number with one of its limits unknown or a black number (SALMERON; PAPAGEORGIOU, 2012). Appendix B details the mathematical operations regarding grey numbers and grey matrices, which are required to the understanding of FGCMs.

A) FUZZY GREY COGNITIVE MAPS

FGCMs are an innovative soft computing technique developed for representing and assessing unstructured knowledge regarding causal relations in grey environments, as well as handling human tacit knowledge (SALMERON; PAPAGEORGIOU, 2012). This process occurs due to the nodes and edges structure of FGCMs: nodes are crisp or fuzzy variables, representing concepts; and the relationships between nodes are represented by directed edges, which assign the influence of the causal variable on the effect variable (SALMERON, 2010). In the case of this study, the causal variables correspond to the OPs and the effect variables to the SCOR[®] performance attributes. Since FGCMs are hybrid methods between grey systems and neural networks, each cause is measured by its grey intensity as in Equation (4.2), where i is the pre-synaptic node and j the post-synaptic one (SALMERON; PAPAGEORGIOU, 2012).

$$\otimes w_{i \rightarrow j} \in [\underline{w_{i \rightarrow j}}, \overline{w_{i \rightarrow j}}] \mid \forall i, j \rightarrow \underline{w_{i \rightarrow j}} \leq \overline{w_{i \rightarrow j}}, \{\underline{w_{i \rightarrow j}}, \overline{w_{i \rightarrow j}}\} \in [-1, +1] \quad (4.2)$$

FGCMs require two inputs: the grey relationship matrix and the initial state vector. Experts identify and determine the number and type of grey concepts (nodes) that compose the FGCM (SALMERON, 2010). With linguistic terms, they are able to assess in pairwise way the cause and effect relationships between criteria. Also, they assess these causal intensities and if they are negative or positive. By associating linguistic terms with grey numbers, the grey relationship matrix is obtained.

In addition to the determination of the relationship matrix, the initial perception of the importance of each criterion must also be determined. Again, by converting the linguistic terms to their respective grey numbers, the grey initial state vector ($\otimes \vec{C}_0$) is obtained as in Equation (4.3).

$$\otimes \vec{C}_0 = \left(\otimes \vec{C}_0^{[1]} \quad \otimes \vec{C}_0^{[2]} \quad \dots \quad \otimes \vec{C}_0^{[n]} \right) = \left(\underline{[\otimes \vec{C}_0^{[1]}, \overline{\otimes \vec{C}_0^{[1]}]} \quad \underline{[\otimes \vec{C}_0^{[2]}, \overline{\otimes \vec{C}_0^{[2]}]} \quad \dots \quad \underline{[\otimes \vec{C}_0^{[n]}, \overline{\otimes \vec{C}_0^{[n]}]} \right) \quad (4.3)$$

It is noteworthy that if there are multiple decision-makers, the aggregation of the grey numbers present on the initial state vector and the relationship matrix of each decision-maker should be performed according to Equation (4.4), where $\otimes G^k_{ij}$ corresponds to the judgement of the k th decision-maker regarding the impact of criterion i over criterion j (MEMOM; LEE; MARI, 2015).

$$\otimes G_{ij} = \sqrt[k]{\otimes G^1_{ij} \times \otimes G^2_{ij} \times \dots \times \otimes G^n_{ij}} \quad (4.4)$$

Linguistic terms should be defined to help decision-makers in evaluating the interactions between variables. They are usually set as causal intensity qualitative measures associated with grey numbers in a normalized scale: very low, low, medium, high and very high. Therefore, the values of the initial state vector will be in the $[0,1]$ range, requiring the unipolar sigmoid

function to be applied for activating the system composed both by the vector and the relationship matrix.

The activation consists in iteratively multiplying the initial state vector and the relationship matrix within the chosen activation function, used to monotonically map these values in a normalized range. Equation (4.5) shows how the system activation occurs.

$$\begin{aligned} \otimes \overrightarrow{C_{(t+1)}} &= S[\otimes \overrightarrow{C_t} \cdot A(\otimes)] = S[\otimes \overrightarrow{C'_t}] = S[(\otimes C'_t^{[1]} \quad \otimes C'_t^{[2]} \quad \dots \quad \otimes C'_t^{[n]})] = \\ &\quad \left(S(\otimes C'_t^{[1]}) \quad S(\otimes C'_t^{[2]}) \quad \dots \quad S(\otimes C'_t^{[n]}) \right) = \\ &\quad (\otimes C_{(t+1)}^{[1]} \quad \otimes C_{(t+1)}^{[2]} \quad \dots \quad \otimes C_{(t+1)}^{[n]}) \end{aligned} \quad (4.5)$$

In Equation (4.5), $\otimes \overrightarrow{C_t}$ is the grey vector at the iteration or state t ; $S(x)$ is the sigmoid activation function and $A(\otimes)$ is the grey relationship matrix (SALMERON; PAPAGEORGIOU, 2012). The component i of the vector state $\otimes C_{(t+1)}^{[i]}$ is expressed as in Equation (4.6), where λ is a constant value that determines the slope degree of the sigmoid functions.

$$\otimes C_{(t+1)}^{[i]} \in \left[\left(1 + e^{-\lambda \cdot \underline{C'_t}^{[i]}} \right)^{-1}, \left(1 + e^{-\lambda \cdot \overline{C'_t}^{[i]}} \right)^{-1} \right] \quad (4.6)$$

Kang et al. (2016) state that values of λ equal to or close to 1 are ideal, since they provide the possibility of differentiation between the results after convergence of the system, providing better interpretability.

The state of the grey dynamic system evolves along the process (SALMERON, 2010). According to Salmeron and Papageorgiou (2012), after the iterative loops, the FGCM can converge to a fixed pattern of node values or it can reach a chaotic state. For the output analysis after convergence, FGCMs allow calculating the degree of uncertainty associated with each of the obtained values, called greyness (SALMERON, 2010). High values of this indicator lead to the conclusion that the results have high associated uncertainty. Greyness is calculated as in

Equation (4.7), where $|l(\otimes C_i)|$ corresponds to the absolute value of the grey node length of the final state vector and $l(\otimes \psi)$ is determined by Equation (4.8).

$$\varphi(\otimes C_i) = |l(\otimes C_i)|/l(\otimes \psi) \quad (4.7)$$

$$l(\otimes \psi) = \begin{cases} 1 & \text{if } \{\otimes C_i, \otimes w_i\} \subseteq [0,1] \\ 2 & \text{if } \{\otimes C_i, \otimes w_i\} \subseteq [-1, +1] \end{cases} \quad \begin{matrix} \forall \otimes C_i, \otimes w_i \\ \forall \otimes C_i, \otimes w_i \end{matrix} \quad (4.8)$$

Finally, whitenization is performed according to Equation (4.9). Whitenization is the process of converting a grey number into a white one (SALMERON; PAPAGEORGIOU, 2012). If $\alpha=0.5$, the process is called equal weight mean whitenization (LIU; LIN, 2006).

$$\widehat{\otimes} G = \alpha \underline{G} + (1 - \alpha) \overline{G} \mid \alpha \in [0,1] \quad (4.9)$$

B) GREY CLUSTERING

The grey clustering technique was developed based on the GST for classifying relational data associated with uncertainty and human judgments. Grey whitenization functions are used to calculate the criteria membership degree to predefined classes, associating the criteria with the class corresponding to the highest membership (DELGADO; ROMERO, 2016). This soft computing technique requires only one input, a grey relationship matrix, denoted by $\alpha(\otimes) = [\otimes \dot{a}_{ij}]$, which stores the relational data regarding criteria interaction. It is generally obtained through the linguistic assessment of impacts between criteria.

Normalization of matrix $\alpha(\otimes) = [\otimes \dot{a}_{ij}]$ values should be performed according to Equations (4.10), (4.11) and (4.12) (RAJESH, 2018).

$$\underline{\otimes} \tilde{a}_{ij} = (\underline{\otimes} \dot{a}_{ij} - \min_j \underline{\otimes} \dot{a}_{ij}) / \Delta_{min}^{max} \quad (4.10)$$

$$\overline{\otimes} \tilde{a}_{ij} = \left(\overline{\otimes} \dot{a}_{ij} - \min_j \overline{\otimes} \dot{a}_{ij} \right) / \Delta_{min}^{max} \quad (4.11)$$

$$\Delta_{min}^{max} = \max_j \underline{\otimes} \dot{a}_{ij} - \min_j \underline{\otimes} \dot{a}_{ij} \quad (4.12)$$

According to Rajesh (2018), the b_{ij} matrix should store the normalized grey values so they can be converted to white values, which compose the matrix $B = [b_{ij}^*]$ as in Equations (4.13) and (4.14).

$$b_{ij} = \left(\frac{\underline{\otimes} \tilde{a}_{ij} (1 - \underline{\otimes} \tilde{a}_{ij}) + (\overline{\otimes} \tilde{a}_{ij} \times \overline{\otimes} \tilde{a}_{ij})}{(1 - \underline{\otimes} \tilde{a}_{ij} + \overline{\otimes} \tilde{a}_{ij})} \right) \quad (4.13)$$

$$b_{ij}^* = \left(\min \underline{\otimes} \dot{a}_{ij} + (b_{ij} \times \Delta_{min}^{max}) \right) \quad (4.14)$$

Then, the grey classes into which the criteria will be classified need to be determined. According to Delgado and Romero (2016), the center-point triangular whitenization weight functions (CTWF) method is the most recommended for its objectivity and reliability. Further, the CTWF method is also able to better handle uncertainties, as it only needs one point for mathematical determination of the grey classes, and it is not necessary for decision-makers to determine their limits, which is often difficult due to the lack of reliable data (CHEN et al., 2019).

The CTWF method consists of the following steps. Firstly, the numerical range of the criteria values is divided into the number of grey classes to be obtained. Thus, the central points $(\lambda_1, \lambda_2, \dots, \lambda_s)$ of classes 1, 2, ..., s are also determined (DELGADO; ROMERO, 2016). The defined grey classes are increased by adding classes 0 and $(s + 1)$, with central points λ_0 and λ_{s+1} , respectively (CHEN et al., 2019). Thus, according to the authors, the CTWF for the k th grey class, regarding the impact of criterion i on criterion j , denoted as x_{ij} , is defined by Equation (4.15), where $f_j^k(x_{ij})$ corresponds to the CTWF of the k th grey class for the j th criterion.

$$f_j^k(x_{ij}) = \begin{cases} 0, & x \notin [\lambda_{k-1}, \lambda_{k+1}] \\ \frac{x - \lambda_{k-1}}{\lambda_k - \lambda_{k-1}}, & x \in [\lambda_{k-1}, \lambda_k] \\ \frac{\lambda_{k+1} - x}{\lambda_{k+1} - \lambda_k}, & x \in [\lambda_k, \lambda_{k+1}] \end{cases} \quad (4.15)$$

Delgado and Romero (2016) affirm that the clustering coefficient can be calculated as $\sigma_i^k = \sum_{j=1}^m f_j^k(x_{ij})$ and the criteria can be classified into the grey classes. The authors state that if $\sigma_i^{k*} = \max_{i \leq k \leq s} \{\sigma_i^k\}$, then the criterion i belongs to the class k^* . In case many criteria belong to the same grey class k^* , they can be ordered according to the magnitudes of their respective clustering coefficients.

It is interesting to note that in a situation in which an FGCM is being applied, the GC could be useful because matrix $\alpha(\otimes)$ can be considered equivalent to the FGCM matrix $A(\otimes)$, since both are composed by pairwise evaluations of impacts between criteria, as shown by Equation (4.16).

$$\alpha(\otimes) = A(\otimes) = \begin{matrix} & \begin{matrix} \text{Criterion 1} & \text{Criterion 2} & \cdots & \text{Criterion } n \end{matrix} \\ \begin{matrix} \text{Criterion 1} \\ \text{Criterion 2} \\ \vdots \\ \text{Criterion } n \end{matrix} & \begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nn} \end{pmatrix} \end{matrix} \quad (4.16)$$

Thus, the GC can be applied to classify matrix $A(\otimes)$ of criteria based on the information it contains regarding the intensity of their interactions. The GC would classify the criteria into grey classes defined according to the same linguistic terms used to build matrix $A(\otimes)$. Since each grey class has an associated grey number, the initial state vector is obtained as Equation (4.17).

<i>Impact on the system</i>	<i>Grey numbers associated with each grey class</i>
$\otimes \vec{C}_0 = \begin{matrix} \text{Criterion 1} \\ \text{Criterion 2} \\ \vdots \\ \text{Criterion n} \end{matrix} \begin{bmatrix} \text{Grey class}_{\text{Criterion 1}} \\ \text{Grey class}_{\text{Criterion 2}} \\ \vdots \\ \text{Grey class}_{\text{Criterion n}} \end{bmatrix}$	$= \begin{bmatrix} \underline{\otimes \vec{C}_0^{[1]}}, \overline{\otimes \vec{C}_0^{[1]}} \\ \underline{\otimes \vec{C}_0^{[2]}}, \overline{\otimes \vec{C}_0^{[2]}} \\ \vdots \\ \underline{\otimes \vec{C}_0^{[n]}}, \overline{\otimes \vec{C}_0^{[n]}} \end{bmatrix}$

(4.17)

Having $\alpha(\otimes) = A(\otimes)$ and applying GC to obtain $\otimes \vec{C}_0$, the FGCM iterations start. The advantage of conducting this process is justified since it halves the required inputs for FGCM execution and, therefore, reduces the level of data uncertainty inserted into the system. The step-by-step of this procedure and its potential contributions will be exemplified in two pilot applications presented in Section 4.4.

C) FUZZY INFERENCE SYSTEMS

FISs have been widely applied in multicriteria decision-making due to their ability to model uncertainty (FARAJPOUR et al., 2018) as well as processing human reasoning through fuzzy if-then rules (KHAN et al., 2018). In an FIS, output fuzzy variable is inferred from input fuzzy variables according to a set of fuzzy logic inference rules expressed in linguistic terms (OSIRO et al., 2014). In the popular Mamdani fuzzy rule-based systems, both the input and the output variables are partitioned by fuzzy sets and a linguistic term is associated with each fuzzy set. Thus, these systems allow representing the experts' reasoning process in a very natural and intuitive form (GHADIMI; TOOSI; HEAVEY, 2018), making them particularly suitable in our domain for evaluating whether culture is fostering supply chain performance.

Inference process in an FIS relies on a database, which encompasses the input and output variables employed in the FIS, their respective linguistic terms and their corresponding meanings expressed in terms of fuzzy sets (RAFIE; NAMIN, 2015). The numerical values of the input variables are fuzzified and go through operations of implication and composition of activated rules to finally be aggregated so as to generate the output fuzzy set (GERAMIAN; MEHREGAN; MOKHTARZADEH, 2017), which is finally defuzzified.

Let $X_1, \dots, X_F$ and Y be the F input variables and the output variable, respectively. A typical fuzzy rule R^j is expressed as:

$$R^j = \text{IF } X_1 \text{ is } \tilde{A}_{1,2} \text{ AND } X_2 \text{ is } \tilde{A}_{2,3} \text{ AND } \dots \text{ AND } X_F \text{ is } \tilde{A}_{F,2} \text{ THEN } Y \text{ is } \tilde{C}_3$$

where $\tilde{A}_{f,i}$ and $\tilde{C}_j$ are linguistic terms associated with fuzzy sets defined on the universes of discourse of the input and output variables, respectively.

The conjunction "AND" between propositions expressed in linguistic terms in the antecedents of rules is implemented by a t-norm operator (PEDRYCZ; GOMIDE, 2007). Generally, minimum is used as t-norm and applied as in Equation (4.18) for each activated rule (POURJAVAD; SHAHIN, 2018a). A rule is activated if each element of the input vector $\hat{x} = [\hat{x}_1, \dots, \hat{x}_F]$ belongs to each corresponding fuzzy set in the antecedent of rule R^j with a membership degree different from 0.

$$\mu_{Ant}^j = \text{Min} (\mu_{\tilde{A}_{1,2}}(\hat{x}_1), \mu_{\tilde{A}_{2,3}}(\hat{x}_2), \dots, \mu_{\tilde{A}_{F,2}}(\hat{x}_F)) \quad (4.18)$$

For each activated decision rule, the fuzzy inference engine executes the implication operator between the antecedent and the consequent $\tilde{C}$ of the rule (POURJAVAD; SHAHIN, 2018a). The minimum (Mamdani) implication operator expressed as in Equation (4.19) is commonly used:

$$\mu^j(y) = \text{Min} (\mu_{Ant}^j, \mu_{\tilde{C}_3}(y)) \quad (4.19)$$

The resulting outputs of each rule are aggregated into a single fuzzy set by means of an aggregation operator. Different aggregation operators can be used such as Min, Max, arithmetic or geometric means. The Max operator presented in Equation (4.20) is used when compensation between input variables is preferred, where Q is the number of the activated rules (VON ALTROCK, 1996).

$$AG(y) = \text{Max} (\mu^1(y), \mu^2(y), \dots, \mu^Q) \quad (4.20)$$

Finally, the defuzzification interface converts the output fuzzy number into a crisp number. In order to perform the defuzzification, the center of area (CoA) method can be used, which takes into account all membership values to calculate the output value (ZIMMERMANN, 2010). The center of area is calculated according to Equation (4.21), where $\bar{y}$ is the output generated by the FIS.

$$CoA = \bar{y} = \frac{\int y \cdot AG(y) dy}{\int AG(y) dy} \quad (4.21)$$

4.3 THE DECISION-MAKING MODEL

Figure 4.1 presents the proposed decision-making model to analyze and quantify the causal relationship between organizational culture and supply chain performance, based on the combination of FGCM, GC and FIS. The model consists of three steps that aim to set guidelines for action plans to promote the alignment between organizational culture and supply chain performance management. The model seeks to internalize culture as an enabler of performance improvement initiatives in organizations and can be applied to supply chains of different competitive strategies.

Figure 4.1 - The proposed decision-making model for analyzing the relations between supply chain performance and organizational culture.

Source: own authorship.

The integration between culture and performance in a single model brings to the decision-makers a holistic vision about managerial gaps that should be addressed. Also, the possibility of simulating multiple scenarios favors the prediction of performance outcomes. Finally, the model proposes a new indicator which enhances the culture-performance interaction interpretability. The steps of the proposed model are described next.

Step 1: Data collection

The data collection procedure starts from consulting academic experts (AEs) with an in-depth knowledge of supply chain management and organizational culture to analyze how the OPs could impact supply chain performance in each of the SCOR[®] attributes. The linguistic terms presented in Table 4.5 were used for this assessment. The terms in Table 4.5 are associated with grey numbers since this information will be processed afterwards by the soft computing techniques. Tables 4.6-4.9 present the results of the assessment performed by the four AEs.

Table 4.5 - Linguistic terms and respective grey numbers.

Linguistic Term	Code	$\underline{G}$	$\overline{G}$
Null	N	0	0
Very Low	VL	0.1	0.3
Low	L	0.3	0.5
Medium	M	0.5	0.6
High	H	0.6	0.8
Very High	VH	0.8	1

Source: own authorship.

Table 4.6 - OPs impact in the performance of each SCOR® attribute – AE1.

AE1	Reliability	Responsiveness	Agility	Costs	Asset Management
Results	H	VH	VH	M	M
Employee	L	L	L	VL	VL
Open	M	H	H	L	M
Loose	M	H	H	L	L
Normative	H	H	H	H	M
Market	M	VH	VH	H	L
Process	H	H	M	H	H
Job	VH	VH	H	L	L
Closed	M	L	L	M	M
Tight	VH	M	M	H	H
Pragmatic	H	VH	VH	H	VH
Internal	VH	M	M	VH	VH

Source: own authorship.

Table 4.7 - OPs impact in the performance of each SCOR® attribute – AE2.

AE2	Reliability	Responsiveness	Agility	Costs	Asset Management
Results	H	H	H	H	H
Employee	VL	VL	VL	VL	VL
Open	M	M	M	M	M
Loose	H	H	H	H	H
Normative	H	H	H	M	H
Market	VH	VH	VH	H	H
Process	H	H	H	H	H
Job	M	M	M	VL	M
Closed	M	M	M	M	M
Tight	H	H	H	M	H
Pragmatic	H	H	H	H	H
Internal	VH	VH	VH	VH	VH

Source: own authorship.

Table 4.8 - OPs impact in the performance of each SCOR® attribute – AE3.

AE3	Reliability	Responsiveness	Agility	Costs	Asset Management
Results	M	H	VH	L	L
Employee	H	M	M	L	L
Open	M	H	H	L	L
Loose	VL	VH	VH	VL	VL
Normative	H	L	VL	M	M
Market	L	VH	H	L	VL
Process	VH	L	L	H	H
Job	M	H	H	L	L
Closed	H	N	N	H	H
Tight	H	VL	VL	H	H
Pragmatic	M	H	H	H	H
Internal	VH	L	VL	H	H

Source: own authorship.

Table 4.9 - OPs impact in the performance of each SCOR® attribute – AE4.

AE4	Reliability	Responsiveness	Agility	Costs	Asset Management
Results	VH	H	VH	H	H
Employee	H	M	M	VH	H
Open	H	H	H	N	L
Loose	L	VH	VH	L	M
Normative	VH	VH	H	H	L
Market	VH	VH	VH	VH	H
Process	VH	VH	H	H	H
Job	VH	H	H	H	L
Closed	VH	H	VH	M	L
Tight	L	M	L	M	H
Pragmatic	H	H	VH	H	M
Internal	H	H	H	VH	H

Source: own authorship.

The results presented in Tables 4.6-4.9 were then aggregated using Equation (4.4), leading to a general relationship matrix (GRM), shown in Table 4.10. This matrix contains all the possible interactions between OPs and the SCOR® performance attributes and can be used as a tool to enlighten the discussed culture-performance dynamics in supply chains. The GRM can be complemented in future applications with the contributions of other experts, generating a new GRM and updating the information in Table 4.10.

Table 4.10 - General relationship matrix between OPs and SCOR® attributes.

GRM	Reliability	Responsiveness	Agility	Costs	Asset Management
Results	H	H	VH	M	M
Employee	L	L	L	L	L
Open	M	H	H	N	L
Loose	L	H	H	L	L
Normative	H	H	M	H	M
Market	H	VH	VH	H	L
Process	H	H	M	H	H
Job	H	H	H	L	L
Closed	H	N	N	M	M
Tight	H	L	L	H	H
Pragmatic	H	H	H	H	H
Internal	VH	H	M	VH	H

Source: own authorship.

Therefore, as shown in Figure 4.1, data collection in the focus company can begin, consisting in the cultural profile diagnosis and the performance diagnosis. This process will differentiate one application case from others since no two companies have the exact same culture and performance. The in-company data collection is conducted with enterprise experts. The experts are asked to answer the aforementioned Cadden et al. (2015) questionnaire for the cultural profile diagnosis and to linguistically assess the current performance of the company in each SCOR® attribute according to the linguistic terms defined in Table 4.5. This performance diagnosis will serve as input for the FIS in Step 3.

The cultural profile consists in verifying if the company is more result- or process-oriented, if it has a more open or closed management style, and so on. Therefore, this diagnosis makes possible to obtain the enterprise relationship matrix (ERM), which consists in a reduced version of the GRM with only the OPs associated with the cultural profile of the focus company, illustrating how the practices impact the performance on each SCOR® attribute.

Step 2: GC-FGCM algorithm

Step 2 starts from using grey clustering algorithm to process the information gathered in the ERM. The linguistic terms in the ERM are converted into their respective grey numbers and the GC algorithm calculates the Δ_{min}^{max} and the b_{ij} and b_{ij}^* matrices. Then, grey classes are defined analogously to the set of linguistic terms in Table 4.5, since the classes should reflect

the criteria importance in the system. As the grey classes are associated with grey numbers distributed in a normalized scale, the CTWF method can be applied. With the whitenization functions, the clustering coefficient then calculates the membership degree of each criterion to each grey class. Regarding the culture-performance context, this means assigning each OP to a class corresponding to its impact on performance: very low, low, medium, high or very high. Thus, the output of the GC technique is a classification of the OPs according to their impact on performance.

This classification composes the initial state vector required for the FGCM execution along with the ERM. The system activation then occurs with the application of the unipolar sigmoid function and finishes when convergence is reached. After convergence, the final vector is obtained, the uncertainty degree is calculated and, finally, the results are whitened. Practically, what the FGCM dynamics conducts is to iteratively update criteria importance in the system – represented by the initial state vector – with the information present in the relationship matrix. This process finishes when the vector values stabilize. Therefore, the output of the FGCM in the context of this study is the relative importance of SCOR[®] performance attributes according to the degree of cultural influence. The results obtained so far allow the identification of crucial elements regarding the focus company cultural profile and performance.

Step 3: Alignment assessment

At this point, the model has provided two important pieces of information regarding each SCOR[®] attribute: the degree of cultural influence, calculated in Step 2, and the attribute performance, inferred from the enterprise experts in Step 1, as shown in Figure 4.1. Next, to infer whether culture is fostering performance, the FIS technique is required in this last step of the decision-making model, leading to the definition of a new indicator, named Alignment Index (AI). In this way, the higher the Alignment Index, the higher the positive influence of culture over performance. The proposal of the AI, unifying in one indicator all needed information, aims to improve result interpretability and potential managerial actions.

The calculated numerical value of the degree of cultural influence (in step 2) and the performance of each SCOR[®] attribute (in step 1) compose the antecedents of the FIS rule base, and AI composes the consequent. Five FISs are required to calculate the AI for agility, reliability, responsiveness, costs and asset management. The AI is defined in a numerical scale

from 0-10. To parameterize the FIS, linguistic terms and corresponding fuzzy sets should be defined for the experts to design the rule base. Uniform partitions with partially superposed triangular fuzzy sets are usually adopted for this kind of application (KAUSHAL; BASAK, 2018). Five terms are employed for evaluating the antecedents as well as the consequent: “very low”, “low”, “medium”, “high” and “very high”. The corresponding fuzzy sets for these linguistic terms are presented in Table 4.11. Figure 4.2 shows the membership functions.

Table 4.11 - Linguistic terms and corresponding fuzzy sets to evaluate the antecedents and the consequent.

Linguistic terms	Corresponding fuzzy sets
Very Low	(0, 0, 2.5)
Low	(0, 2.5, 5)
Medium	(2.5, 5, 7.5)
High	(5, 7.5, 10)
Very High	(7.5, 10, 10)

Source: own authorship.

Figure 4.2 - Fuzzy partition of the linguistic terms in Table 4.11.

Source: own authorship.

The rule base consists of 25 if-then rules and is presented in Table 4.12. The rules were defined by academic experts aiming to grasp how the influence of organizational culture over

performance determine the AI indicator. For example, considering rule 21, if the cultural influence received by the attribute is very high and the attribute performance is very low, then the AI is very low. Once defined the rule base, the fuzzy inference process is applied to determine the AI value.

Table 4.12 - Rule base for the Alignment Index determination.

Rule	<i>If</i>		<i>Then</i>	
	Cultural Influence	Operator	Performance	Alignment Index
1	Very Low	AND	Very Low	Very Low
2	Very Low	AND	Low	Very Low
3	Very Low	AND	Medium	Low
4	Very Low	AND	High	Low
5	Very Low	AND	Very High	Low
6	Low	AND	Very Low	Very Low
7	Low	AND	Low	Very Low
8	Low	AND	Medium	Low
9	Low	AND	High	Medium
10	Low	AND	Very High	Medium
11	Medium	AND	Very Low	Low
12	Medium	AND	Low	Low
13	Medium	AND	Medium	Medium
14	Medium	AND	High	High
15	Medium	AND	Very High	High
16	High	AND	Very Low	Very Low
17	High	AND	Low	Very Low
18	High	AND	Medium	Medium
19	High	AND	High	Very High
20	High	AND	Very High	Very High
21	Very High	AND	Very Low	Very Low
22	Very High	AND	Low	Very Low
23	Very High	AND	Medium	Medium
24	Very High	AND	High	Very High
25	Very High	AND	Very High	Very High

Source: own authorship.

The FIS outputs are portrayed by means of a response surface, considering all possible scenarios of culture as an element that leverages performance. In this space, the x-axis represents the attribute performance, the y-axis the degree of received cultural influence and

the z-axis indicates AI. The surface then represents the AI as a function of performance and received cultural influence. In addition, with the final vector and the ERM, the cognitive map can be represented visually. This, along with the five crisp FIS outputs of the AI located in the culture-performance surface, enables scenario simulation, aiding prioritization, anticipation and development of guidelines for action plans.

The computational routines for all three steps of the proposed approach were implemented in MATLAB[®]. Two real case applications are presented in the next section.

4.4 REAL APPLICATION CASES

The pilot applications were conducted in two companies of different industrial sectors, with the aim of enabling comparisons between results and the analysis of how different cultures impact each supply chain performance. Company A is part of a business group from the automotive and financial segments, is more than 70 years old and has over 3000 employees distributed over seven plants. Its competitive strategy is based on low cost, high operational performance, high reliability and low risk. Company B is a multinational enterprise that manufactures and supplies pet food, exporting it worldwide. It is one of the biggest players in the sector, is more than 50 years old and has over 8000 employees distributed throughout its sites. Its competitive strategy is based on premium products with high quality, high aggregated value, product innovation and supply chain agility.

The application followed the procedure in Figure 4.1 and is described in detail next. For both companies, supply chain teams were contacted in order to obtain information as accurate as possible. In Company A, data was provided by a group of ten experts of the supply chain management team. In Company B, data was provided by a team of six managers responsible for the supply chain coordination in one of its plants.

Step 1: Data collection

For data collection, a website with an embedded formulary was developed for enabling managers to input data easily and for storing it automatically. The website, also mobile phone friendly, is available at the following link: <https://sites.google.com/view/cultureandperformance>. The form consists of two parts: performance diagnosis and cultural profile diagnosis.

Therefore, managers from both companies linguistically assessed the current performance on each SCOR® attribute according to the linguistic terms defined in Table 4.5. The evaluations were aggregated using Equation (4.4) and converted into a scale from zero to 10. The performance diagnosis is shown in Figure 4.3. By comparing both companies, it can be noted that Company B has a better performance on agility, responsiveness, costs and asset management, while Company A is currently performing better on reliability.

Figure 4.3 - SCOR® attributes' performance diagnosis.

Source: own authorship.

Then, by answering the Cadden et al. (2015) OPs questionnaire, presented in full in Appendix A, it was possible to diagnose the organizational culture profile of both companies. Company A profile is process-focused, employee-oriented, open, managerially tight, normative and market concerned. Company B on the other hand is result-oriented, but also employee-focused, open, managerially tight, normative and market concerned in a lower intensity. Figure 4.4 illustrates these diagnoses.

Figure 4.4 - Cultural profile diagnoses of companies A and B.

Source: own authorship.

With the cultural profile diagnosis, the ERM can be obtained from the GRM, as detailed in Section 4.3. Tables 4.13 and 4.14 for Company A and B, respectively, present the ERM for both companies with the linguistic terms already converted to their corresponding grey numbers. To ease visualization, the SCOR[®] performance attributes will be referred to as p1 to p5 for reliability, responsiveness, agility, costs and asset management, respectively.

Table 4.13 - Enterprise relationship matrix for Company A.

ERM _A	$\underline{G}$					$\overline{G}$				
	p1	p2	p3	p4	p5	p1	p2	p3	p4	p5
Process	0.6	0.6	0.5	0.6	0.6	0.8	0.8	0.6	0.8	0.8
Employee	0.3	0.3	0.3	0.3	0.3	0.5	0.5	0.5	0.5	0.5
Open	0.5	0.6	0.6	0	0.3	0.6	0.8	0.8	0	0.5
Loose	0.3	0.6	0.6	0.3	0.3	0.5	0.8	0.8	0.5	0.5
Normative	0.6	0.6	0.5	0.6	0.5	0.8	0.8	0.6	0.8	0.6
Market	0.6	0.8	0.8	0.6	0.3	0.8	1	1	0.8	0.5

Source: own authorship.

Table 4.14 - Enterprise relationship matrix for Company B.

ERM _B	$\underline{G}$					$\overline{G}$				
	p1	p2	p3	p4	p5	p1	p2	p3	p4	p5
Results	0.6	0.6	0.8	0.5	0.5	0.8	0.8	1	0.6	0.6
Employee	0.3	0.3	0.3	0.3	0.3	0.5	0.5	0.5	0.5	0.5
Open	0.5	0.6	0.6	0	0.3	0.6	0.8	0.8	0	0.5
Loose	0.3	0.6	0.6	0.3	0.3	0.5	0.8	0.8	0.5	0.5
Normative	0.6	0.6	0.5	0.6	0.5	0.8	0.8	0.6	0.8	0.6
Market	0.6	0.8	0.8	0.6	0.3	0.8	1	1	0.8	0.5

Source: own authorship.

Step 2: GC-FGCM algorithm

Having the ERMs for both companies, step 2 of the decision-making model can begin. First, the GC technique is executed. The Δ_{min}^{max} can be calculated with Equations (4.10) to (4.12) (presented in Table 4.15) and consequently the b_{ij}^* matrices can be obtained with Equations (4.13) and (4.14). The matrices are shown in Tables 4.16 and 4.17.

Table 4.15 - Δ max-min calculation for Companies A and B.

Δ_{min}^{max}	Process (A) / Results (B)	Employee	Open	Loose	Normative	Market	p1	p2	p3	p4	p5
Company A	0	0	0	0	0	0	0.8	1	1	0.8	0.8
Company B	0	0	0	0	0	0	0.8	1	1	0.8	0.6

Source: own authorship.

Table 4.16 - bij* matrix for Company A.

bij*	Process	Employee	Open	Loose	Normative	Market	p1	p2	p3	p4	p5
Proc.	0.000	0.000	0.000	0.000	0.000	0.000	0.754	0.673	0.551	0.587	0.587
Emp.	0.000	0.000	0.000	0.000	0.000	0.000	0.383	0.370	0.350	0.248	0.230
Open	0.000	0.000	0.000	0.000	0.000	0.000	0.531	0.682	0.645	0.000	0.370
Loose	0.000	0.000	0.000	0.000	0.000	0.000	0.356	0.843	0.797	0.289	0.318
Norm.	0.000	0.000	0.000	0.000	0.000	0.000	0.703	0.673	0.478	0.508	0.435
Market	0.000	0.000	0.000	0.000	0.000	0.000	0.600	0.967	0.854	0.538	0.342
p1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
p2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
p3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
p4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
p5	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Source: own authorship.

Table 4.17 - bij* matrix for Company B.

bij*	Process	Employee	Open	Loose	Normative	Market	P1	p2	p3	p4	p5
Result.	0.000	0.000	0.000	0.000	0.000	0.000	0.618	0.786	0.854	0.438	0.386
Emp.	0.000	0.000	0.000	0.000	0.000	0.000	0.362	0.370	0.350	0.233	0.190
Open	0.000	0.000	0.000	0.000	0.000	0.000	0.502	0.682	0.645	0.000	0.306
Loose	0.000	0.000	0.000	0.000	0.000	0.000	0.337	0.843	0.797	0.272	0.263
Norm.	0.000	0.000	0.000	0.000	0.000	0.000	0.665	0.673	0.478	0.478	0.360
Market	0.000	0.000	0.000	0.000	0.000	0.000	0.568	0.967	0.854	0.506	0.283
p1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
p2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
p3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
p4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
p5	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Source: own authorship.

Table 4.18 illustrates the grey class determination procedure. The classes are defined analogously to the set of linguistic terms in Table 4.5 since the classes should reflect the criteria importance. As the grey classes are associated with normalized grey numbers, the CTWF method can be applied. With Equation (4.15), the whitenization functions are obtained. These functions calculate the membership degree of each criterion to each grey class. Therefore, $f_1(x)$ calculates the criterion membership degree to the grey class VL and so on, as in Equations (4.22) to (4.26). The classes and whitenization functions are the same for both companies.

Table 4.18 - Grey classes determination.

Grey Classes	$\underline{G}$	$\overline{G}$	Center Point	λ
VL	0	0.2	0.1	1
L	0.2	0.4	0.3	2
M	0.4	0.6	0.5	3
H	0.6	0.8	0.7	4
VH	0.8	1	0.9	5

Source: own authorship.

$$f_1(x) = \begin{cases} 0, & x \notin [0; 0.3] \\ \frac{x}{0.1}, & x \in [0; 0.1] \\ \frac{0.3-x}{0.2}, & x \in [0.1; 0.3] \end{cases} \quad (22)$$

$$f_2(x) = \begin{cases} 0, & x \notin [0.1; 0.5] \\ \frac{x-0.1}{0.2}, & x \in [0.1; 0.3] \\ \frac{0.5-x}{0.2}, & x \in [0.3; 0.5] \end{cases} \quad (23)$$

$$f_3(x) = \begin{cases} 0, & x \notin [0.5; 0.7] \\ \frac{x-0.3}{0.2}, & x \in [0.3; 0.5] \\ \frac{0.7-x}{0.2}, & x \in [0.5; 0.7] \end{cases} \quad (24)$$

$$f_4(x) = \begin{cases} 0, & x \notin [0.5; 0.9] \\ \frac{x-0.5}{0.2}, & x \in [0.5; 0.7] \\ \frac{0.9-x}{0.2}, & x \in [0.7; 0.9] \end{cases} \quad (25)$$

$$f_5(x) = \begin{cases} 0, & x \notin [0.7; 1] \\ \frac{x-0.7}{0.2}, & x \in [0.7; 0.9] \\ \frac{1-x}{0.1}, & x \in [0.9; 1] \end{cases} \quad (26)$$

After calculation of the grey clustering coefficient the criteria are classified into one of the classes. For instance, in Table 4.19, $\sigma_{Process}^{k*} = \max_{1 \leq k \leq 5} \{0; 0; 2.01; 2.72; 0.27\} = 2.72 \rightarrow k^* = H$. Tables 4.19 and 4.20 show the criteria classification for companies A and B.

Table 4.19 - Clustering for Company A.

σ_i^k	GC-VL	GC-L	GC-M	GC-H	GC-VH	σ_i^{k*}	AGC
Process	0.00	0.00	2.01	2.72	0.27	2.72	H
Employee	0.61	3.37	1.02	0.00	0.00	3.37	L
Open	0.00	0.65	1.56	1.79	0.00	1.79	H
Loose	0.05	2.58	0.37	0.80	1.20	2.58	L
Normative	0.00	0.44	2.66	1.89	0.02	2.66	M
Market	0.00	0.79	1.52	0.92	1.10	1.52	M
p1	0.00	0.00	0.00	0.00	0.00	0.00	N
p2	0.00	0.00	0.00	0.00	0.00	0.00	N
p3	0.00	0.00	0.00	0.00	0.00	0.00	N
p4	0.00	0.00	0.00	0.00	0.00	0.00	N
p5	0.00	0.00	0.00	0.00	0.00	0.00	N

Source: own authorship.

Table 4.20 - Clustering for Company B.

σ_i^k	GC-VL	GC-L	GC-M	GC-H	GC-VH	σ_i^{k*}	AGC
Results	0.00	0.88	1.53	1.39	1.20	1.53	M
Employee	0.88	3.20	0.91	0.00	0.00	3.20	L
Open	0.00	0.97	1.39	1.64	0.00	1.64	H
Loose	0.32	2.49	0.18	0.80	1.20	2.49	L
Normative	0.00	0.92	2.39	1.69	0.00	2.39	M
Market	0.08	0.92	1.63	0.60	1.10	1.63	M
p1	0.00	0.00	0.00	0.00	0.00	0.00	N
p2	0.00	0.00	0.00	0.00	0.00	0.00	N
p3	0.00	0.00	0.00	0.00	0.00	0.00	N
p4	0.00	0.00	0.00	0.00	0.00	0.00	N
p5	0.00	0.00	0.00	0.00	0.00	0.00	N

Source: own authorship.

Therefore, each OP is now associated with its general impact on performance. For example, the fact that Company A management style is process-oriented has a high impact on its performance. Figure 4.5 shows the OPs according to their influence on the SCOR[®] attributes' performance for each company after whitening the grey numbers associated with the assigned classes.

Figure 4.5 - OPs influence over performance.

Source: own authorship.

The GC output is the initial state vector required for the FGCM execution along with the ERM for each company. Both FGCMs are then activated according to Equations (4.5) and (4.6), considering $\lambda = 1.1$ as in Kang et al. (2016). After convergence, the final vector for each company is obtained and represent the SCOR[®] performance attributes according to the degree of received cultural influence, as shown in Tables 4.21, 4.22 and as illustrated in Figure 4.6.

Table 4.21 - Final vector for Company A.

Final vector	$\underline{G}$	$\overline{G}$	Lenght	Greyness
Process	0.678	0.678	0.000	0.000
Employee	0.678	0.678	0.000	0.000
Open	0.678	0.678	0.000	0.000
Loose	0.678	0.678	0.000	0.000
Normative	0.678	0.678	0.000	0.000
Market	0.678	0.678	0.000	0.000
Agility	0.966	0.985	0.019	0.019
Reliability	0.974	0.989	0.015	0.015
Responsiveness	0.969	0.987	0.018	0.018
Costs	0.934	0.969	0.035	0.035
Asset Management	0.939	0.975	0.036	0.036

Source: own authorship.

Table 4.22 - Final vector for Company B.

Final vector	$\underline{G}$	$\overline{G}$	Lenght	Greyness
Results	0.678	0.678	0.000	0.000
Employee	0.678	0.678	0.000	0.000
Open	0.678	0.678	0.000	0.000
Loose	0.678	0.678	0.000	0.000
Normative	0.678	0.678	0.000	0.000
Market	0.678	0.678	0.000	0.000
Agility	0.964	0.970	0.006	0.006
Reliability	0.976	0.983	0.007	0.007
Responsiveness	0.974	0.983	0.009	0.009
Costs	0.928	0.943	0.015	0.015
Asset Management	0.934	0.956	0.022	0.022

Source: own authorship.

Figure 4.6 - Degree of received cultural influence by the SCOR® performance attributes.

Source: own authorship.

By conducting the whitenization of the grey values presented in Tables 4.21 and 4.22, it can be concluded that for both companies, but in different intensities, reliability is the attribute that is most affected by organizational culture, followed by responsiveness, agility, asset management and costs.

Step 3: Alignment assessment

As in the decision model of Figure 4.1, the degree of received cultural influence by the SCOR® attributes and the diagnosed performance are the inputs to the FIS that calculates the AI. Tables 4.23 and 4.24 and Figure 4.7 show the results of the inference processes.

Table 4.23 -AI calculation for Company A.

SCOR® attribute	CI	AP	AI
Agility	7.56	5.8	5.93
Reliability	8.19	7.55	9.14
Responsiveness	7.78	6.21	6.33
Costs	5.19	5.73	5.83
Asset Management	5.71	5.04	5.07

Source: own authorship.

Table 4.24 - AI calculation for Company B.

SCOR® attribute	CI	AP	AI
Agility	7.56	5.8	5.93
Reliability	8.19	7.55	9.14
Responsiveness	7.78	6.21	6.33
Costs	5.19	5.73	5.83
Asset Management	5.71	5.04	5.07

Source: own authorship.

Figure 4.7 - Alignment indexes.

Source: own authorship.

The culture-performance surfaces representing the AI as a function of performance and received cultural influence for each company can be seen in Figure 4.8 and Figure 4.9, respectively.

Figure 4.8 - Culture-performance surface for Company A.

Source: own authorship.

Figure 4.9 - Culture-performance surface for Company B.

Source: own authorship.

To aid decision-makers in the development of action plans, the cognitive maps can be visually represented as in Figure 4.10 and Figure 4.11. To facilitate visualization of the causal relationships' intensity, a scale that associates different types of arrows with each linguistic term is proposed. In addition, the criteria are associated with circles of different sizes and colours. White circles are associated with causal criteria (OPs) and grey circles with effect criteria (performance attributes). Regarding their size, for the OPs the bigger the circle the greater the influence over performance. For the SCOR[®] attributes, bigger circles correspond to higher levels of cultural influence.

Figure 4.10 - Final cognitive map for Company A.

Source: own authorship.

Figure 4.11 - Final cognitive map for Company B.

Source: own authorship.

4.5 DISCUSSION

It is interesting to note that the cultural profiles of the studied companies differ only in one OP: “process” vs. “results”. While company A is process-oriented, company B is result-oriented. Verbeke (2000) suggests that the optimal cultural profile regarding performance is an organization results-driven, employee-focused, externally-oriented and where communication is encouraged. This could explain the performance gap between the two companies, since “process” vs. “results” is the OP that has the most influence on performance, followed by “open” vs. “closed”. It can be concluded that the “employee” and “loose” OPs do not have as much impact on performance as other OPs since, by definition, they refer mostly to personal management at the micro level. On the other hand, OPs such as “process” and “normative” are by definition closely related to performance.

Compared to company A, company B performs better in all SCOR® attributes but reliability. For company A, reliability is the attribute with the best performance, while for company B it is agility: this scenario is consistent with their declared competitive strategy.

Company A performs better in reliability and Company B performs better in agility, reliability and responsiveness. This corroborates the existence of positive relationships between organizational culture and the performance of supply chains since these attributes are just those more influenced by culture.

For Company A, the highest alignment index is associated with reliability, thus indicating that culture fosters this attribute performance. According to the cognitive map, reliability is most affected by the OPs “loose” and “market”. For Company B, the highest alignment index is associated with reliability, closely followed by both agility and responsiveness, thus indicating that culture fosters performance on these attributes. According to the cognitive map, reliability is most affected by the OPs “results”, “loose” and “market”; agility by “results”, “normative” and “market” and; responsiveness by “results”, “open”, “loose” and “market”.

This indicates that the organizational characteristics of information sharing, learning, freedom of thought and action, focus on the competitors and on client requirements have a positive effect on the supply chain performance for both companies. The focus on results and flexibility to ensure that goals are met is a plus which justifies the better performance of company B. Asset management has the lowest alignment index and the lowest performance for both companies. Also, for both companies, this SCOR[®] attribute receives less cultural influence in comparison to the others. To guide action plans, asset management process and indicators should be revised in order to improve market focus and to promote information sharing, organizational learning and goal achievement.

4.6 CONCLUSIONS

This paper proposed a group decision-making model to analyze and quantify the causal relationship between organizational culture and supply chain performance. The model is based on the combination of fuzzy grey cognitive maps (FGCMs), grey clustering (GC) and fuzzy inference systems (FISs). To the best of the authors’ knowledge, similar studies are not found in the literature. The development of this research was based on the SCOR[®] (Supply Chain Operations Reference) model attributes and Hofstede’s (2001) organizational practices. The main contribution consists of providing a new approach to explore the relationship between organizational culture and supply chain performance management.

The analysis of two real application cases in companies from different industrial sectors illustrated the expected benefits of the proposed model. Results allowed the identification of crucial elements regarding cultural profile and performance of both companies, aiding scenario simulation, prioritization and the development of guidelines for action plans. The model was capable of showing which organizational culture factors were most relevant considering their capability to foster performance. In addition, the model provided details of how each of these cultural factors affected each of the performance attributes. Finally, the model allowed classification of the attributes based on the level of cultural influence. It is worth noting that the proposed model processes natural human language and it is also capable of considering human judgment hesitation.

As possible implications for practitioners, it is expected that the presented results and the decision model can provide managers with means to operationalize the alignment between organizational culture and performance management efforts. As theoretical contribution, it is expected that the application of soft computing techniques to analyze the impact of cultural factors on supply chain performance can provide novel opportunities regarding how to jointly address both constructs and therefore to expand the knowledge frontier on this subject.

However, it is important to note that the conclusions derived from the model application depend on experts' knowledge. GC, FGCM and FIS require the definition of suitable linguistic terms and appropriate corresponding grey numbers and fuzzy sets. Concerning FIS, the rule base design also affects the model final results. Further, the defuzzified output changes according to variations in the inference operators, such as t-norms and different defuzzification operators. The operators used in this paper are, however, a very popular choice in FIS application domain.

The proposed decision model can, therefore, be further improved. In this regard, consensus techniques could be applied to increase the robustness of the aggregated relationship matrix by minimizing divergence among decision-makers. In addition, a higher number of experts can be consulted to contribute to the GRM content, making it more representative of reality. Further research could also apply the decision model in lean and agile supply chains for comparing the differences on causal relationships between culture and performance for these different competitive strategies. As a final suggestion, the proposed model can also be adapted to explore how culture can foster supply chain sustainability, substituting the SCOR[®] performance attributes with green indicators.

4.7 REFERENCES

AKKAWUTTIWANICH, P.; YENRADEE, P. Fuzzy QFD approach for managing SCOR performance indicators. **Computers & Industrial Engineering**, v. 122, p. 189-201, 2018.

ALTAY, N. et al. Agility and resilience as antecedents of supply chain performance under moderating effects of organizational culture within the humanitarian setting: a dynamic capability view. **Production Planning & Control**, v. 29, n. 14, p. 1158-1174, 2018.

ANJUM, A. et al. Supply Chain Integration and Operational Performance: Moderating role of Organizational Culture. **International Journal of Academic Research in Business and Social Sciences**, v. 6, n. 12, p. 2222-6990, 2016.

AQLAN, F.; LAM, S. S. A fuzzy-based integrated framework for supply chain risk assessment. **International Journal of Production Economics**, v. 161, p. 54-63, 2015.

BALFAQIH, H. et al. Review of supply chain performance measurement systems: 1998–2015. **Computers in Industry**, v. 82, p. 135-150, 2016.

BELLMAN, R. E.; ZADEH, L. A. Decision-making in a fuzzy environment. **Management science**, v. 17, n. 4, p. B-141-B-164, 1970.

BERTRAND, J. W. M.; FRANSOO, J. C. Modelling and simulation. In: **Research methods for operations management**. Routledge, 2016. p. 306-346.

BITITCI, U. S. et al. Managerial processes: business process that sustain performance. **International Journal of Operations & Production Management**, 2011.

BORTOLOTTI, T.; BOSCARI, S.; DANESE, P. Successful lean implementation: Organizational culture and soft lean practices. **International Journal of Production Economics**, v. 160, p. 182-201, 2015.

BRAUNSCHEIDEL, M. J.; SURESH, N. C.; BOISNIER, A. D. Investigating the impact of organizational culture on supply chain integration. **Human Resource Management**, v. 49, n. 5, p. 883-911, 2010.

CADDEN, T. et al. Old habits die hard: exploring the effect of supply chain dependency and culture on performance outcomes and relationship satisfaction. **Production Planning & Control**, v. 26, n. 1, p. 53-77, 2015.

CADDEN, T.; HUMPHREYS, P.; MCHUGH, M. The influence of organisational culture on strategic supply chain relationship success. **Journal of General Management**, v. 36, n. 2, p. 37-64, 2010.

CADDEN, T.; MARSHALL, D.; CAO, G. Opposites attract: organisational culture and supply chain performance. **Supply Chain Management: an international journal**, 2013.

CAI, J. et al. Improving supply chain performance management: A systematic approach to analyzing iterative KPI accomplishment. **Decision support systems**, v. 46, n. 2, p. 512-521, 2009.

CAMERON, K. S.; QUINN, R. E. **Diagnosing and changing organizational culture: Based on the competing values framework**. John Wiley & Sons, 2011.

CAO, Z. et al. The impact of organizational culture on supply chain integration: a contingency and configuration approach. **Supply Chain Management: An International Journal**, 2015.

CHAN, C. K.; HOU, S. H.; LANGEVIN, A. Advances in optimization and design of supply chains. **International journal of production economics**, 2012.

CHEN, K. et al. Grey clustering evaluation based on AHP and interval grey number. **International Journal of Intelligent Computing and Cybernetics**, 2019.

CHEN, W. H.; TSAI, M. S.; KUO, H. L. Distribution system restoration using the hybrid fuzzy-grey method. **IEEE Transactions on Power Systems**, v. 20, n. 1, p. 199-205, 2005.

CONGJUN, R.; XINPING, X.; JIN, P. Novel combinatorial algorithm for the problems of fuzzy grey multi-attribute group decision-making. **Journal of Systems Engineering and Electronics**, v. 18, n. 4, p. 774-780, 2007.

CROOM, S. et al. Information sharing and supply chain performance: the role of connectivity and willingness. **Supply Chain Management: An International Journal**, 2007.

DELGADO, A.; ROMERO, I. Environmental conflict analysis using an integrated grey clustering and entropy-weight method: A case study of a mining project in Peru. **Environmental Modelling & Software**, v. 77, p. 108-121, 2016.

DESHPANDE, R.; WEBSTER J. R., Frederick E. Organizational culture and marketing: defining the research agenda. **Journal of marketing**, v. 53, n. 1, p. 3-15, 1989.

DISSANAYAKE, C. K.; CROSS, J. A. Systematic mechanism for identifying the relative impact of supply chain performance areas on the overall supply chain performance using SCOR model and SEM. **International Journal of Production Economics**, v. 201, p. 102-115, 2018.

DOUGLAS, M. Four cultures: the evolution of a parsimonious model. **GeoJournal**, v. 47, n. 3, p. 411-415, 1999.

DOWTY, R. A.; WALLACE, W. A. Implications of organizational culture for supply chain disruption and restoration. **International Journal of Production Economics**, v. 126, n. 1, p. 57-65, 2010.

DUBEY, R. et al. Big data analytics and organizational culture as complements to swift trust and collaborative performance in the humanitarian supply chain. **International Journal of Production Economics**, v. 210, p. 120-136, 2019.

ESTAMPE, D. et al. A framework for analysing supply chain performance evaluation models. **International Journal of Production Economics**, v. 142, n. 2, p. 247-258, 2013.

FANTAZY, K.; TIPU, S. A. A. Exploring the relationships of the culture of competitiveness and knowledge development to sustainable supply chain management and organizational performance. **Journal of Enterprise Information Management**, 2019.

FARAJPOUR, F. et al. Information sharing assessment in supply chain: hierarchical fuzzy rule-based system. **Journal of Information & Knowledge Management**, v. 17, n. 01, p. 1850002, 2018.

FERNANDEZ, A. et al. Evolutionary fuzzy systems for explainable artificial intelligence: why, when, what for, and where to?. **IEEE Computational intelligence magazine**, v. 14, n. 1, p. 69-81, 2019.

FURNARI, S. A cognitive mapping approach to business models: Representing causal structures and mechanisms. **Advances in Strategic Management**, v. 33, n. 1, p. 207-239, 2015.

GAMBI, L. D. N.; GEROLAMO, Mateus Cecílio; CARPINETTI, Luiz Cesar Ribeiro. A theoretical model of the relationship between organizational culture and quality management techniques. **Procedia-Social and Behavioral Sciences**, v. 81, p. 334-339, 2013.

GERAMIAN, A. et al. Fuzzy inference system application for failure analyzing in automobile industry. **International Journal of Quality & Reliability Management**, 2017.

- GHADIMI, P.; TOOSI, F. G.; HEAVEY, C. A multi-agent systems approach for sustainable supplier selection and order allocation in a partnership supply chain. **European Journal of Operational Research**, v. 269, n. 1, p. 286-301, 2018.
- GROYSBERG, B. et al. The leader's guide to corporate culture. **Harvard Business Review**, v. 96, n. 1, p. 44-52, 2018.
- GUNASEKARAN, A.; PATEL, C.; TIRTIROGLU, E. Performance measures and metrics in a supply chain environment. **International journal of operations & production management**, 2001.
- HAERI, S. A. S.; REZAEI, J. A grey-based green supplier selection model for uncertain environments. **Journal of cleaner production**, v. 221, p. 768-784, 2019.
- HAJEK, P.; FROELICH, W. Integrating TOPSIS with interval-valued intuitionistic fuzzy cognitive maps for effective group decision-making. **Information Sciences**, v. 485, p. 394-412, 2019.
- HOFSTEDE, G. et al. Measuring organizational cultures: A qualitative and quantitative study across twenty cases. **Administrative science quarterly**, p. 286-316, 1990.
- HOFSTEDE, G. **Culture's consequences: Comparing values, behaviors, institutions and organizations across nations**. Sage publications, 2001.
- HULT, G. T. M.; KETCHEN, D. J.; ARRFELT, M. Strategic supply chain management: Improving performance through a culture of competitiveness and knowledge development. **Strategic management journal**, v. 28, n. 10, p. 1035-1052, 2007.
- JAMSHIDI, A. et al. A new decision support tool for dynamic risks analysis in collaborative networks. In: **Working Conference on Virtual Enterprises**. Springer, Cham, 2015. p. 53-62.
- JERMSITTIPARSERT, K.; WAJEETONGRATANA, P. The Role of Organizational Culture and It Competency in Determining the Supply Chain Agility in the Small and Medium-Size Enterprises. **International Journal of Innovation, Creativity and Change**, v. 5, n. 2, p. 416-431, 2019.
- KANG, B. et al. Generalized fuzzy cognitive maps: a new extension of fuzzy cognitive maps. **International Journal of System Assurance Engineering and Management**, v. 7, n. 2, p. 156-166, 2016.

KAUSHAL, J.; BASAK, P. A novel approach for determination of power quality monitoring index of an AC microgrid using fuzzy inference system. **Iranian Journal of Science and Technology, Transactions of Electrical Engineering**, v. 42, n. 4, p. 429-450, 2018.

KESHAVARZ GHORABAEI, M. et al. Supplier evaluation and selection in fuzzy environments: a review of MADM approaches. **Economic research-Ekonomska istraživanja**, v. 30, n. 1, p. 1073-1118, 2017.

KHAN, S. A. et al. Supplier sustainability performance evaluation and selection: A framework and methodology. **Journal of cleaner production**, v. 205, p. 964-979, 2018.

KROEBER, A. L.; KLUCKHOHN, C. Culture: A critical review of concepts and definitions. **Papers. Peabody Museum of Archaeology & Ethnology, Harvard University**, 1952.

LIMA-JUNIOR, F. R.; CARPINETTI, L. C. R. Quantitative models for supply chain performance evaluation: a literature review. **Computers & Industrial Engineering**, v. 113, p. 333-346, 2017.

LIMA-JUNIOR, F. R.; OSIRO, L.; CARPINETTI, L. C. R. A fuzzy inference and categorization approach for supplier selection using compensatory and non-compensatory decision rules. **Applied Soft Computing**, v. 13, n. 10, p. 4133-4147, 2013.

LIMA-JUNIOR, F. R.; CARPINETTI, L. C. R. Combining SCOR[®] model and fuzzy TOPSIS for supplier evaluation and management. **International Journal of Production Economics**, v. 174, p. 128-141, 2016.

LIMA-JUNIOR, F. R.; CARPINETTI, L. C. R. Predicting supply chain performance based on SCOR[®] metrics and multilayer perceptron neural networks. **International Journal of Production Economics**, v. 212, p. 19-38, 2019.

LIU, S.; LIN, Y. **Grey information: theory and practical applications**. Springer Science & Business Media, 2006.

LIU, H. et al. The role of institutional pressures and organizational culture in the firm's intention to adopt internet-enabled supply chain management systems. **Journal of Operations Management**, v. 28, n. 5, p. 372-384, 2010.

LOHMAN, C.; FORTUIN, L.; WOUTERS, M. Designing a performance measurement system: A case study. **European journal of operational research**, v. 156, n. 2, p. 267-286, 2004.

LOHMAN, C.; FORTUIN, L.; WOUTERS, M. Designing a performance measurement system: A case study. **European journal of operational research**, v. 156, n. 2, p. 267-286, 2004.

MAZZUTO, G. et al. Aggregate experts knowledge in Fuzzy Cognitive Maps. In: **2018 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)**. IEEE, 2018. p. 1-6.

MEMON, M. S.; LEE, Y. H.; MARI, S. I. Group multi-criteria supplier selection using combined grey systems theory and uncertainty theory. **Expert Systems with Applications**, v. 42, n. 21, p. 7951-7959, 2015.

NAIR, A.; RECKIEN, D.; VAN MAARSEVEEN, M. A generalised fuzzy cognitive mapping approach for modelling complex systems. **Applied Soft Computing**, v. 84, p. 105754, 2019.

NEELY, A.; GREGORY, M.; PLATTS, K. Performance measurement system design: A literature review and research agenda. **International journal of operations & production management**, v. 25, n. 12, p. 1228-1263, 2005.

NTABE, E. N. et al. A systematic literature review of the supply chain operations reference (SCOR) model application with special attention to environmental issues. **International Journal of Production Economics**, v. 169, p. 310-332, 2015.

O'REILLY, C. A.; CHATMAN, Jennifer A. **Culture as social control: Corporations, cults, and commitment**. 1996.

O'REILLY III, C. A.; CHATMAN, J.; CALDWELL, D. F. People and organizational culture: A profile comparison approach to assessing person-organization fit. **Academy of management journal**, v. 34, n. 3, p. 487-516, 1991.

OSIRO, L.; LIMA-JUNIOR, F. R.; CARPINETTI, L. C. R. A fuzzy logic approach to supplier evaluation for development. **International Journal of Production Economics**, v. 153, p. 95-112, 2014.

PEDRYCZ, W.; GOMIDE, F. **Fuzzy systems engineering: toward human-centric computing**. John Wiley & Sons, 2007.

PORTER, M. G. Supply Chain Integration: Does Organizational Culture Matter?. **Operations and Supply Chain Management: An International Journal**, v. 12, n. 1, p. 49-59, 2019.

POTHUKUCHI, V. et al. National and organizational culture differences and international joint venture performance. **Journal of international business studies**, v. 33, n. 2, p. 243-265, 2002.

POURJAVAD, E.; SHAHIN, A. The application of Mamdani fuzzy inference system in evaluating green supply chain management performance. **International Journal of Fuzzy Systems**, v. 20, n. 3, p. 901-912, 2018a.

POURJAVAD, E.; SHAHIN, A. Hybrid performance evaluation of sustainable service and manufacturing supply chain management: An integrated approach of fuzzy dematel and fuzzy inference system. **Intelligent Systems in Accounting, Finance and Management**, v. 25, n. 3, p. 134-147, 2018b.

PRAJOGO, D. I.; MCDERMOTT, C. M. The relationship between multidimensional organizational culture and performance. **International Journal of Operations & Production Management**, 2011.

QUINN, R. E.; ROHRBAUGH, J. A spatial model of effectiveness criteria: Towards a competing values approach to organizational analysis. **Management science**, v. 29, n. 3, p. 363-377, 1983.

RAFIE, M.; NAMIN, F. S. Prediction of subsidence risk by FMEA using artificial neural network and fuzzy inference system. **International Journal of Mining Science and Technology**, v. 25, n. 4, p. 655-663, 2015.

RAJESH, R. Forecasting supply chain resilience performance using grey prediction. **Electronic Commerce Research and Applications**, v. 20, p. 42-58, 2016.

RAMEZANKHANI, M. J.; TORABI, S. Ali; VAHIDI, F. Supply chain performance measurement and evaluation: A mixed sustainability and resilience approach. **Computers & Industrial Engineering**, v. 126, p. 531-548, 2018.

SALMERON, J. L.; GUTIERREZ, E. Fuzzy grey cognitive maps in reliability engineering. **Applied Soft Computing**, v. 12, n. 12, p. 3818-3824, 2012.

SALMERON, J. L.; PAPAGEORGIOU, E. I. A fuzzy grey cognitive maps-based decision support system for radiotherapy treatment planning. **Knowledge-Based Systems**, v. 30, p. 151-160, 2012.

SALMERON, J. L. Modelling grey uncertainty with fuzzy grey cognitive maps. **Expert Systems with Applications**, v. 37, n. 12, p. 7581-7588, 2010.

SAMBASIVAN, M.; YEN, C. N. Strategic alliances in a manufacturing supply chain. **International Journal of Physical Distribution & Logistics Management**, 2010.

SCC, Supply Chain Council. **Supply Chain Operations Reference Model**, version 12.0. Supply Chain Council, 2017.

SCHEIN, E. H. **Organizational culture and leadership**. John Wiley & Sons, 2010.

SINAGA, O. et al. Does Organizational Culture Capability and Relationship Building Capability Expediate Supply Chain Operational Performance? Evidence from Indonesia. **International Journal of Supply Chain Management**. v. 8, n. 1, p. 242, 2019.

SMIRCICH, L. Concepts of culture and organizational analysis. **Administrative science quarterly**, p. 339-358, 1983.

TOMIC, B. et al. Organizational culture, quality improvement tools and methodologies, and business performance of a supply chain. **Proceedings of the institution of mechanical engineers, Part B: Journal of Engineering Manufacture**, v. 231, n. 13, p. 2430-2442, 2017.

TSENG, M. L. et al. Decision-making model for sustainable supply chain finance under uncertainties. **International Journal of Production Economics**, v. 205, p. 30-36, 2018.

VERBEKE, W. A revision of Hofstede et al.'s (1990) organizational practices scale. **Journal of Organizational Behavior**, v. 21, n. 5, p. 587-602, 2000.

VON ALTROCK, C. **Fuzzy logic and neurofuzzy applications in business and finance**. Prentice-Hall, Inc., 1996.

WALLACH, E. J. Individuals and organizations: The cultural match. **Training & Development Journal**, 1983.

WHITFIELD, G.; LANDEROS, R. Supplier diversity effectiveness: does organizational culture really matter?. **Journal of Supply Chain Management**, v. 42, n. 4, p. 16-28, 2006.

WILLIAMS, Z.; PONDER, N.; AUTRY, C. W. Supply chain security culture: measure development and validation. **The International Journal of Logistics Management**, v. 20, n. 2, p. 243-260, 2009.

WINKLHOFER, H.; PRESSEY, A.; TZOKAS, N. A cultural perspective of relationship orientation: using organisational culture to support a supply relationship orientation. **Journal of Marketing Management**, v. 22, n. 1-2, p. 169-194, 2006.

YUNUS, E. N.; TADISINA, S. K. Drivers of supply chain integration and the role of organizational culture. **Business Process Management Journal**, 2016.

ZADEH, L. A. Fuzzy sets. **Information and control**, v. 8, n. 3, p. 338-353, 1965.

ZADEH, L. A. Fuzzy logic, neural networks, and soft computing. In: **Fuzzy Sets, Fuzzy Logic, And Fuzzy Systems: Selected Papers by Lotfi A Zadeh**. 1996. p. 775-782.

ZADEH, L. A. Fuzzy logic= computing with words. In: **Computing with Words in Information/Intelligent Systems 1**. Physica, Heidelberg, 1999. p. 3-23.

ZIMMERMANN, H. J. Fuzzy set theory. **Wiley Interdisciplinary Reviews: Computational Statistics**, v. 2, n. 3, p. 317-332, 2010.

Appendix A: Practices questionnaire reproduced from Cadden et al. (2015).

Questions asked about the participant's workplace, how much do you agree or disagree with the following statements (from 1 - strongly agree to 5 - strongly disagree).

PROCESS

- (1) When confronted with problems, the people of a department are rarely being helped by people of other departments.
- (2) The tasks of employees that are absent are rarely taken over by colleagues.
- (3) Requests from other departments are only carried out if the formal procedures have been followed.
- (4) On special projects, there is a laborious cooperation between the various departments.
- (5) The employees contribute their bit by directly following the prescribed methods of the managers.

EMPLOYEE

- (6) With respect to people who do not feel too happy about their job, but who still perform well, new possibilities are being searched for them.
- (7) Whenever an employee is ill, or when something has happened in his personal life, managers ask after their problems with interest.
- (8) Employees are encouraged to take courses and to go to seminars and conferences to help their self-development.
- (9) If there are personal conflicts between employees within a department, the managers will attempt to solve these problems.
- (10) With respect to birthdays, marriages and births, my manager shows a personal interest.
- (11) In matters that directly involve them, employees usually have a say.
- (12) My manager compliments employees on work well done.
- (13) Senior management ensure my job doesn't become too pressurized.

OPEN

- (14) If a manager has a criticism of an employee, he/she discusses it openly with them.
- (15) Employees express any criticisms of management directly to the management.
- (16) At my work employees are asked for constructive criticism to help their managers performance.
- (17) The mistakes of a colleague are personally discussed with him/her.

TIGHT

- (18) Managers always check if the employees are working.
- (19) If one is a little late for an appointment with the manager, s/he will be rapped on her/his knuckles.

(20) If an employee goes to the dentist during working hours, there is a check on how long s/he stays.

(21) Concerning the employees' expenses, the costs have to be specified in detail.

(22) If an employee is 15 min late for work, but goes on for an extra 15 min at the end of the day s/he is called to account.

(23) The number and duration of the breaks employees take are always checked by the managers.

(24) If an employee has to go to an important appointment, he/she has to convince the manager of the importance of the appointment.

NORM

(25) In my organization, major emphasis is on meeting customer needs.

(26) Results are more important than procedures.

(27) Employees never talk about the history of the organization.

(28) I believe the company where I work contributes little to society.

(29) I believe the company where I work actively honors its ethical responsibilities.

MARKET

(30) The satisfaction of the customers is measured regularly.

(31) Product promotions/ actions by the competition are reported in detail to everyone.

(32) The consumers preferences are investigated thoroughly.

(33) The company provides products/ services that meet the needs of the various target-groups.

(34) The future needs of the customers are discussed extensively with the various departments.

(35) In talks with customers, people try to find out about the future needs of the customers

Appendix B: Grey operations

Let $\otimes G_1 \in [\underline{G}_1, \overline{G}_1]$, $\underline{G}_1 \leq \overline{G}_1$, and $\otimes G_2 \in [\underline{G}_2, \overline{G}_2]$, $\underline{G}_2 \leq \overline{G}_2$, be two grey numbers and let λ be a positive real number. Then, the following operations are defined according to Equations (4.22)-(4.26) (SALMERON, 2010).

$$\otimes G_1 + \otimes G_2 \in [\underline{G}_1 + \underline{G}_2, \overline{G}_1 + \overline{G}_2] \quad (4.22)$$

$$\otimes G_1 - \otimes G_2 \in [\underline{G}_1 - \overline{G}_2, \overline{G}_1 - \underline{G}_2] \quad (4.23)$$

$$\begin{aligned} & \otimes G_1 \times \otimes G_2 \in \\ & \left[\min(\underline{G}_1 \cdot \underline{G}_2, \underline{G}_1 \cdot \overline{G}_2, \overline{G}_1 \cdot \underline{G}_2, \overline{G}_1 \cdot \overline{G}_2), \max(\underline{G}_1 \cdot \underline{G}_2, \underline{G}_1 \cdot \overline{G}_2, \overline{G}_1 \cdot \underline{G}_2, \overline{G}_1 \cdot \overline{G}_2) \right] \end{aligned} \quad (4.24)$$

$$\begin{aligned} \otimes G_1 \div \otimes G_2 & \in [\underline{G}_1, \overline{G}_1] \times [1/\overline{G}_2, 1/\underline{G}_2] \\ & \in \left[\min(\underline{G}_1 \cdot 1/\overline{G}_2, \underline{G}_1 \cdot 1/\underline{G}_2, \overline{G}_1 \cdot 1/\overline{G}_2, \overline{G}_1 \cdot 1/\underline{G}_2), \right. \\ & \quad \left. \max(\underline{G}_1 \cdot 1/\overline{G}_2, \underline{G}_1 \cdot 1/\underline{G}_2, \overline{G}_1 \cdot 1/\overline{G}_2, \overline{G}_1 \cdot 1/\underline{G}_2) \right] \end{aligned} \quad (4.25)$$

$$\lambda \cdot \otimes G_1 \in [\lambda \cdot \underline{G}_1, \lambda \cdot \overline{G}_1] \quad (4.26)$$

Grey matrices, denoted as $A(\otimes)$, are generically represented as in Equation (4.27) (SALMERON, 2010). The grey matrix elements are denoted as $\otimes a_{ij}$ for the i th row and the j th column (SALMERON; PAPAGEORGIOU, 2012). It is worth to note that unidimensional grey matrices are called n-dimensional grey vectors.

$$A(\otimes) = \begin{pmatrix} \otimes a_{11} & \dots & \otimes a_{1n} \\ \dots & \otimes a_{ij} & \dots \\ \otimes a_{n1} & \dots & \otimes a_{nn} \end{pmatrix} \quad (4.27)$$

Therefore, let Equations (4.28) and (4.29) represent respectively a grey matrix and a grey vector. Then, with the previously defined grey operations, the multiplication of the matrix by the vector is defined as in Equation (4.30) (SALMERON, 2010).

$$B(\otimes) = \begin{pmatrix} \otimes b_{11} & \otimes b_{12} \\ \otimes b_{21} & \otimes b_{22} \end{pmatrix} \quad (4.28)$$

$$\otimes \vec{C} = (\otimes C_1 \quad \otimes C_2) \quad (4.29)$$

$$\begin{aligned} \vec{R}(\otimes) &= \vec{C}(\otimes) \cdot B(\otimes) = \\ &= ((\otimes C_1 \cdot \otimes b_{11}) + (\otimes C_2 \cdot \otimes b_{21}) \quad ((\otimes C_1 \cdot \otimes b_{12}) + (\otimes C_2 \cdot \otimes b_{22}))) \end{aligned} \quad (4.30)$$

5. CONCLUSION

The closing chapter of this dissertation is organized as follows. Section 5.1 summarizes, relates and assesses the results and contributions of its three composing papers; section 5.2 brings the research challenges and limitations; finally, section 5.3 discusses and suggests some identified future research opportunities.

5.1 RESULTS AND CONTRIBUTIONS

Successful organizations understand that adopting management practices consistent with their culture improves their performance (ALTAY et al., 2018). In this way previous studies have generally acknowledged organizational culture as guide for organizational strategies (KHAZANCHI; LEWIS; BOYER, 2007; BRAUNSCHEIDEL; SURESH; BOISNIER, 2010; LIU et al. 2010). In addition, many papers discussing supply chain performance make fleeting or inferential references to the significance of culture in achieving increased and sustained performance (LAMMING; CALDWELL; HARRISON, 2004; PRAHINSKI; BENTON, 2004; CADDEN; MARSHALL; CAO, 2013). Dubey et al. (2019) also argue that organizational culture can influence a manager's ability to process information, rationalize, and efficiently conduct judgments in their decision-making processes, which can consequently impact performance. In this direction, Keshavarz Ghorabae et al. (2017) highlighted that human judgment always contains some subjectivity which, according to Congjun, Xinpeng and Jin (2007) are best handled by soft computing techniques for their ability to process uncertainty and extract assertive conclusions. However, no study has been produced so far proposing a multicriteria group decision-making model based on soft computing techniques for analyzing the influence of organizational culture over supply chain performance.

To Velasquez and Hester (2013) a tendency regarding the use of multicriteria decision-making techniques is to combine two or more of them, in order to compensate the drawbacks that the application of one technique individually could present. Therefore, this dissertation presents a decision model to analyze and quantify the causal relationship between organizational culture and supply chain performance based on the combination of fuzzy grey cognitive maps, grey clustering and fuzzy inference systems. The model uses as reference for both culture and performance the Hofstede's (2001) organizational practices and the SCOR® model performance attributes (SCC, 2017).

Hence, the present dissertation expanded knowledge frontiers in the operations management and soft computing fields with the following contributions:

- **Literature review regarding FCMs, FGCMs and GST applications to supply chain management:** with the execution of this review it was possible to conclude, among other points, that although FGCMs are derived from the union of FCMs and GST and both theories have been applied to supply chain management, there is no publication proposing the use of FGCMs in this context, even though this technique has advantages over the previous ones with regard to its applicability and ability to model uncertainty.
- **Mapping the state of the art regarding new developments on the organizational culture and supply chain performance interface:** the review enabled the identification of the main gaps related to the way by which the culture/performance management relation is addressed by the literature. It was possible to conclude, therefore, that there is a need to develop quantitative models capable of dealing with both constructs in a tangible way, but also capable of considering qualitative factors. In addition, no model was found applying Hofstede's (2001) organizational practices to analyze culture along with the SCOR[®] performance attributes (SCC, 2017) to measure supply chain performance.

These two contributions, resulting from papers 1 and 3 respectively, answer the first specific research question and correspond to the accomplishment of the first specific objective. The analysis of soft computing literature provided the possibility of identifying an opportunity of improving existing techniques and approaches, which resulted in the following next two contributions:

- **The combination of the GC and FGCM techniques:** the development of a combined algorithm of both techniques provided the possibility to reduce the required inputs and the level of imprecise data in the computational model, which can enhance speed of execution and results reliability. In this proposition, GC is applied as a mean to obtain the initial state vector from the relationship matrix, composed by experts' judgments.
- **The development of a computational model integrating the GC and FGCM combined algorithm with multiple FISs for supporting group decision-making on causal relations:** the GC-FGCM-FIS computational model provided a new possibility

of efficiently assessing causal relations in complex and uncertain environments. Its central idea is to improve the extraction and processing of relevant information from pairwise evaluations of multiple criteria so as decision-makers better understand each criterion role and importance. This therefore has the potential to lead to more assertive conclusions made by the decision-makers. In addition, the computational model execution takes place with natural human language processing and is also capable of considering hesitation. The FIS makes it possible to handle nonlinear relationships between input and output variables and also to the capacity of modeling human reasoning through fuzzy if-then rules.

These two contributions, resulting from papers 2 and 3 respectively, answer the third and partially the second specific research questions and correspond to the accomplishment of the second specific objective. Therefore, considering the potential of the developed GC-FGCM-FIS approach for assessing causal relationships, it was possible to structure the decision-making model focused on the culture-performance interface in supply chains, which resulted in the following contributions:

- **The proposition of a novel group decision-making model for assessing the causal relation between organizational culture and supply chain performance based on Hofstede's (2001) organizational practices and the SCOR[®] performance attributes (SCC, 2017):** The proposition was able to use the potential of soft computing techniques to model complex systems with the presence of uncertainty and imprecision to analyze the influence of organizational culture over supply chain performance. The GC technique was applied to classify the organizational practices according to their quantified influence on performance. The FGCM then uses this information to rank the SCOR[®] attributes according to their degree of received cultural influence. Finally, the FIS enables the definition of a new indicator to evaluate how culture fosters performance in supply chains. Thus, it was possible to conclude that the model provides the possibility to promote the alignment between organizational culture and supply chain management, internalizing culture as a driver for performance improvement efforts. In addition, it is relevant to note that the development of a matrix relating Hofstede's (2001) organizational practices and the SCOR[®] performance attributes

(SCC, 2017) such as the one in Table 3.10 is innovative in the literature and can be used as reference for related applications regarding the interface between culture and supply chain performance.

- **The conduction of two real pilot applications in companies from different industrial sectors in order to exemplify the model step by step in practice, to compare the obtained results and to foster its use in new cases:** it was possible to conclude that the model is able to provide the identification of crucial elements regarding cultural profile and performance for both organizations. This information is valuable since it aids prioritization, anticipation and enables the development of guidelines for action plans with the final aim to internalize culture as a driver for performance improvement efforts.

These two contributions, resulting from paper 3, answer the second specific research question and correspond to the accomplishment of the third and fourth specific objectives, respectively. In addition, the third paper also analyzes the obtained results from the pilot applications as well as addresses research opportunities and limitations regarding the model proposition, which consists in the accomplishment of the fifth and last specific objective.

With this summarization of the main contributions, it can be noted that the three papers are well integrated due to their clear connection structure, where the results of one paper are inputs or build the basis for the development of the subsequent paper, answering all specific research questions (derived from the general research question) and satisfying all specific objectives (derived from the general research objective). Therefore, another main contribution of this dissertation, now viewing it as the sum of its three composing papers, is the consolidation of a connection between the literature from the supply chain performance management and organizational culture with the literature from the soft computing field, since, as mentioned as a result from the conducted reviews, no study was found applying these computational tools in this context. In addition, it is important to mention the positive feedback received from the managers of both companies where the model was applied regarding the model itself and the research theme, which integrates in innovative manner supply chain performance and organizational culture in a single perspective.

Finally, it is relevant to note that there is currently a global trend regarding the application of soft computing techniques when dealing with qualitative variables and intangible

factors. However, there is still limited research in Brazil exploring the use of such techniques in operations management, especially considering such an important construct as organizational culture. Therefore, it is also expected that this dissertation can be of value for the academic community interested in related applications and that it and its related papers (GANGA; CARPINETTI; 2011; LIMA-JUNIOR; CARPINETTI; 2016; ZANON; CARPINETTI, 2018; LISBOA; ZANON; CARPINETTI, 2019; LIMA-JUNIOR; CARPINETTI; 2019; LIMA-JUNIOR; CARPINETTI; 2020; ZANON et al., 2020) can contribute to foster new developments considering soft computing to handle the cultural role in operations management.

5.2 RESEARCH CHALLENGES AND LIMITATIONS

In addition to the already mentioned topics in each of the three papers that compose this dissertation, the main challenges related to the execution of this research were:

- **To find interested companies:** the process of finding interested organizations for the model application was cumbersome, since most companies do not show interest in contacts from the academy or, if interested, are confronted with obstacles such as bureaucracy and information privacy restrictions. This challenge was surpassed with the development of a website (<https://sites.google.com/view/cultureandperformance>) containing the research description and an illustrative application for making it feasible to managers to understand the potential impacts and contributions of this dissertation proposition.
- **To collect data from the companies of the pilot applications:** the process of data collection was also challenging since it required the judgement of multiple decision-makers regarding multiple criteria, as well as considering constructs from different areas (organizational culture and supply chain performance). For example, the experts from the companies were asked to answer the Cadden et al. (2015) questionnaire and to linguistically assess the performance of the SCOR[®] attributes. Therefore, to overcome this challenge, the data collection procedure was embedded into the developed website, which is mobile phone friendly. This improved the acceptance by the experts due to the flexibility of answering quickly and independently of emails, personal visits or without breaking operational routine.

In addition to the already mentioned aspects in each of the three papers that compose this dissertation, the main general limitations related to the execution of this research were:

- **Lack of deepness in the conducted pilot applications:** the data collection procedure did not contemplate presential visits to the facilities from both companies. Therefore, it was not possible to obtain and confront personal observations from the researcher with the obtained judgements by the developed website.
- **The exploratory character of the research:** since no similar research was found combining soft computing techniques, supply chain performance and organizational culture, which are constructs generally dissociated in the literature, in a single multicriteria group decision-making model, the study acquires an exploratory character. Therefore, this dissertation main interests are to provide new perspectives for the literature as well as to foster the execution of similar studies in order to expand the knowledge regarding this multidisciplinary research theme. In this direction, the next section presents some identified future research opportunities.

5.3 FUTURE RESEARCH OPPORTUNITIES

In addition to the future research opportunities identified and presented in the conclusion section of each of the three papers that compose this dissertation, other suggestions for future studies that can contribute to expanding the literature regarding supply chain performance, organizational culture and soft computing are:

- To apply the decision model cyclically, in an extensive case study, to monitor performance evolution over its use and therefore measure its long-term effectiveness.
- To apply the decision model for assessing the relations between organizational subcultures and firm performance, which would provide the novel possibility for assessing culture and performance at an intra-company and micro level.
- To integrate change management concepts to the model's outputs, in order to minimize resistance to change when implementing the action plans.
- To capture performance data in the company's management systems and not from expert's judgments, in order to reduce the uncertainty inserted in the decision model.
- To integrate to the decision model a big data approach for assessing supply chain performance with the SCOR[®] model attributes and indicators, considering the growing interest to connect supply chain management with big data analytics (CHEHBI-GAMOURA et al., 2020).

- To apply the proposed model to compare the role and influence of organizational culture in supply chains of different types, such as medical and humanitarian, and adept of distinct strategies, such as agile and lean.
- To adapt the proposed model to analyze and quantify the relationship between circular economy principles (British Standards Institution, 2017) and supply chain performance, focusing on leveraging the shift to the circular supply chain paradigm.

5.4 REFERENCES

ALTAY, N. et al. Agility and resilience as antecedents of supply chain performance under moderating effects of organizational culture within the humanitarian setting: a dynamic capability view. **Production Planning & Control**, v. 29, n. 14, p. 1158-1174, 2018.

BRAUNSCHEIDEL, M. J.; SURESH, N. C.; BOISNIER, A. D. Investigating the impact of organizational culture on supply chain integration. **Human Resource Management**, v. 49, n. 5, p. 883-911, 2010.

BRITISH STANDARDS INSTITUTION. Framework for implementing the principles of the circular economy in organizations - guide, **BSI standards publication BS.**, Frankfurt am Main, 2017.

CADDEN, T. et al. Old habits die hard: exploring the effect of supply chain dependency and culture on performance outcomes and relationship satisfaction. **Production Planning & Control**, v. 26, n. 1, p. 53-77, 2015.

CADDEN, T.; MARSHALL, D.; CAO, G. Opposites attract: organisational culture and supply chain performance. **Supply Chain Management: an international journal**, v. 18, n. 1, p. 86-103, 2013.

CHEHBI-GAMOURA, S. et al. Insights from big Data Analytics in supply chain management: an all-inclusive literature review using the SCOR model. **Production Planning & Control**, v. 31, n. 5, p. 355-382, 2020.

CONGJUN, R.; XINPING, X.; JIN, P. Novel combinatorial algorithm for the problems of fuzzy grey multi-attribute group decision-making. **Journal of Systems Engineering and Electronics**, v. 18, n. 4, p. 774-780, 2007.

DUBEY, R. et al. Big data analytics and organizational culture as complements to swift trust and collaborative performance in the humanitarian supply chain. **International Journal of Production Economics**, v. 210, p. 120-136, 2019.

GANGA, G.M.D., CARPINETTI, L.C.R. A *fuzzy* logic approach to supply chain performance management. **International journal of production economics**. v.134, p.177–187, 2011.

HOFSTEDE, G. **Culture's consequences: comparing values, behaviors, institutions, and organizations across nations**. 2nd ed. Thousand Oaks, CA: Sage Publications, 2001.

KESHAVARZ GHORABAE, M. et al. Supplier evaluation and selection in fuzzy environments: a review of MADM approaches. **Economic research-Ekonomska istraživanja**, v. 30, n. 1, p. 1073-1118, 2017.

KHAZANCHI, Shalini; LEWIS, Marianne W.; BOYER, Kenneth K. Innovation-supportive culture: The impact of organizational values on process innovation. **Journal of operations management**, v. 25, n. 4, p. 871-884, 2007.

LAMMING, R.; CALDWELL, N.; HARRISON, D. Developing the concept of transparency for use in supply relationships. **British Journal of Management**, v. 15, n. 4, p. 291-302, 2004.

LIMA-JUNIOR, F. R.; CARPINETTI, L. C. R. Combining SCOR[®] model and fuzzy TOPSIS for supplier evaluation and management. **International Journal of Production Economics**, v. 174, p. 128-141, 2016.

LIMA-JUNIOR, F. R.; CARPINETTI, L. C. R. Predicting supply chain performance based on SCOR[®] metrics and multilayer perceptron neural networks. **International Journal of Production Economics**, v. 212, p. 19-38, 2019.

LIMA-JUNIOR, F. R.; CARPINETTI, L. C. R. An adaptive network-based fuzzy inference system to supply chain performance evaluation based on SCOR[®] metrics. **Computers & Industrial Engineering**, v. 139, p. 106191, 2020.

LISBOA, V. S.; ZANON, L. G.; CARPINETTI, L. C. R. Relações entre cultura organizacional e o desempenho de uma startup de tecnologia: uma análise baseada em fuzzy cognitive maps. In: **SIMPÓSIO DE ENGENHARIA DE PRODUÇÃO - SIMPEP**, 2019, Bauru. Anais... Bauru, UNESP, 2019.

LIU, Hefu et al. The role of institutional pressures and organizational culture in the firm's intention to adopt internet-enabled supply chain management systems. **Journal of Operations Management**, v. 28, n. 5, p. 372-384, 2010.

PRAHINSKI, C.; BENTON, W. C. Supplier evaluations: communication strategies to improve supplier performance. **Journal of operations management**, v. 22, n. 1, p. 39-62, 2004.

SCC, Supply Chain Council. **Supply Chain Operations Reference Model**, version 12.0. Supply Chain Council, 2017.

VELASQUEZ, M.; HESTER, P. T. An analysis of multi-criteria decision-making methods. **International journal of operations research**, v. 10, n. 2, p. 56-66, 2013.

ZANON, L. G. et al. A decision-making model based on fuzzy inference to predict the impact of SCOR[®] indicators on customer perceived value. **International Journal of Production Economics**, p. 107520, 2020.

ZANON, L. G.; CARPINETTI, L. C. R. Fuzzy cognitive maps and grey systems theory in the supply chain management context: A literature review and a research proposal. In: **2018 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)**. IEEE, 2018. p. 1-8.