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Exploring the relations between supply chain performance and organizational culture: A fuzzy grey group decision model

Lucas Gabriel Zanon [a], Francesco Marcelloni [b], Mateus Cecílio Gerolamo [a], Luiz Cesar Ribeiro Carpinetti [a,*]

[a] Production Engineering Department, São Carlos School of Engineering, University of São Paulo, Av. Trabalhador São-Carlense, 400, São Carlos, São Paulo, 13566-590, Brazil

[b] Department of Information Engineering – University of Pisa, Largo Lucio Lazzarino 1, 56122, Pisa, Italy

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A B S T R A C T

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, following the quantitative axiomatic prescriptive model-based research. 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 cultural profile and performance for both organizations, aiding prioritization, anticipation and enabling the development of guidelines for action plans.

1. Introduction

Supply Chain Management is a key strategic factor for better achieving organizational goals such as competitiveness, customer service and increased profitability (Gunasekaran et al., 2001). It is considered essential for supplier and customer integration with the aim of improving operational effectiveness (Fawcett et al., 2008). 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 et al., 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 (Winklhofer et al., 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 & Cao (2013) also highlight the significant influence of organizational culture on operational performance.

* Corresponding author. Av. Trabalhador São-Carlense, 400, 13566-590, São Carlos, São Paulo, Brazil.
E-mail addresses: lucasgab.zanon@gmail.com (L.G. Zanon), francesco.marcelloni@unipi.it (F. Marcelloni), gerolamo@sc.usp.br (M.C. Gerolamo), carpinet@sc.usp.br (L.C. Ribeiro Carpinetti).

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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 & 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 and 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 et al., 2019).

In this direction, Keshavarz Ghorabaee et al. (2017) highlighted that human judgment always contains some uncertainty and ambiguity. According to Congjun et al. (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 et al., 2007; Cadden et al., 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 modeling 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 and 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 and 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 and Lam, 2015; Ghadimi et al., 2018; Kaushal and 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 and Shahin, 2018b), and also to the capacity of modeling human reasoning through fuzzy if-then rules (Khan et al., 2018). Here, as in Chen et al. (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 and 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 and 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 2 presents a literature review addressing organizational culture, supply chain performance and the aforementioned soft computing techniques. Section 3 details the proposed decision-making model. Section 4 illustrates the use of the model by describing its application to the two real cases. Section 5 addresses discussions on the results obtained in both companies. Finally, Section 6 draws some conclusions and gives suggestions for further research.

2. Literature review

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 et al., 2004; Neely et al., 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 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 et al., 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 and 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 and 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 and Carpinetti, 2016; SCC, 2017). The five SCOR® Performance Attributes are described in Table 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).

The SCOR® is widely used by the industry community as well as in the academic field (Akkawuttiwanich and 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 & 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.

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 2 presents some formalizations of the concept.

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.

Table 1
The SCOR® performance attributes (SCC, 2017).

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.

Table 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.
Smircich (2017)	Organizations do not have cultures, they are cultures; culture is a kind of social glue that connects the organization within itself.
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.
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.
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.

To analyze how culture manifests itself in organizations, models are developed in order to materialize its main aspects and make it manageable (Bortolotti et al., 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 et al., 2013). This tool is widely used in inter organizational research (Cadden et al., 2015; Cadden et al., 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 3 presents the definitions for each OP.

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.

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 et al., 2010; Sambasivan and Yen, 2010).

Thus, a misaligned view on organizational culture and supply chain

Table 3
Organizational practices scale and definition (Cadden et al., 2015).

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.

management can negatively affect the chain performance (Whitfield and Landeros, 2006). According to Cadden et al. (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 summarizes the results.

The results presented in Table 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 et al., 2010; Cao et al., 2015; Yunus and 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 et al., 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 & Boisnier (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.

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 and Carpinetti, 2017; Salmeron and 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 and 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 and 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 and Zadeh, 1970; Zimmermann, 2010).

A triangular fuzzy set, described by the membership function in equation (1), is a fuzzy set that meets the properties of normality and convexity (Zadeh, 1965).

$$\mu_{\tilde{A}}(x_i) = \begin{cases} 0 & for\ x_i < a, \\ \dfrac{x_i - a}{m - a} & for\ a \le x_i \le m, \\ \dfrac{b - x_i}{b - m} & for\ m \le x_i \le b, \\ 0 & for\ x_i > b. \end{cases} \tag{1}$$

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

Table 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
Jermsittiparsert & 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 & 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
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 & 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 & 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 & Boisnier	Human Resource Management	2010	To investigate the impact of organizational culture on supply chain integration.	CVF	Qualitative and quantitative
Cadden, Humphreys & McHugh	Journal of General Management	2010	To investigate the impact of organizational culture in forming strategic alliances in supply chains.	Hofstede	Qualitative
Sambasivan & 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 & 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 & 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

completely unknown it is called a black system (Salmeron and 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 $\otimes G \in \left[\underline{G}, \overline{G}\right], \underline{G} \leq \overline{G}$. If the grey number $\otimes G$ has only a lower limit, it is denoted as $\otimes G \in \left[\underline{G}, +\infty\right)$ 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, $\otimes G \in \left[\underline{G}, \overline{G}\right], \underline{G} = \overline{G}$ (Salmeron, 2010). The length of a grey number can be calculated as $l(\otimes G) = |\overline{G} - G|$: 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 and Papageorgiou, 2012). Appendix B details the mathematical operations regarding grey numbers and grey matrices, which are required to the understanding of FGCMs.

2.4.1. *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 and 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 (2), where i is the pre-synaptic node and j the post-synaptic one (Salmeron and Papageorgiou, 2012).

$$\otimes w_{i\rightarrow j} \in \left[\underline{w_{i\rightarrow j}}, \overline{w_{i\rightarrow j}}\right] \Big| \forall i, j \rightarrow \underline{w_{i\rightarrow j}} \leq \overline{w_{i\rightarrow j}}, \left\{\underline{w_{i\rightarrow j}}, \overline{w_{i\rightarrow j}}\right\} \in [-1, +1] \quad (2)$$

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 ($\otimes \overrightarrow{C_0}$) is obtained as in equation (3).

$$\otimes \overrightarrow{C_0} = \left(\otimes \overrightarrow{C_0}^{[1]} \ \otimes \overrightarrow{C_0}^{[2]} \ \ldots \ \otimes \overrightarrow{C_0}^{[n]}\right) = \left(\left[\underline{\otimes \overrightarrow{C_0}}^{[1]}, \overline{\otimes \overrightarrow{C_0}}^{[1]}\right]\left[\underline{\otimes \overrightarrow{C_0}}^{[2]}, \overline{\otimes \overrightarrow{C_0}}^{[2]}\right] \ldots \left[\underline{\otimes \overrightarrow{C_0}}^{[n]}, \overline{\otimes \overrightarrow{C_0}}^{[n]}\right]\right) \tag{3}$$

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), where $\otimes G_{ij}^{k}$ corresponds to the judgement of the kth decision maker regarding the impact of criterion i over criterion j (Memon et al., 2015).

$$\otimes G_{ij} = \sqrt[k]{\otimes G_{ij}^{1} \mathrm{x} \otimes G_{ij}^{2} \mathrm{x} \ldots \mathrm{x} \otimes G_{ij}^{n}}, \tag{4}$$

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 (5) shows how the system activation occurs.

$$\begin{aligned}\otimes \overrightarrow{C_{(t+1)}} &= S\left[\otimes \overrightarrow{C_t} \cdot A(\otimes)\right] = S\left[\otimes \overrightarrow{C'_t}\right] = S\left[\left(\otimes C'^{[1]}_{t} \ \otimes C'^{[2]}_{t} \ \ldots \ \otimes C'^{[n]}_{t}\right)\right] \\ &= \left(S\left(\otimes C'^{[1]}_{t}\right) S\left(\otimes C'^{[2]}_{t}\right) \ldots S\left(\otimes C'^{[n]}_{t}\right)\right) \\ &= \left(\otimes C_{(t+1)}{}^{[1]} \ \otimes C_{(t+1)}{}^{[2]} \ \ldots \ \otimes C_{(t+1)}{}^{[n]}\right)\end{aligned} \tag{5}$$

where $\otimes \overrightarrow{C_t}$ 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 and Papageorgiou, 2012). The component *i* of the vector state $\otimes C_{(t+1)}^{[i]}$ is expressed as in equation (6), where λ is a constant value that determines the slope degree of the sigmoid functions.

$$\otimes C_{(t+1)}{}^{[i]} \in \left[\left(1 + e^{-\lambda \cdot \underline{C'_t}^{[i]}}\right)^{-1}, \left(1 + e^{-\lambda \cdot \overline{C'_t}^{[i]}}\right)^{-1}\right] \tag{6}$$

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 (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 (8).

$$\phi(\otimes C_i) = |l(\otimes C_i)| \,/\, l(\otimes \psi) \tag{7}$$

$$l(\otimes \psi) = \begin{cases} 1 & if \quad \{\otimes C_i, \otimes w_i\} \subseteq [0, 1] \quad \forall \otimes C_i, \otimes w_i \\ 2 & if \quad \{\otimes C_i, \otimes w_i\} \subseteq [-1, +1] \quad \forall \otimes C_i, \otimes w_i \end{cases} \tag{8}$$

Finally, whitenization is performed according to equation (9). Whitenization is the process of converting a grey number into a white one (Salmeron and Papageorgiou, 2012). If α = 0.5, the process is called equal weight mean whitenization (Liu and Lin, 2006).

$$\hat{\otimes} G = \alpha \underline{G} + (1 - \alpha) \overline{G} \Big| \alpha \in [0, 1] \tag{9}$$

2.4.2. 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 and 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 (10)–(12) (Rajesh, 2016).

$$\underline{\otimes} \tilde{a}_{ij} = \left(\underline{\otimes} \dot{a}_{ij} - {}^{min}_{j} \underline{\otimes} \dot{a}_{ij}\right) \Big/ \Delta^{max}_{min} \tag{10}$$

$$\overline{\otimes} \tilde{a}_{ij} = \left(\overline{\otimes} \dot{a}_{ij} - {}^{min}_{j} \overline{\otimes} \dot{a}_{ij}\right) \Big/ \Delta^{max}_{min} \tag{11}$$

$$\Delta^{max}_{min} = {}^{max}_{j} \overline{\otimes} \dot{a}_{ij} - {}^{min}_{j} \underline{\otimes} \dot{a}_{ij} \tag{12}$$

According to Rajesh (2016), 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 (13) and (14).

$$b_{ij} = \left(\frac{\underline{\otimes} \tilde{a}_{ij}\left(1 - \underline{\otimes} \tilde{a}_{ij}\right) + \left(\overline{\otimes} \tilde{a}_{ij} \ \mathrm{x} \ \overline{\otimes} \tilde{a}_{ij}\right)}{\left(1 - \underline{\otimes} \tilde{a}_{ij} + \overline{\otimes} \tilde{a}_{ij}\right)}\right) \tag{13}$$

$$b^{*}_{ij} = \left(min \underline{\otimes} \dot{a}_{ij} + \left(b_{ij} \Delta^{max}_{min}\right)\right) \tag{14}$$

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 ($\lambda_1, \lambda_2, \ldots, \lambda_s$) of classes 1, 2, …, s are also determined (Delgado and 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 kth grey class, regarding the impact of criterion i on criterion j, denoted as x_{ij}, is defined by equation (15), where $f_j^k(x_{ij})$ corresponds to the CTWF of the kth grey class for the jth criterion.

$$f_j^k(x_{ij}) = \begin{cases} 0, & x \notin [\lambda_{k-1}, \lambda_{k+1}] \\ \dfrac{x-\lambda_{k-1}}{\lambda_k-\lambda_{k-1}}, & x \in [\lambda_{k-1}, \lambda_k] \\ \dfrac{\lambda_{k+1}-x}{\lambda_{k+1}-\lambda_k} & x \in [\lambda_k, \lambda_{k+1}] \end{cases} \tag{15}$$

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 $\sigma_i^{k*} = max_{i \le k \le s}\{\sigma_i^k\}$, 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 $\alpha(\otimes) = [\otimes \dot{a}_{ij}]$ 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 (16).

$$\alpha(\otimes) = A(\otimes) = \begin{array}{c} \\ \textit{Criterion } 1 \\ \textit{Criterion } 2 \\ \cdots \\ \textit{Criterion } n \end{array} \begin{array}{c} \begin{array}{cccc} \textit{Criterion } 1 & \textit{Criterion } 2 & \cdots & \textit{Criterion } n \end{array} \\ \begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nn} \end{pmatrix} \end{array} \tag{16}$$

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 (17).

$$\begin{array}{ccc} \textit{Impact on the system} & & \textit{Grey number associated with each grey class} \end{array} \quad \otimes\overrightarrow{C_0} = \begin{array}{c} \textit{Criterion } 1 \\ \textit{Criterion } 2 \\ \vdots \\ \textit{Criterion } n \end{array} \begin{bmatrix} \textit{Grey class}_{Criterion\ 1} \\ \textit{Grey class}_{Criterion\ 2} \\ \vdots \\ \textit{Grey class}_{Criterion\ n} \end{bmatrix} = \begin{bmatrix} \underline{\otimes \overrightarrow{C_0}}^{[1]}, \overline{\otimes \overrightarrow{C_0}}^{[1]} \\ \underline{\otimes \overrightarrow{C_0}}^{[2]}, \overline{\otimes \overrightarrow{C_0}}^{[2]} \\ \vdots \\ \underline{\otimes \overrightarrow{C_0}}^{[n]}, \overline{\otimes \overrightarrow{C_0}}^{[n]} \end{bmatrix} \tag{17}$$

Having $\alpha(\otimes) = A(\otimes)$ and applying GC to obtain $\otimes \overrightarrow{C_0}$, 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.

2.4.3. 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 et al., 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 and 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 et al., 2017), which is finally defuzzified.

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

$$R^j = \text{IF-}X_1 \text{ is } \widetilde{A}_{1,2} \text{ AND } X_2 \text{ is } \widetilde{A}_{2,3} \text{ AND } \ldots \text{AND } X_F \text{ is } \widetilde{A}_{F,2} \text{ THEN } Y \text{ is } \widetilde{C_3}$$

where $\widetilde{A}_{f,i}$ and $\widetilde{C}_j$ 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 and Gomide, 2007). Generally, minimum is used as t-norm and applied as in equation (18) for each activated rule (Pourjavad and Shahin, 2018a). A rule is activated if each element of the input vector $\hat{x} = [\hat{x}_1, \ldots, \hat{x}_F]$ belongs to each corresponding fuzzy set in the antecedent of rule R^j with a membership degree different from 0.

$$\mu_{Ant}^j = Min\left(\mu_{\widetilde{A}_{1,2}}\left(\hat{x}_1\right), \mu_{\widetilde{A}_{2,3}}\left(\hat{x}_2\right), \ldots, \mu_{\widetilde{A}_{F,2}}\left(\hat{x}_F\right)\right) \tag{18}$$

For each activated decision rule, the fuzzy inference engine executes the implication operator between the antecedent and the consequent $\widetilde{C}$ of the rule (Pourjavad and Shahin, 2018a). The minimum (Mamdani) implication operator expressed as in equation (19) is commonly used:

$$\mu^j(y) = Min\left(\mu_{Ant}^j, \mu_{\widetilde{C}_3}(y)\right) \tag{19}$$

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 (20) is used when compensation between input variables is preferred, where Q is the number of the activated rules (Von Altrock, 1996).

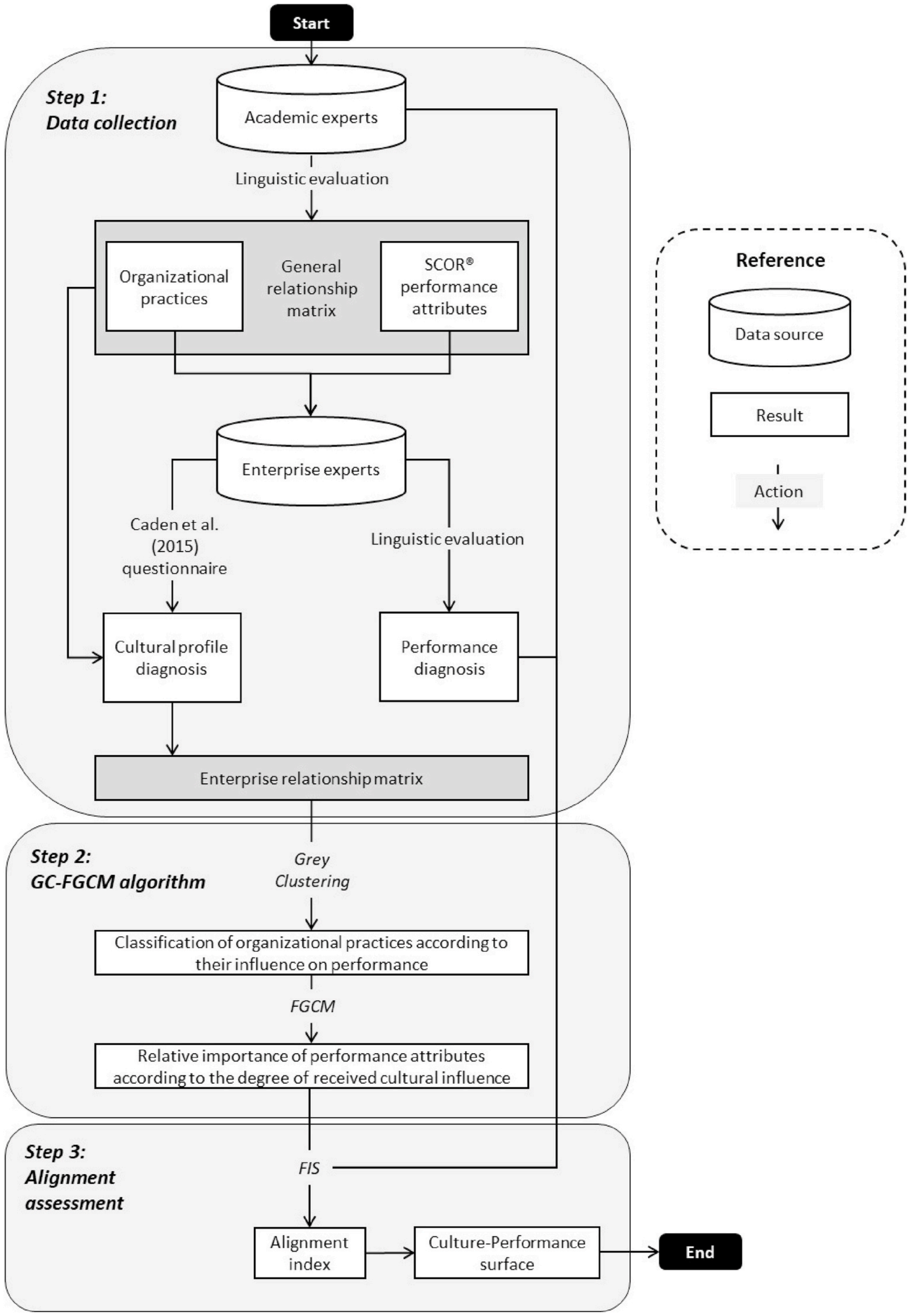

Fig. 1. The proposed decision-making model for analyzing the relations between supply chain performance and organizational culture.

$$AG(y) = Max\left(\mu^1(y), \mu^2(y), \ldots, \mu^Q\right) \tag{20}$$

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 (21), where $\bar{y}$ is the output generated by the FIS.

$$CoA = \bar{y} = \frac{\int y \cdot AG(y)dy}{\int AG(y)dy} \tag{21}$$

3. The decision-making model

Fig. 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.

Table 5
Data collection procedure.

Required inputs for the model	Data source	Data collection approach	Role in the model	Justification for the chosen approach
General relationship matrix	Judgments from Academic experts	Computing with words	To store all the possible interactions between OPs and the SCOR® performance attributes	Keshavarz Ghorabaee et al. (2017) highlighted that the human judgment always contains some uncertainty and ambiguity. According to Zadeh (1996), computing with words (CW) is needful when the accessible information is not sufficiently precise to justify the use of numbers. CW involves a fusion of natural language and computation with fuzzy or grey variables. Therefore, the application of CW is justified due to the fact that it is one of the most efficient tools to process the uncertainty of evaluation processes (Keshavarz Ghorabaee et al., 2017).
The performance of the company in the SCOR® attributes	Judgments from Managers of the company	Computing with words	To compose the alignment index	
The cultural profile diagnosis	Judgments from Managers of the company	Cadden et al. (2015) questionnaire	To generate the ERM from the GRM	The questionnaire is a validated cultural measurement tool, suitable for research in production-related and supply chain organizations (Cadden et al., 2015).

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 is associated with the three required inputs for the model and summarized in Table 5. The first required input consists in evaluating the relations between the OPs and the SCOR performance attributes. This paper proposes that academic experts, with an in-depth knowledge of supply chain management and organizational culture, provide this data using linguistic terms computed as grey numbers, accordingly to the computing with words procedure. The second input consists in assessing the company's performance in the SCOR attributes. Performance assessment is based on the managers' evaluation of the companies' performance on each of the SCOR attributes, expressed linguistically (Martinez et al., 2010), and not on quantitative measures of the SCOR model's metrics, which may not be always available and may also contain imprecisions. Hence, the fuzzy-grey techniques allow for fast and flexible data collection through linguistic terms based on the computing with words approach proposed by Zadeh (1999). Also, this approach grants the model adaptability to a wide range of organizations and supply chains with diverse characteristics.

Managers from each company are asked to make this assessment also using linguistic terms and grey numbers. They are leaders with a deep inside knowledge and competence to conduct judgements regarding the organizational reality. They therefore are able to qualitative assess supply chain performance through the aforementioned computing with words approach. These managers have direct access to performance data, which guarantees the validity, reliability and adaptability of the model even when KPI's measures are not available.

The final input regards the cultural profile diagnosis, so as to identify the dominant organizational practices. Specifically developed for this

Table 6
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

Table 7
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

Table 8
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

Table 9
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

Table 10
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

Table 11
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

purpose, the Cadden et al. (2015) questionnaire was adopted, since it consists in a validated data collection instrument. Hence, managers from the companies under analysis are required to answer the questionnaire, which is presented in full in Appendix A.

Computing with words is needful when the available information is not precise enough to allow the use of numbers. The relationship between organizational culture and supply chain performance is not a quantitative concept and therefore subjectivity and uncertainty are present. Hence, to deal with that, academic experts and managers make their assessments regarding culture and performance with the use of natural language, making it possible to surpass the challenges brought by imprecision. The linguistic terms used by the experts and managers are afterwards associated and converted to grey numbers, which are processed by the soft computing techniques.

As mentioned, the data collection procedure starts from consulting the academic experts (AEs). They were asked to judge how the OPs could impact supply chain performance in each of the SCOR® attributes. The linguistic terms presented in Table 6 were used for this assessment. The terms in Table 6 are associated with grey numbers since this information will be processed afterwards by the soft computing techniques. Tables 7–10 present the results of the assessment performed by the four AEs.

The results presented in Tables 7–10 were then aggregated using equation (4), leading to a general relationship matrix (GRM), shown in Table 11. This matrix contains all the possible interactions between OPs and the SCOR® performance attributes and can be used as a trial 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 11.

Therefore, as shown in Fig. 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

Table 12
Operational measures and definitions for the SCOR® attributes (SCC, 2017).

Attribute	Operational measure	Operational definition	Unit
Agility	Upside SC flexibility	The number of days required to achieve an unplanned sustainable 20% increase in quantities delivered.	Days
	Downside SC adaptability	The reduction in quantities ordered sustainable at 30 days prior to delivery with no inventory or cost penalties.	Percentage
	Overall value at risk	The sum of the probabilities of risk events times the monetary impact of the events in any supply chain core functions.	Monetary
	Upside SC adaptability	The maximum sustainable percentage increase in quantity delivered than can be achieved in 30 days.	Percentage
Reliability	Perfect order fulfilment	The percentage of orders meeting delivery performance with complete and accurate documentation and no delivery damage.	Percentage
Responsiveness	Order fulfilment cycle time	The average actual cycle time consistently achieved to fulfill customers' orders.	Days
Costs	Total cost to serve	The sum of the direct and indirect costs to deliver products and services to customers: planning cost, sourcing cost, material landed cost, production cost, order management cost, fulfilment cost, and returns cost.	Monetary
Asset Management	Return on working capital	The rate between the profit (which refers to the difference between supply chain revenue and total cost to serve) and the sum of working capital (inventory + accounts receivable - accounts payable).	Percentage
	Inventory days of supply	The amount of inventory (stock) expressed in days of sales.	Days

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 6. This performance diagnosis will serve as input for the FIS in Step 3.

Table 12 brings operational measures and operational definitions for the SCOR® attributes based on the hierarchical structure of the SCOR® metrics (Lima-Junior; Carpinetti, 2019; SCC, 2017). It aims to make it easier for companies to apply the proposed model, especially regarding data collection for the performance diagnosis. Thus, the operational definitions in Table 12 can be used as a reference for the companies to better relate the suitable linguistic term in correspondence with the performance level of each SCOR® attribute.

In that regard, combining the linguistic terms with the operational definitions is context dependent; that is, the operational definition to be used and the level of performance considered "very high" and so on varies from company to company. Therefore, a suggestion could be to compare the current performance on the operational measure related to a particular attribute with the goal set by the company to be achieved for that measure. Based on that, the linguistic terms have now a reference to better reflect performance. For instance, the linguistic term "very high" can correspond to a performance level which is over the goal. And the other terms are also defined accordingly. To exemplify, for diagnosing a company's performance on Reliability according to Table 12, let's suppose that the perfect order fulfilment operational measure is of 60% and the target figure for the measure corresponds to 90%. This would indicate that the company has a "medium" performance on Reliability.

The process of linguistically evaluating the performance of criteria followed in the present study is common in the literature that applies soft computing models to supply chain performance assessment (Lima Junior; Carpinetti, 2017) and refers to linguistic decision making (Martinez et al., 2010). Moreover, this process of linguistically assessing performance follows a logical structure likewise a questionnaire, in the sense that the respondent must assess performance on each attribute with the suggested linguistic terms.

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 6, 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 explained in section 2.4.2 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 Fig. 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 to 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 and 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 13. Fig. 2 shows the membership functions.

Table 13
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)

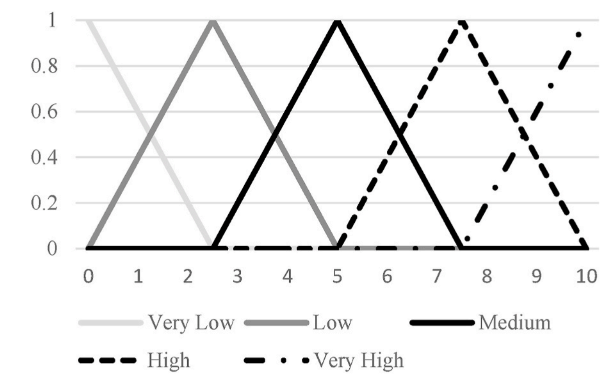

Fig. 2. Fuzzy partition of the linguistic terms in Table 13.

Table 14
Rule base for the Alignment Index determination.

Rule	*If*			*Then*
	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

The rule base consists of 25 if-then rules and is presented in Table 14. 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 inference process described in Section 2.4.3 is applied to determine the AI value.

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 the software MATLAB®, where an application was developed integrating all the soft computing techniques and producing therefore a friendly interface for executing the group decision making model in practice. Two real case applications are presented in the next section, for exemplifying how this was conducted. In these cases, the collected data was inputted in the MATLAB® application, which processed this data and returned the final results presented in Section 4.

4. Real application cases

The pilot applications were conducted in two companies of different industrial sectors, with the aim of analyzing 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 Fig. 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 in the companies, a website with an embedded formulary was developed for enabling managers to input data easily and store 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. In the performance diagnosis section, managers are asked to assess the performance of the company in the SCOR attributes with linguistic terms. For example, they should tell if the company's performance in agility is very low, low, medium, high or very high. In the cultural profile diagnosis section, managers answer the questions from the Cadden et al. (2015) questionnaire, presented in Appendix A. The period covered by the data collection is the same for both companies and corresponds to their current performance (month-to-date on September 2019).

Ten managers from the supply management team of Company A and six from Company B provided all the required data. For Company A, one of the managers was responsible for the entire supply chain operation, answering to the board of directors. For Company B, the six managers were in charge of running the company's operations in one of its biggest sites in terms of sales volume worldwide. They said they already have had contact with the conceptualization of organizational culture as an important factor for business performance.

The sample size is justified by considering that this study works upon the opinion of the leaders and for the connection between leadership and culture (Groysberg et al., 2018). In fact, leaders can easily sense and influence organizational behavior due to their high hierarchical position, company time and firm knowledge, which guarantee them the power of transmitting values and behavioral patterns. Ensley, Hmieleski and Pearce (2006) argue that the individual characteristics and behavior of leaders can become imprinted into the organizational culture of firms, which is then institutionalized and difficult to later modify. Chatterji et al. (2019) state that organizational culture is closely linked to leadership and has a profound impact on the behavior of individuals. Hence, it is more effective for understanding culture to interview a small set of managers than a hundred younger employees (Groysberg et al., 2018). In addition, the fuzzy grey techniques, which are the basis of the proposed decision making model, were specifically developed for handling small and incomplete datasets, as well as for handling uncertainty, and were chosen for being applied in this study due to their potential of providing reliable results by processing the data collected from the managers (Salmeron, 2010).

The considered sample size is also justifiable since the study is exploratory by nature. No similar study was found in the literature bringing such an analysis over supply chain performance and organizational culture. In addition, it should be noted that this paper presents pilot applications, instead of case studies. In this regard, pilot applications by nature do not require extensive samples, since their objective is to be informative and, more importantly, to guide future and more profound applications. Nevertheless, the considered sample size corresponds to the whole supply chain managerial team for both focus companies.

Therefore, the managers from both companies linguistically assessed the current performance on each SCOR® attribute according to the linguistic terms defined in Table 6. The evaluations were aggregated using equation (4) and converted into a scale from zero to 10. Figs. 3(b) and 4(b) bring the performance diagnosis at the end of this section. It can be noted that Company B performs better on agility, responsiveness, costs and asset management. Company A is currently performing better on reliability, responsiveness, agility, costs and asset management.

Then, by answering the Cadden et al. (2015) OPs questionnaire, detailed in section 2.2 and 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 is result-oriented, but also employee-focused, open, managerially tight, normative and market concerned in a lower intensity. Figs. 3(a) and 4(a) show these diagnoses for both Company A and Company B respectively.

With the cultural profile diagnosis, the ERM can be obtained from the GRM, as detailed in Section 3. Tables 15 and 16 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.

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 (10)–(12) (presented in Table 17) and

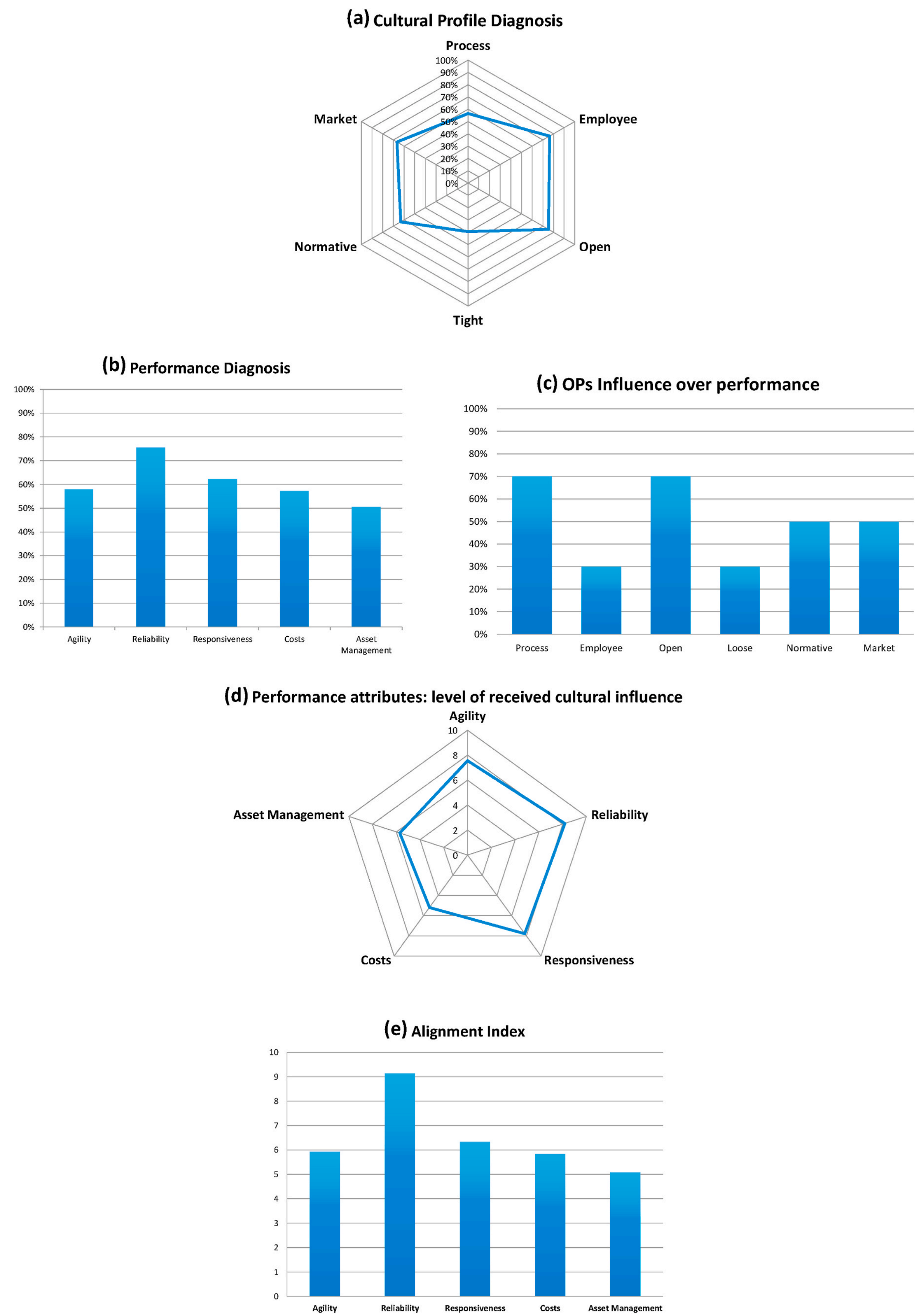

Fig. 3. Results dashboard for Company A.

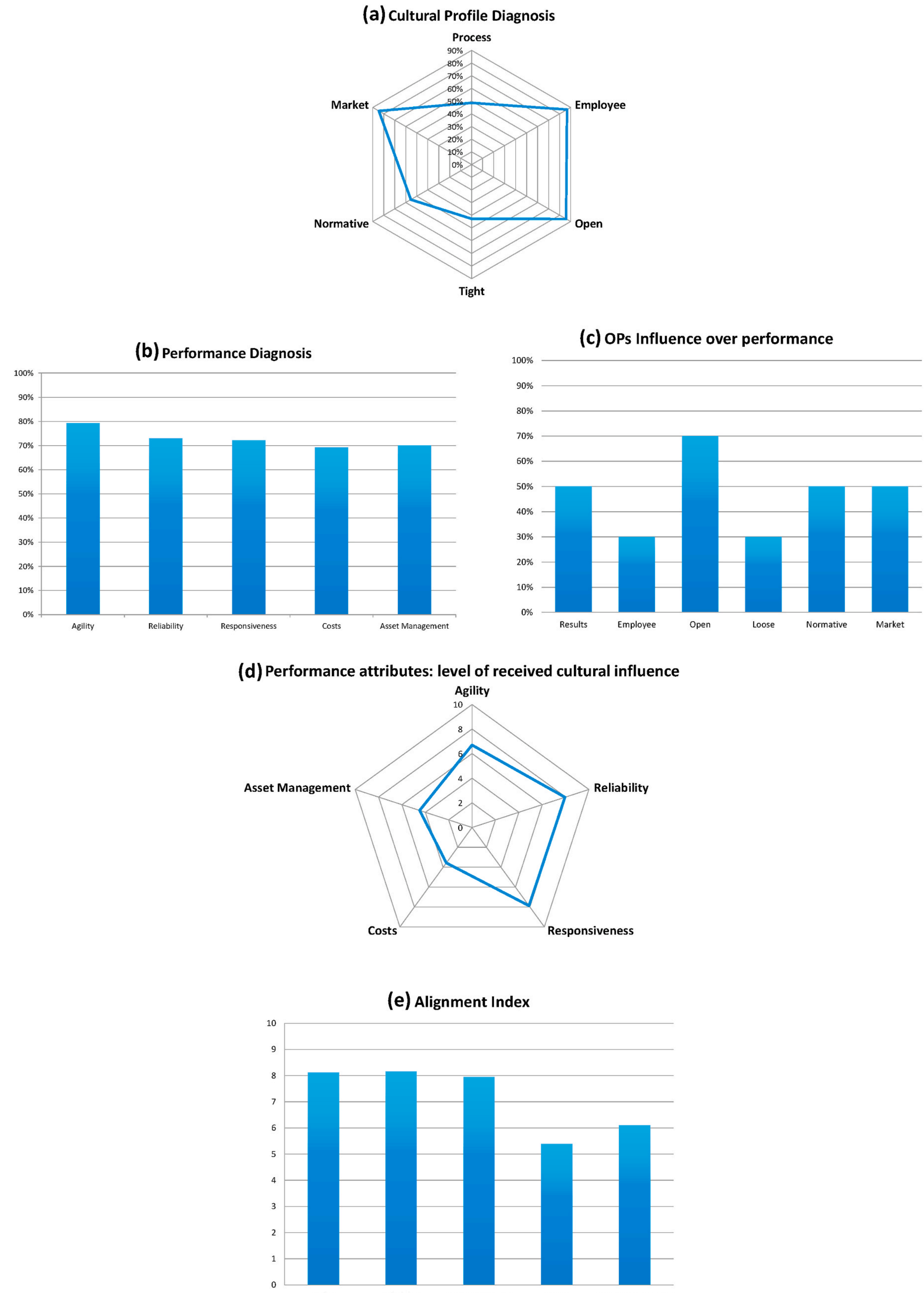

Fig. 4. Results dashboard for Company B.

Table 15
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

Table 16
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

Table 17
Δ_{min}^{max} 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

Table 18
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

consequently the b_{ij}^{*} matrices can be obtained with equations (13) and (14). The matrices are shown in Tables 18 and 19.

Table 20 illustrates the grey class determination procedure. The classes are defined analogously to the set of linguistic terms in Table 6 since the classes should reflect the criteria importance. As the grey classes are associated with normalized grey numbers, the CTWF method presented in section 2.4.2 can be applied. With equation (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

Table 19
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

Table 20
Grey classes determination.

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

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

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

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

$$f_4(x)=\begin{cases}0, & x\notin[0.7;1]\\ \frac{x-0.7}{0.2}, & x\in[0.7;0.9]\\ \frac{\frac{1-x}{0.1}}{0.2}, & x\in[0.9;1]\end{cases} \tag{26}$$

Grey Classes	$\underline{G}$	$\underline{G}$	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

Table 21
Clustering for company A.

σ_i^k	GC-VL	GC-L	GC-M	GC-H	GC-VH	$\sigma_i^{k^*}$	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

Table 22
Clustering for company B.

σ_i^k	GC-VL	GC-L	GC-M	GC-H	GC-VH	$\sigma_i^{k^*}$	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

Table 23
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

Table 24
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

on, as in equations (22)–(26). The classes and whitenization functions are the same for both companies.

After calculation of the grey clustering coefficient the criteria are classified into one of the classes. For instance, in Table 21,$\sigma^{k^*}_{Process} = max_{1\le k\le 5}\{0;0;2.01;2.72;0.27\} = 2.72\rightarrow\ k^* = H.$ Tables 21 and 22 show the criteria classification for companies A and B.

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. Figs. 3(c) and 4 (c) bring a visual representation of the OPs according to their influence on the SCOR® attributes' performance for each company after whitening the grey numbers associated with the assigned classes.

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 (5) and (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 23 and 24 and as illustrated in the dashboards of Figs. 3(d) and 4(d).

By conducting the whitenization of the grey values presented in Tables 23 and 24, 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

Table 25
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

Table 26
AI calculation for Company B.

SCOR® attribute	CI	AP	AI
Agility	6.7	7.93	8.12
Reliability	7.95	7.29	8.16
Responsiveness	7.88	7.22	7.95
Costs	3.57	6.92	5.39
Asset Management	4.49	7.01	6.11

As in the decision model of Fig. 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 25 and 26 present the AI calculation. And Figs. 3(e) and 4(e) show the results of the inference processes bringing a graphical visualization of the AI levels.

The culture-performance surfaces representing the AI as a function of performance and received cultural influence for each company can be seen in Fig. 5 and Fig. 6, respectively.

To aid decision makers in the development of action plans, the cognitive maps can be visually represented as in Fig. 7 and Fig. 8. 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.

5. Discussion

5.1. Regarding the results

The following diagnosis was obtained regarding the cultural profile of both companies, according to the defined OPs. Company A is based on processes, employee-focused, open, with a loose management approach, normative and market oriented. Company B is based on results, employee-focused, open, with a loose management approach, normative and market 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 relates to the obtained results, since "process" vs. "results" is the OP that has the most influence on performance, followed by "open" vs. "closed". In this direction, 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.

For company A, reliability is the attribute with the best performance, followed by responsiveness, agility, costs and asset management. For company B agility the attribute with the best performance, followed by

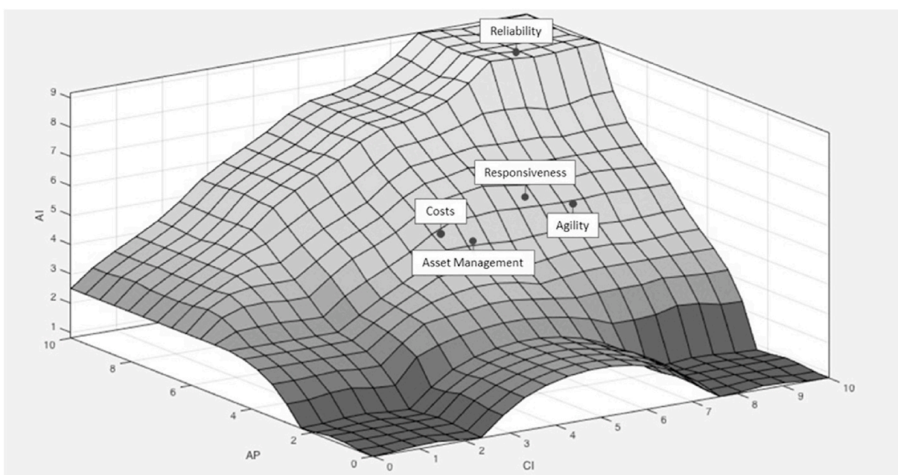

Fig. 5. Culture-performance surface for Company A.

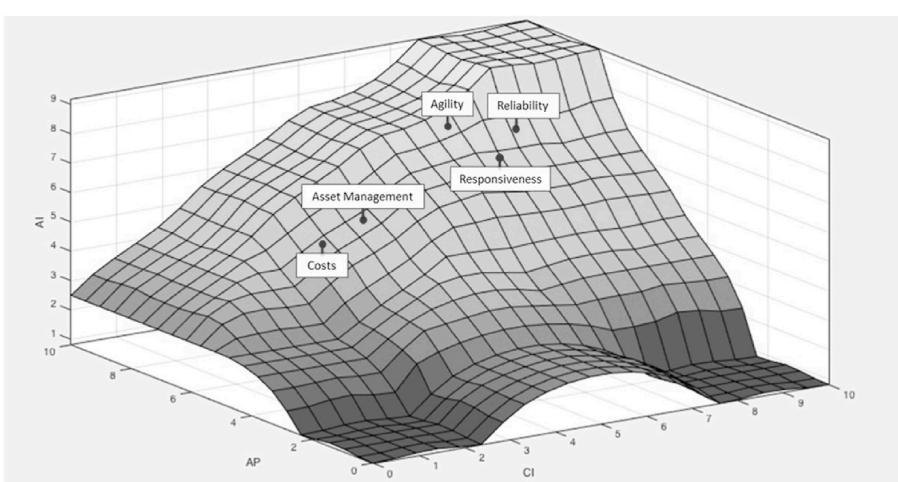

Fig. 6. Culture-performance surface for Company B.

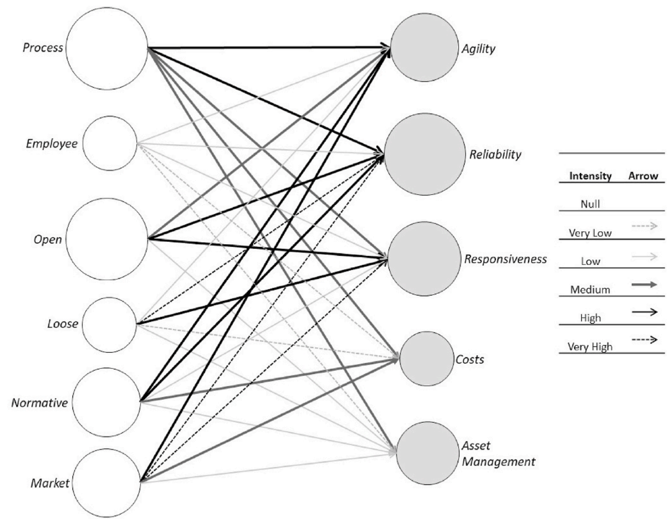

Fig. 7. Final cognitive map for Company A.

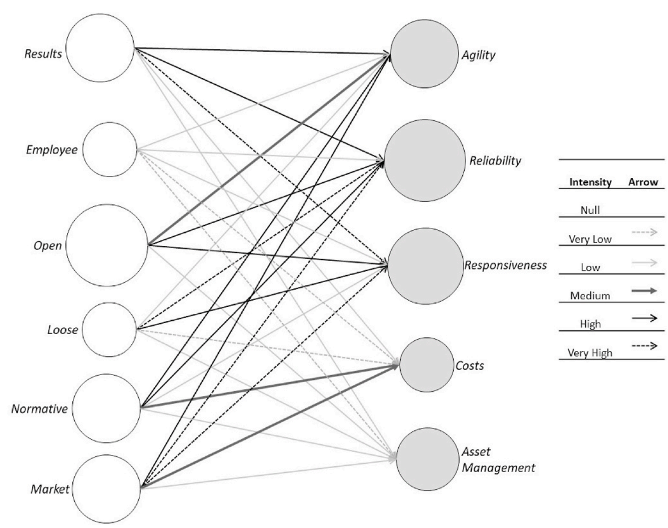

Fig. 8. Final cognitive map for Company B.

reliability, responsiveness, asset management and costs. This scenario is consistent with their declared competitive strategy. 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 consist also in factors that foster performance. 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.

Table 27 provides details regarding how the methods were implemented for the pilot applications. The first column identifies each soft computing technique that composes the group decision making model proposed in this paper. In the second and third columns, the inputs and outputs of each method in the pilot applications are shown, in order to clarify their role in the model and their implementation. The fourth column presents a summary of the results of the pilot applications. The fifth column discusses the contribution of each method considering the need to assess the organizational culture and supply chain performance relationship. Therefore, this table is able to connect the methods, the way how they contribute to assessing the relationship between culture and performance in supply chains and the results they provided for each company.

5.2. Regarding the adaptability, reliability and validity of the proposed model

It is relevant to note that the model is not proposed to a cohort of organizations with certain organizational/supply chain characteristics. The proposed model is developed based on the theoretical constructs of Hofstede's organizational practices and the SCOR attributes since both have been specifically proposed to be adaptable for a wide range of organizations and supply chains with diverse characteristics. According to Akkawuttiwanich and Yenradee (2018), the SCOR model consists in a reference model that allows companies to communicate using a common terminology that is understandable within and across organizations. According to the authors, it has been widely applied in supply chains of diverse types and natures and universally recognized for its adaptability. Regarding the organizational practices, Cadden et al. (2015) argue that the proposition can adapt to several supply chains configurations and is able to rapidly detect cultural changes.

In addition, the model adaptability is reinforced since the Hofstede's organizational practices can be replaced with other organizational culture constructs and the SCOR performance attributes can as well be replaced with other indicators from the company in analysis. In this direction, the SCOR model was chosen as a reference since it is one of the most generic and broad models to assess supply chain performance (Estampe et al., 2013). The model proposed in this paper essentially aims to map the causal relationship between culture and supply chain performance based on soft computing techniques and on the structured decision process. Changing the theoretical constructs for organizational culture and supply chain performance would therefore only alter the nodes and edges of the fuzzy grey cognitive map-based model. This also corroborates the reliability and validity of the proposed model in light of the fact that the nature of the supply chain and culture can change due to many factors.

Expanding the discussion, reliability and validity also come from the soft computing techniques, which are robust and well established through several applications in other studies. In addition, the Cadden et al. (2015) questionnaire is a validated data collection instrument and the performance data collection through computing with words and the SCOR attributes was benchmarked from other studies (Zanon et al., 2020; Lima-Junior; Carpinetti, 2016).

Moreover, regarding reliability and validity, it can be said that the study has external validity since it has the ability of being applied to other people and other situations. This is justified by the fact that a novel decision making model is proposed, with the aim of being adaptable and tested in real world scenarios (Roberts et al., 2006). In addition, the study has internal validity through content validity, from the conduction of two real case applications in similar companies to the ones the model was developed to be applied on (Roberts et al., 2006).

Finally, it is important to mention that the results of the model come

Table 27
Computational methods implementation for the pilot applications.

Chosen method	Input	Output	Result in the pilot applications		Contribution
			Company A	Company B	
GC	ERM.	Classification of the OPs according to their level of influence over the SCOR attributes' performance.	OPs with the most influence over performance: process and open; normative and market; employee and loose (Fig. 3(c)).	OPs with the most influence over performance: open; results, normative and market; employee and loose (Fig. (4(c)).	GC provides the possibility to identify which organizational culture characteristics for each organization impact most its supply chain performance.
FGCM	GC's output.	Ranking of the SCOR performance attributes according to the level of received cultural influence.	Ranking of the SCOR attributes according to the level of received cultural influence (0–10 scale): reliability (8.19); responsiveness (7.78); agility (7.56); asset management (5.71); costs (5.19). + Table 23, Figs. 3(d), Fig. 7.	Ranking of the SCOR attributes according to the level of received cultural influence (0–10 scale): reliability (7.95); responsiveness (7.88); agility (6.70); asset management (4.49); costs (3.57). + Table 24, Figs. 4(d), Fig. 8.	FGCM uniquely provides the possibility to map, quantify and visualize how organizational culture impacts each of the company's supply chain performance.
FIS	FGCM's output and the diagnosed performance of the company in each SCOR attribute.	the AI and the culture-performance surface.	The attributes most leveraged by culture are: -Reliability (AI = 9.14) -Responsiveness (AI = 6.33) -Agility (AI = 5.93) -Costs (AI = 5.83) -Asset Management (AI = 5.07) + Table 25, Figs. 3(e) and Fig. 5.	The attributes most leveraged by culture are: -Reliability (AI = 8.16) -Agility (AI = 8.12) -Responsiveness (AI = 7.95) - Asset Management (AI = 6.11) -Costs (AI = 5.39) + Table 26, Figs. 4(e) and Fig. 6.	FIS enables the definition of a new indicator, named Alignment Index (AI), for analyzing how culture leverages supply chain performance. Along with the cognitive maps, this makes possible to develop guidelines for action plans to promote the alignment between organizational culture and supply chain management, internalizing culture as a driver for performance improvement efforts.

out instantaneously after data insertion. Data collection (judgements by decision makers) is the most time-consuming activity when applying the model. However, for both companies it did not take longer than one week, as a consequence of adopting the computing with words approach, which corroborates the model's applicability.

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 of this paper 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. In addition, other contributions come as a consequence of the development of this model, such as: a summary of the state of the art regarding new developments on the organizational culture and supply chain performance interface; the General Relationship Matrix (GRM), which contains all the possible interactions between Organizational Practices (OPs) and the SCOR® performance attributes, and therefore can be used as basis to improve the understanding of how culture affects supply chain performance; the combination of the GC and FGCM techniques, in which GC is used as a mean to improve the FGCM algorithm execution and to reduce its required inputs; the development of a computational model integrating the GC and FGCM combined algorithm with multiple FISs for supporting group decision-making on causal relations; two pilot applications and related discussion in companies operating in different sectors.

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. Further research could also apply the developed model iteratively to compare the results within the same organization over several time periods under certain conditions. 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.

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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 $\otimes G_1 \in \left[\underline{G_1}, \overline{G_1}\right]$, $\underline{G_1} \leq \overline{G_1}$, and $\otimes G_2 \in \left[\underline{G_2}, \overline{G_2}\right]$, $\underline{G_2} \leq \overline{G_2}$, be two grey numbers and let λ be a positive real number. Then, the following operations are defined according to equations B.1-B.5 (Salmeron, 2010).

$$\otimes G_1 + \otimes G_2 \in \left[\underline{G_1} + \underline{G_2}, \overline{G_1} + \overline{G_2}\right] \tag{B.1}$$

$$\otimes G_1 - \otimes G_2 \in \left[\underline{G_1} - \overline{G_2}, \overline{G_1} - \underline{G_2}\right] \tag{B.2}$$

$$\otimes G_1 \text{ x} \otimes G_2 \in \left[\min\left(\underline{G_1} \cdot \underline{G_2}, \underline{G_1} \cdot \overline{G_2}, \overline{G_1} \cdot \underline{G_2}, \overline{G_1} \cdot \overline{G_2}\right), \max\left(\underline{G_1} \cdot \underline{G_2}, \underline{G_1} \cdot \overline{G_2}, \overline{G_1} \cdot \underline{G_2}, \overline{G_1} \cdot \overline{G_2}\right)\right] \tag{B.3}$$

$$\otimes G_1 \div \otimes G_2 \in \left[\underline{G_1}, \overline{G_1}\right] \text{x} \left[1/\overline{G_2}, 1/\underline{G_2}\right] \in \left[\begin{array}{l}\min\left(\underline{G_1} \cdot 1/\overline{G_2}, \underline{G_1} \cdot 1/\underline{G_2}, \overline{G_1} \cdot 1/\overline{G_2}, \overline{G_1} \cdot 1/\underline{G_2}\right), \\ \max\left(\underline{G_1} \cdot 1/\overline{G_2}, \underline{G_1} \cdot 1/\underline{G_2}, \overline{G_1} \cdot 1/\overline{G_2}, \overline{G_1} \cdot 1/\underline{G_2}\right)\end{array}\right]$$

$$\lambda \cdot \otimes G_1 \in \left[\lambda \cdot \underline{G_1}, \lambda \cdot \overline{G_1}\right] \tag{B.5}$$

Grey matrices, denoted as $A(\otimes)$, are generically represented as in equation B.6 (Salmeron, 2010). The grey matrix elements are denoted as $\otimes a_{ij}$ for the ith row and the jth column (Salmeron and Papageorgiou, 2012). It is worth to note that unidimensional grey matrices are called n-dimensional grey vectors.

$$A(\otimes) = \begin{pmatrix} \otimes a_{11} & \dots & \otimes a_{1n} \\ \dots & \otimes a_{ij} & \dots \\ \otimes a_{n1} & \dots & \otimes a_{nn} \end{pmatrix} \tag{B.6}$$

Therefore, let equations B.7 and B.8 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 B.9 (Salmeron, 2010).

$$B(\otimes) = \begin{pmatrix} \otimes b_{11} & \otimes b_{12} \\ \otimes b_{21} & \otimes b_{22} \end{pmatrix} \tag{B.7}$$

$$\otimes \vec{C} = (\otimes C_1 \quad \otimes C_2) \tag{B.8}$$

$$\vec{R}(\otimes) = \vec{C}(\otimes) \cdot B(\otimes) = ((\otimes C_1 \cdot \otimes b_{11}) + (\otimes C_2 \cdot \otimes b_{21})) \quad ((\otimes C_1 \cdot \otimes b_{12}) + (\otimes C_2 \cdot \otimes b_{22})) \tag{B.9}$$

References

Akkawuttiwanich, P., Yenradee, P., 2018. Fuzzy QFD approach for managing SCOR performance indicators. Comput. Ind. Eng. 122, 189–201.

Altay, N., Gunasekaran, A., Dubey, R., Childe, S.J., 2018. Agility and resilience as antecedents of supply chain performance under moderating effects of organizational culture within the humanitarian setting: a dynamic capability view. Prod. Plann. Contr. 29 (14), 1158–1174.

Anjum, A., Kashif, M.T., Riaz, W., 2016. Supply chain integration and operational performance: moderating role of organizational culture. Int. J. Acad. Res. Bus. Soc. Sci. 6 (12), 2222–6990.

Aqlan, F., Lam, S.S., 2015. A fuzzy-based integrated framework for supply chain risk assessment. Int. J. Prod. Econ. 161, 54–63.

Balfaqih, H., Nopiah, Z.M., Saibani, N., Al-Nory, M.T., 2016. Review of supply chain performance measurement systems: 1998–2015. Comput. Ind. 82, 135–150.

Bellman, R.E., Zadeh, L.A., 1970. Decision-making in a fuzzy environment. Manag. Sci. 17 (4), B–141.

Bertrand, J.W.M., Fransoo, J.C., 2016. Modelling and simulation. In: Research Methods for Operations Management. Routledge, pp. 306–346.

Bititci, U.S., Ackermann, F., Ates, A., Davies, J., Garengo, P., Gibb, S., et al., 2011. Managerial processes: business process that sustain performance. Int. J. Oper. Prod. Manag.

Bortolotti, T., Boscari, S., Danese, P., 2015. Successful lean implementation: organizational culture and soft lean practices. Int. J. Prod. Econ. 160, 182–201.

Braunscheidel, M.J., Suresh, N.C., Boisnier, A.D., 2010. Investigating the impact of organizational culture on supply chain integration. Hum. Resour. Manag. 49 (5), 883–911.

Cadden, T., Marshall, D., Humphreys, P., Yang, Y., 2015. Old habits die hard: exploring the effect of supply chain dependency and culture on performance outcomes and relationship satisfaction. Prod. Plann. Contr. 26 (1), 53–77.

Cadden, T., Humphreys, P., McHugh, M., 2010. The influence of organisational culture on strategic supply chain relationship success. J. Gen. Manag. 36 (2), 37–64.

Cadden, T., Marshall, D., Cao, G., 2013. Opposites attract: organisational culture and supply chain performance. Supply Chain Manag.: Int. J.

Cai, J., Liu, X., Xiao, Z., Liu, J., 2009. Improving supply chain performance management: a systematic approach to analyzing iterative KPI accomplishment. Decis. Support Syst. 46 (2), 512–521.

Cameron, K.S., Quinn, R.E., 2011. Diagnosing and Changing Organizational Culture: Based on the Competing Values Framework. John Wiley & Sons.

Cao, Z., Huo, B., Li, Y., Zhao, X., 2015. The impact of organizational culture on supply chain integration: a contingency and configuration approach. Supply Chain Manag.: Int. J.

Chan, C.K., Hou, S.H., Langevin, A., 2012. Advances in optimization and design of supply chains. Int. J. Prod. Econ.

Chatterji, A., Delecourt, S., Hasan, S., Koning, R., 2019. When does advice impact startup performance? Strat. Manag. J. 40 (3), 331–356.

Chen, K., Chen, P., Yang, L., Jin, L., 2019. Grey clustering evaluation based on AHP and interval grey number. International Journal of Intelligent Computing and Cybernetics.

Chen, W.H., Tsai, M.S., Kuo, H.L., 2005. Distribution system restoration using the hybrid fuzzy-grey method. IEEE Trans. Power Syst. 20 (1), 199–205.

Congjun, R., Xinping, X., Jin, P., 2007. Novel combinatorial algorithm for the problems of fuzzy grey multi-attribute group decision making. J. Syst. Eng. Electron. 18 (4), 774–780.

Croom, S., Fawcett, S.E., Osterhaus, P., Magnan, G.M., Brau, J.C., McCarter, M.W., 2007. Information sharing and supply chain performance: the role of connectivity and willingness. Supply Chain Manag.: Int. J.

Delgado, A., Romero, I., 2016. Environmental conflict analysis using an integrated grey clustering and entropy-weight method: a case study of a mining project in Peru. Environ. Model. Software 77, 108–121.

Deshpande, R., Webster Jr., F.E., 1989. Organizational culture and marketing: defining the research agenda. J. Market. 53 (1), 3–15.

Dissanayake, C.K., Cross, J.A., 2018. Systematic mechanism for identifying the relative impact of supply chain performance areas on the overall supply chain performance using SCOR model and SEM. Int. J. Prod. Econ. 201, 102–115.

Douglas, M., 1999. Four cultures: the evolution of a parsimonious model. Geojournal 47 (3), 411–415.

Dowty, R.A., Wallace, W.A., 2010. Implications of organizational culture for supply chain disruption and restoration. Int. J. Prod. Econ. 126 (1), 57–65.

Dubey, R., Gunasekaran, A., Childe, S.J., Roubaud, D., Wamba, S.F., Giannakis, M., Foropon, C., 2019. Big data analytics and organizational culture as complements to swift trust and collaborative performance in the humanitarian supply chain. Int. J. Prod. Econ. 210, 120–136.

Ensley, M.D., Hmieleski, K.M., Pearce, C.L., 2006. The importance of vertical and shared leadership within new venture top management teams: implications for the performance of startups. Leader. Q. 17 (3), 217–231.

Estampe, D., Lamouri, S., Paris, J.L., Brahim-Djelloul, S., 2013. A framework for analysing supply chain performance evaluation models. Int. J. Prod. Econ. 142 (2), 247–258.

Fantazy, K., Tipu, S.A.A., 2019. Exploring the relationships of the culture of competitiveness and knowledge development to sustainable supply chain management and organizational performance. J. Enterprise Inf. Manag.

Farajpour, F., Taghavifard, M.T., Yousefli, A., Taghva, M.R., 2018. Information sharing assessment in supply chain: hierarchical fuzzy rule-based system. J. Inf. Knowl. Manag. 17, 1850002, 01.

Fawcett, S., Osterhaus, P., Magnan, G., Brau, J., Mccarter, M., 2008. Information sharing and supply chain performance: the role of connectivity and willingness. Supply Chain Manag.: Int. J. 12 (5), 358–368.

Fernandez, A., Herrera, F., Cordon, O., del Jesus, M.J., Marcelloni, F., 2019. Evolutionary fuzzy systems for explainable artificial intelligence: why, when, what for, and where to? IEEE Comput. Intell. Mag. 14 (1), 69–81.

Furnari, S., 2015. A cognitive mapping approach to business models: representing causal structures and mechanisms. Adv. Strat. Manag. 33 (1), 207–239.

Gambi, L.D.N., et al., 2013. A theoretical model of the relationship between organizational culture and quality management techniques. Procedia-Social and Behavioral Sciences 81, 334–339.

Geramian, A., Mehregan, M.R., Mokhtarzadeh, N.G., Hemmati, M., 2017. Fuzzy inference system application for failure analyzing in automobile industry. Int. J. Qual. Reliab. Manag.

Ghadimi, P., Toosi, F.G., Heavey, C., 2018. A multi-agent systems approach for sustainable supplier selection and order allocation in a partnership supply chain. Eur. J. Oper. Res. 269 (1), 286–301.

Groysberg, B., Lee, J., Price, J., Cheng, J., 2018. The leader's guide to corporate culture. Harv. Bus. Rev. 96 (1), 44–52.

Gunasekaran, A., Patel, C., Tirtiroglu, E., 2001. Performance measures and metrics in a supply chain environment. Int. J. Oper. Prod. Manag.

Haeri, S.A.S., Rezaei, J., 2019. A grey-based green supplier selection model for uncertain environments. J. Clean. Prod. 221, 768–784.

Hajek, P., Froelich, W., 2019. Integrating TOPSIS with interval-valued intuitionistic fuzzy cognitive maps for effective group decision making. Inf. Sci. 485, 394–412.

Hofstede, G., Neuijen, B., Ohayv, D.D., Sanders, G., 1990. Measuring organizational cultures: a qualitative and quantitative study across twenty cases. Adm. Sci. Q. 286–316.

Hofstede, G., 2001. Culture's Consequences: Comparing Values, Behaviors, Institutions and Organizations across Nations. Sage publications.

Hult, G.T.M., Ketchen, D.J., Arrfelt, M., 2007. Strategic supply chain management: improving performance through a culture of competitiveness and knowledge development. Strat. Manag. J. 28 (10), 1035–1052.

Jermsittiparsert, K., Wajeetongratana, P., 2019. 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 5 (2), 416–431.

Kang, B., Mo, H., Sadiq, R., Deng, Y., 2016. Generalized fuzzy cognitive maps: a new extension of fuzzy cognitive maps. International Journal of System Assurance Engineering and Management 7 (2), 156–166.

Kaushal, J., Basak, P., 2018. 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 42 (4), 429–450.

Keshavarz Ghorabaee, M., Amiri, M., Zavadskas, E.K., Antucheviciene, J., 2017. Supplier evaluation and selection in fuzzy environments: a review of MADM approaches. Economic research-Ekonomska istraživanja 30 (1), 1073–1118.

Khan, S.A., Kusi-Sarpong, S., Arhin, F.K., Kusi-Sarpong, H., 2018. Supplier sustainability performance evaluation and selection: a framework and methodology. J. Clean. Prod. 205, 964–979.

Kroeber, A., Kluckhohn, C., 1952. Culture: A Critical Review of Concepts and Definitions. Random House, NY.

Lima-Junior, F.R., Osiro, L., Carpinetti, L.C.R., 2013. A fuzzy inference and categorization approach for supplier selection using compensatory and non-compensatory decision rules. Appl. Soft Comput. 13 (10), 4133–4147.

Lima-Junior, F.R., Carpinetti, L.C.R., 2016. Combining SCOR® model and fuzzy TOPSIS for supplier evaluation and management. Int. J. Prod. Econ. 174, 128–141.

Lima-Junior, F.R., Carpinetti, L.C.R., 2017. Quantitative models for supply chain performance evaluation: a literature review. Comput. Ind. Eng. 113, 333–346.

Lima-Junior, F.R., Carpinetti, L.C.R., 2019. Predicting supply chain performance based on SCOR® metrics and multilayer perceptron neural networks. Int. J. Prod. Econ. 212, 19–38.

Liu, S., Lin, Y., 2006. Grey Information: Theory and Practical Applications. Springer Science & Business Media.

Liu, H., Ke, W., Wei, K.K., Gu, J., Chen, H., 2010. The role of institutional pressures and organizational culture in the firm's intention to adopt internet-enabled supply chain management systems. J. Oper. Manag. 28 (5), 372–384.

Lohman, C., Fortuin, L., Wouters, M., 2004. Designing a performance measurement system: a case study. Eur. J. Oper. Res. 156 (2), 267–286.

Martinez, L., Ruan, D., Herrera, F., 2010. Computing with words in decision support systems: an overview on models and applications. Int. J. Comput. Intell. Syst. 3 (4), 382–395.

Mazzuto, G., Bevilacqua, M., Stylios, C., Georgopoulos, V.C., 2018. Aggregate experts knowledge in fuzzy cognitive maps. In: 2018 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE). IEEE, pp. 1–6.

Memon, M.S., Lee, Y.H., Mari, S.I., 2015. Group multi-criteria supplier selection using combined grey systems theory and uncertainty theory. Expert Syst. Appl. 42 (21), 7951–7959.

Nair, A., Reckien, D., Van Maarseveen, M., 2019. A generalised fuzzy cognitive mapping approach for modelling complex systems. Appl. Soft Comput. 84, 105754.

Neely, A., Gregory, M., Platts, K., 2005. Performance measurement system design: a literature review and research agenda. Int. J. Oper. Prod. Manag. 25 (12), 1228–1263.

Ntabe, E.N., LeBel, L., Munson, A.D., Santa-Eulalia, L.A., 2015. A systematic literature review of the supply chain operations reference (SCOR) model application with special attention to environmental issues. Int. J. Prod. Econ. 169, 310–332.

O'reilly, C.A., Chatman, J.A., 1996. Culture as Social Control: Corporations, Cults, and Commitment.

O'Reilly III, C.A., Chatman, J., Caldwell, D.F., 1991. People and organizational culture: a profile comparison approach to assessing person-organization fit. Acad. Manag. J. 34 (3), 487–516.

Osiro, L., Lima-Junior, F.R., Carpinetti, L.C.R., 2014. A fuzzy logic approach to supplier evaluation for development. Int. J. Prod. Econ. 153, 95–112.

Pedrycz, W., Gomide, F., 2007. Fuzzy Systems Engineering: toward Human-Centric Computing. John Wiley & Sons.

Porter, M.G., 2019. Supply chain integration: does organizational culture matter? Operations and Supply Chain Management 12 (1), 49–59.

Pothukuchi, V., Damanpour, F., Choi, J., Chen, C.C., Park, S.H., 2002. National and organizational culture differences and international joint venture performance. J. Int. Bus. Stud. 33 (2), 243–265.

Pourjavad, E., Shahin, A., 2018a. The application of Mamdani fuzzy inference system in evaluating green supply chain management performance. Int. J. Fuzzy Syst. 20 (3), 901–912.

Pourjavad, E., Shahin, A., 2018b. Hybrid performance evaluation of sustainable service and manufacturing supply chain management: an integrated approach of fuzzy dematel and fuzzy inference system. Intell. Syst. Account. Finance Manag. 25 (3), 134–147.

Prajogo, D.I., McDermott, C.M., 2011. The relationship between multidimensional organizational culture and performance. Int. J. Oper. Prod. Manag.

Quinn, R.E., Rohrbaugh, J., 1983. A spatial model of effectiveness criteria: towards a competing values approach to organizational analysis. Manag. Sci. 29 (3), 363–377.

Rafie, M., Namin, F.S., 2015. Prediction of subsidence risk by FMEA using artificial neural network and fuzzy inference system. International Journal of Mining Science and Technology 25 (4), 655–663.

Rajesh, R., 2016. Forecasting supply chain resilience performance using grey prediction. Electron. Commer. Res. Appl. 20, 42–58.

Ramezankhani, M.J., Torabi, S.A., Vahidi, F., 2018. Supply chain performance measurement and evaluation: a mixed sustainability and resilience approach. Comput. Ind. Eng. 126, 531–548.

Roberts, P., Priest, H., 2006. Reliability and validity in research. Nurs. Stand. 20 (44), 41–46.

Salmeron, J.L., Gutierrez, E., 2012. Fuzzy grey cognitive maps in reliability engineering. Appl. Soft Comput. 12 (12), 3818–3824.

Salmeron, J.L., Papageorgiou, E.I., 2012. A fuzzy grey cognitive maps-based decision support system for radiotherapy treatment planning. Knowl. Base Syst. 30, 151–160.

Salmeron, J.L., 2010. Modelling grey uncertainty with fuzzy grey cognitive maps. Expert Syst. Appl. 37 (12), 7581–7588.

Sambasivan, M., Yen, C.N., 2010. Strategic alliances in a manufacturing supply chain. Int. J. Phys. Distrib. Logist. Manag.

Supply Chain Council (SCC), 2017. Supply Chain Operations Reference Model (SCOR). Supply Chain Council. Version 12.0.

Schein, E.H., 2010. Organizational Culture and Leadership, vol. 2. John Wiley & Sons.

Sinaga, O., Saragih, N.I., Rachmawati, R., Alaeddin, O., 2019. Does organizational culture capability and relationship building capability expediate supply chain operational performance? Evidence from Indonesia. Int. J Sup. Chain. Mgt 8 (1), 242.

Smircich, L., 2017. Concepts of culture and organizational analysis. In: The Anthropology of Organisations. Routledge, pp. 255–274.

Tomic, B., Spasojević Brkić, V., Karapetrovic, S., Pokrajac, S., Milanović, D.D., Babić, B., Djurdjevic, T., 2017. Organizational culture, quality improvement tools and methodologies, and business performance of a supply chain. Proc. IME B J. Eng. Manufact. 231 (13), 2430–2442.

Tseng, M.L., Wu, K.J., Hu, J., Wang, C.H., 2018. Decision-making model for sustainable supply chain finance under uncertainties. Int. J. Prod. Econ. 205, 30–36.

Verbeke, W., 2000. A revision of Hofstede et al.'s (1990) organizational practices scale. J. Organ. Behav. 21 (5), 587–602.

Von Altrock, C., 1996. Fuzzy Logic and Neurofuzzy Applications in Business and Finance. Prentice-Hall, Inc.

Wallach, E.J., 1983. Individuals and organizations: the cultural match. Train. Dev. J.

Whitfield, G., Landeros, R., 2006. Supplier diversity effectiveness: does organizational culture really matter? J. Supply Chain Manag. 42 (4), 16–28.
Williams, Z., Ponder, N., Autry, C.W., 2009. Supply chain security culture: measure development and validation. Int. J. Logist. Manag. 20 (2), 243–260.
Winklhofer, H., Pressey, A., Tzokas, N., 2006. A cultural perspective of relationship orientation: using organisational culture to support a supply relationship orientation. J. Market. Manag. 22 (1–2), 169–194.
Yunus, E.N., Tadisina, S.K., 2016. Drivers of supply chain integration and the role of organizational culture. Bus. Process Manag. J.
Zadeh, L.A., 1965. Fuzzy sets. Inf. Contr. 8 (3), 338–353.
Zadeh, L.A., 1996. Fuzzy logic, neural networks, and soft computing. In: Fuzzy Sets, Fuzzy Logic, and Fuzzy Systems: Selected Papers by Lotfi A Zadeh, pp. 775–782.
Zadeh, L.A., 1999. Fuzzy logic= computing with words. In: Computing with Words in Information/In6telligent Systems, vol. 1. Physica, Heidelberg, pp. 3–23.
Zanon, L.G., Arantes, R.F.M., Calache, L.D.D.R., Carpinetti, L.C.R., 2020. A decision making model based on fuzzy inference to predict the impact of SCOR® indicators on customer perceived value. Int. J. Prod. Econ. 223, 107520.
Zimmermann, H.J., 2010. Fuzzy set theory. Wiley Interdisciplinary Reviews: Comput. Stat. 2 (3), 317–332.