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A decision making model based on fuzzy inference to predict the impact of SCOR® indicators on customer perceived value

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ABSTRACT

Customer perceived value (CPV) is critical for supply chain management, due to its link with satisfaction and market share. In addition, value perception is a consequence of several factors including operational performance. Hence, analyzing the cause and effect relationship between CPV and supply chain performance can help decision makers to identify attributes of performance that need improvement efforts so as to enhance CPV. However, modeling this relationship is very dependent of cognitive judgments associated with incomplete or imprecise information. To overcome this, fuzzy inference has been largely used in supply chain management. However, no study was found that applies this soft computing technique with natural language processing to investigate the impact of supply chain performance on CPV. Therefore, this article proposes a decision making model based on fuzzy inference to help predicting the impact on CPV of the performance indicators of the SCOR® (Supply Chain Operations Reference) model. The SCOR® level 1 indicators were applied as a mean to assess CPV in a multidimensional way, to enable benchmarking with other supply chains and to facilitate the communication with stakeholders. It is an axiomatic prescriptive model-based research that includes an illustrative application based on the distribution of beverages to final customers. Analysis of the response surfaces of both Fuzzy Inference Systems allowed identification of the attributes of performance that most impact CPV, therefore providing the possibility of anticipation and prioritization. The model is adaptable to various supply chain configurations. Also, it provides the possibility of internalizing CPV as a driver for supply chain continuous improvement initiatives.

1. Introduction

Customer satisfaction generally leads to greater levels of customer loyalty and positive word-of-mouth, which can contribute to a stronger competitive position, higher market share (Beneke et al., 2013; Gummerus, 2013) and profitability (Okongwu et al., 2016; Luo et al., 2010). Although the literature presents many definitions of customer perceived value (CPV), there is no doubt about the positive relationship between customer perceived value and customer satisfaction.

Parasuraman and Grewal (2000) argue that in supply chains, customer perceived value is enhanced by performance excellence, which in turn is mostly dependent on responsiveness, efficiency and reliability of the supply chain (Aqlan and Lam, 2015). The Supply Chain Operations Reference (SCOR®) model was proposed by the Supply Chain Council (SCC) and adopts hierarchic performance indicators focused on five main performance dimensions: reliability, responsiveness, agility, cost and asset management (Supply Chain Council (SCC), 2017). The SCOR® model is widely applied in decision making problems related to supply chain performance management (Lima-Junior and Carpinetti, 2016; Ntabe et al., 2015). Following the argument presented by Parasuraman and Grewal (2000), the SCOR® performance indicators could be used as driver indicators to enable the prediction of customer perceived value as a consequence of operational performance.

Few studies propose models to aid decision makers for enhancing customer value creation but related to product development and marketing. Li et al. (2015) address costumer requirements on remanufacturing decision making process. Miao et al. (2014) propose a model to yield higher customer perceived value of electric vehicles. Kang and

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Sharma (2012) investigate the potential of brand personality to enhance perceived value. Gautam and Singh (2008) propose a model to maximize customer perceive value importance in product redesign. However, they do not model the impact of supply chain dimensions of performance on customer perceived value. Also, these studies do not address the inherent imprecision brought by the intangible aspects of the cognitive judgment of customer perceived value along the value stream. Moreover, imprecision is inherent in supply chain performance evaluation, since it is, in some cases, qualitative by nature or even because of lack of data.

In this direction, 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 and elucidates that CW involves a fusion of natural language and computation with fuzzy variables. Therefore, the application of fuzzy set theory in this paper is justified due to the fact that it is one of the most efficient tools to deal with the uncertainty of evaluation processes (Keshavarz Ghorabaee et al., 2017). For that purpose, Fuzzy Inference System (FIS) has been largely applied in supply chain management problems to overcome the intrinsic vagueness in the evaluation of criteria (Aqlan and Lam, 2015; Ghadimi et al., 2018; Wang et al., 2018; Kaushal and Basak, 2018; Pourjavad and Shahin; 2018a; Khan et al., 2018). In addition, the FIS application in the context of this paper is appropriate due to its potential for handling nonlinear relationship between input and output variables (Pourjavad and Shahin, 2018b), and also, due to the capacity to modeling human reasoning through fuzzy if-then rules (Khan et al., 2018; Segundo et al., 2017).

Considering the outlined arguments in the previous paragraphs, this article presents a new decision making model to aid decision makers to predict the impact of supply chain dimensions of performance on customer perceived value. The proposed model combines the performance indicators of the SCOR® model within two fuzzy inference systems to evaluate how this perceived value changes according to the variation of the SCOR® performance indicators to enable scenario simulation for maximizing the contribution of supply chain performance to customer value perception. The fuzzy inference theory was selected to be applied in this decision making problem since it allows the evaluation of qualitative factors and subjective information in a concise way (Herrera and Martínez, 2001; Jang, 1993).

The study has followed the quantitative axiomatic prescriptive model-based research as presented by Bertrand and Fransoo (2016). The fuzzy inference systems were implemented in MATLAB® and an illustrative application was developed based on the context of a company that produces and distributes beverages. To validate the results, a sensitivity analysis was conducted through the Minitab 17® software.

This paper is organized as follows: section 2 presents the research method; section 3 a literature review addressing customer perceived value in supply chains, the SCOR® model and fuzzy inference systems; section 4 presents the proposed decision making model for supply chain improvement based on customer perceived value; section 5 brings an illustrative application case; section 6 addresses discussions; finally, section 7 draws some conclusions and suggestions for further researches.

2. Research method

This study was designed according to the quantitative axiomatic prescriptive research method. It is axiomatic because it aims to develop a quantitative model to produce knowledge concerning 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 explain the behavior of CPV in supply chains based on assumptions about the SCOR® customer-focused performance attributes. Moreover, this study is prescriptive since it is primarily interested in developing policies, strategies and actions to improve the results available in the existing literature to find a solution for a newly defined problem (Bertrand and Fransoo, 2016). Therefore, the research method is mainly related with the model itself, its implementation and test. Fig. 1 illustrates the method's main elements.

Firstly, a literature review was conducted in order to strengthen the model formulation. This review was guided by three main theoretical constructs: customer perceived value, supply chain performance and fuzzy set theory. In regards to CPV, a search was executed inserting the strings "customer perceived value" and "supply chain" in the Web of Science and Scopus databases since both have an extensive collection of journals on issues related to Operations Management. Concerning supply chain performance, the SCOR® model was analyzed with focus in its attributes and indicators. The applicability of fuzzy set theory was then assessed for the supply chain context and for dealing with the subjectivity related to measuring the perception of value.

Secondly, the decision making model was developed. Its main steps are described in section 4. The model is based on the mathematical formulation of the fuzzy inference system and is structured over the prescriptive policies and rules that describe the cause and effect relationship between the SCOR® customer-focused metrics and CPV in supply chains. This procedure also included the development and test of both FIS computational model.

Thirdly, an illustrative application was conducted in order to demonstrate to the reader how the model works. An illustrative application is based on a real problem; it uses real data and involves an expert close to the problem. It is not a real application since the outcome of the decision model does not modify the management process in practice.

The data collection procedure is associated to the two required inputs for the model. The first one is the current SCOR® customer-focused indicators performance. This quantitative information comes from the company's enterprise resource planning systems. The second required input is the knowledge of an expert, which consists in his perceptions about the particularities of the company's environment, used to build the FIS rule base and to set the fuzzy membership functions of the linguistic terms. It is important to note that the illustrative application is presented in section 5 to exemplify in detail how the data collection procedure should occur when applying the model in a real case. The outputs are the quantitative CPV level and directives for action plans so as managers can improve it.

Regarding validation, detailed sensitivity analysis was conducted by applying a full 3^k factorial technique to test the rules and fuzzy operations of the inference systems. 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, since it proposes an illustrative application with people that are similar to the intended study participants (Roberts et al., 2006).

3. Literature review

3.1. Customer perceived value in supply chains

Sweeney and Soutar (2001) state that understanding the concept of perceived value is crucial for increasing competitive advantage since customers are nowadays more value conscious. According to the authors, there has been relatively little empirical research to develop an in-depth understanding of the concept. They also argue that even less research has focused on developing a practical and operational way of analyzing objectively perceived value in a multidimensional perspective. Table 1 presents several perceived value definitions in different contexts.

Songailiene et al. (2011) highlights that, despite the variety of definitions of the concept, there is a general agreement in the literature that: perceived value is individual and subjective; it also involves a trade-off between what is received and what is given up; it is always

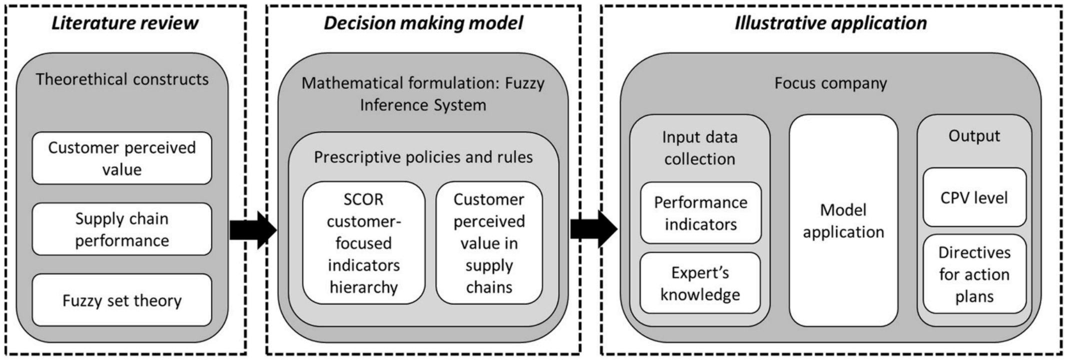

Fig. 1. Illustrative view of the research method steps and elements.

Table 1
Customer perceived value definitions.

Authors	Field	Journal	Year	Proposition	Customer Perceived Value Definition
Sweeney and Soutar, 2001	Retail	Journal of Retailing	2001	To develop a scale to assess customer perceived value (PERVAL)	A combination of four dimensions: emotional, social, quality/performance and price/value for money
Song et al., 2016	Marketing/ Services	Industrial Marketing Management	2016	To understand how product-centric or knowledge-centric supply services create customer perceived value	A business buyer's assessment of the economic, technical, and relational bene fits received, in exchange for the price paid
Hänninen and Karjaluoto, 2017	Environmental supply	Journal of Cleaner Production	2017	To test the effect of environmental values on overall value perceptions	The assessment of value that is gained from the supplier relationship
Walsh et al., 2014	Retail	Journal of Business Research	2014	To assess Sweeney and Soutar (2001) PERVAL scale	The consumer's overall assessment of the utility of a product (or service) based on perceptions of what is given
Li et al., 2015	Decision-making	Discrete Dynamics in Nature and Society	2015	To study the impacts of consumers' perceived value on the decision-making process	Consumer willingness to pay in regard of what a product offers
Petrick, 2002	Leisure	Journal of Leisure Research	2002	To develop a multidimensional scale to measure the perceived value of a service	What the consumer gets for what they give.
Boksberger and Melsen, 2011	Marketing/ Services	Journal of Services Marketing	2011	To provide a comprehensive and systematic overview of the research on perceived value	A combined assessment of consumers' perception of benefits and sacrifices with the behavioral preference affecting the overall evaluation
Songailiene et al., 2011	B2B services	European Journal of Marketing	2011	To provide a conceptualization of perceived value in business relationships for B2B services	The assessment of the financial, strategic, and co-creating value dimensions determined by the customer

relative to competition; it is a higher order construct driven by a number of lower order constructs.

According to Song et al. (2016), perceived value is one of the most important measures for gaining competitive edge and improving purchase intentions. Yang and Peterson (2004) highlight that customer perceived value significantly influences customer satisfaction. Petrick (2002) also states that it has been recognized as one of the most salient determinants of customer loyalty. Based on Palominos et al. (2019) it is possible to understand the importance of considering the customer perspective when managing performance indicators. However, current efforts to measure perceived value have shown the difficulty of quantifying it. In this direction, Trigos et al. (2019) demonstrates that applying techniques to improve the performance of operational indicators directly related to the customer, it is also possible to improve its perception of delivered value.

In supply chains, customer perceived value is related to the value that is created by the supplier relationship. Therefore, comprehending the interplay of supply performance dimensions to value creation is essential to guide the formulation of appropriate strategies that respond to customers' value desires (Hänninen and Karjaluoto, 2017). Swaddling and Miller (2002) highlight that there are three components of measuring CPV: attributes, relative importance and relative performance. The authors also point that CPV attributes are whatever factors prospective customers use to compare one offering against another. In addition, Lapierre (2000) states that flexibility, responsiveness and reliability are CPV main attributes in industrial contexts focusing the distribution sector. It is important to note that responsiveness and reliability are two of the three SCOR® customer-focused attributes, while flexibility indicators are one of agility's (the third customer-focused attribute) main components.

3.2. The SCOR® model

The Supply Chain Council established the Supply Chain Operations Reference (SCOR®) model in 1996 in a unique format that links processes, elements, indicators, best practices and a guideline for supply chain excellence to meet customer's demand (Supply Chain Council (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.

The SCOR® model was selected to be applied in this study due to the fact that, in a comparative study between 16 supply chain performance assessment models, Estampe et al. (2013) concluded that the SCOR® model meets the majority 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). Other reason for choosing the SCOR® metrics is 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, enabling the targeting of competitive requirements for improvement (Lima-Junior and Carpinetti, 2019).

The SCOR® reference model proposes a hierarchical structure that evaluates five dimensions of performance, called Performance Attributes (Supply Chain Council (SCC), 2017). 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, Supply Chain Council (SCC), 2017). The five SCOR® Performance Attributes are described in Table 2. These performance attributes are divided in two groups: the customer-focused group that involves reliability, responsiveness and agility and; internal-focused group, which involves cost and assets management efficiency (Supply Chain Council (SCC), 2017).

Fig. 2 illustrates the hierarchical structure between attributes and indicators proposed by the Supply Chain Council (Supply Chain Council (SCC), 2017). It deploys the supply chain strategy into operational metrics (Ganga and Carpinetti, 2011; Kocaoğlu et al., 2013). Dissanayake and Cross (2018) highlight that this structure enables practitioners to select only measures relevant for application. This structure is composed by level-1, level-2 and level-3 indicators (Supply Chain Council (SCC), 2017). Therefore, level-1 indicators can be divided in level-2 indicators, which serve as diagnosis for performance gaps or improvements for level-1 indicators, and, similarly, level-2 indicators can be decomposed in level-3 indicators that can provide diagnostics for level-2 indicators (Supply Chain Council (SCC), 2017).

However, Akkawuttiwanich and Yenradee, 2018 affirm that a logical method to manage these indicators for supply chain improvement is still unclear. According to Dissanayake and Cross (2018), several techniques, including fuzzy logic, can be applied successfully to address this issue. In this paper, fuzzy inference systems are proposed to evaluate how the customer perceived value changes according to variations of the SCOR® performance attributes agility, reliability and responsiveness.

3.3. Fuzzy inference systems

Tseng et al. (2018) states that uncertainties affect decision making in supply chains and, therefore, appropriate techniques should be applied to deal with their influence. Proposed by Zadeh (1965), the fuzzy inference system (FIS) has been widely applied in multicriteria decision making due to its ability to model uncertainty (Abdullah, 2013; Farajpour et al., 2018) as well as modeling human reasoning through fuzzy if-then rules (Khan et al., 2018; Segundo et al., 2017). In addition, the FIS application in the context of this paper is appropriate due to its potential for handling nonlinear relationship between input and output variables (Pourjavad and Shahin, 2018a).

In supply chain management, FIS is being applied to solve a wide range of problems, as presented in Table 3.

Table 2
The SCOR® performance attributes (Supply Chain Council (SCC), 2017).

Performance attributes	Definition
Reliability	How tasks are executed as expected 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 in 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 is operating processes, with focus in labor, material, transportation and management costs. A typical indicator is cost of goods sold.
Asset Management Efficiency (Assets)	How efficiently are assets used, with focus in inventory reduction and insourcing vs. outsourcing. Typical indicators include inventory days of supply and capacity utilization.

A fuzzy set can be defined as a class of objects characterized by a membership function, which determines the exact degree of belonging of imprecise information to a corresponding value, usually in a degree from zero to one (Zadeh, 1965). Let X be the universe of discourse and x be an element in X. The set $\tilde{A}$ in X is defined by a membership function $\mu_A(x)$ that associates the element x in X to a real value $\in [0,1]$ in order to represent the membership degree x in $\tilde{A}$ (Zadeh, 1965; Pourjavad and Shahin, 2018b). In other words, if $\mu_A(x) = 0$, x does not belong to the set $\tilde{A}$, if $\mu_A(x) = 1$, x is totally included in the set A and if $\mu_A(x)$ has a value between 0 and 1, it partially belongs to the fuzzy set $\tilde{A}$ (Pourjavad and Shahin, 2018b). Therefore, $\forall\, x \in X$, $\tilde{A} = \{x,\ \mu_A(x)\}$, where the degree of membership of any x can be calculated by the membership functions (Zadeh, 1965; Bellman and Zadeh, 1970; Zimmermann, 2010).

A triangular fuzzy number, described by the membership function as in equation (1), is a fuzzy set that meets the properties of normality and convexity (Zadeh, 1965). A fuzzy set is considered as normal if there is at least one element with $\mu_A(x) = 1$. A fuzzy set is considered as convex if $\forall$ x_1 and $x_2 \in X$ and $\forall\, \lambda \in [0,1]$, $\mu_A\ [\lambda x_1 + (1-\lambda)x_2] \geq min[\mu_A\ (x_1),\ \mu_A\ (x_2)]$ (Zadeh, 1965; Bellman and Zadeh, 1970).

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

The inference system is a process in which it is possible to draw conclusions about a phenomenon through deductions obtained from the observation of evidences or premises (Khan et al., 2018). In the Mamdani inference method, the consequents in the rule base are defined by experts' opinions (Ghadimi et al., 2018), which makes this method more suitable for the evaluation of how customers perceive value creation as a consequence of SCOR® performance attributes.

The FIS can be divided into five main elements, illustrated in Fig. 3 (Zimmermann, 2010). The database encompasses a number of input and output variables, their respective linguistic terms and their corresponding fuzzy numbers (Rafie and Namin, 2015). Fuzzification is the conversion of the numerical value of the input variables into the membership degree of the activated linguistic terms and the rule base contains the set of if-then rules that models the problem according to the experts' knowledge (Geramian et al., 2017). The inference structure includes the operations of implication and composition of activated rules to finally aggregate them so as to generate the output fuzzy set (Geramian et al., 2017). Defuzzification corresponds to the fuzzy output (obtained by the inference structure) conversion into a crisp format.

The rule base has "AND" connectors to generate an implication relation between the linguistic terms of the input variables of each activated rule (Pedrycz and Gomide, 2007). Due to the smaller computational effort required, the t-norm (minimum) operator, as in equation (2), is usually adopted.

$$\mu_A(x)\ AND\ \mu_B(y) = Min\ (\mu_A(x),\ \mu_B(y)) \tag{2}$$

The fuzzy inference structure executes the implication relation between the fuzzy numbers resulting from the logic operations and the consequent $\tilde{B}$, for each activated decision rule (Pourjavad and Shahin, 2018a). The minimum (Mamdani) implication operator expressed as equation (3) is commonly used.

$$\mu_{R_{A\to B}}(x,y) = Min\ (\mu_A(x),\ \mu_B(y)) \tag{3}$$

The composition between a fuzzy singleton and the implication relation defines the output fuzzy number for each rule. The Max-Min and Max-Prod fuzzy composition relationship methods are usually applied (Pourjavad and Shahin, 2018a). Each fuzzy composition relation

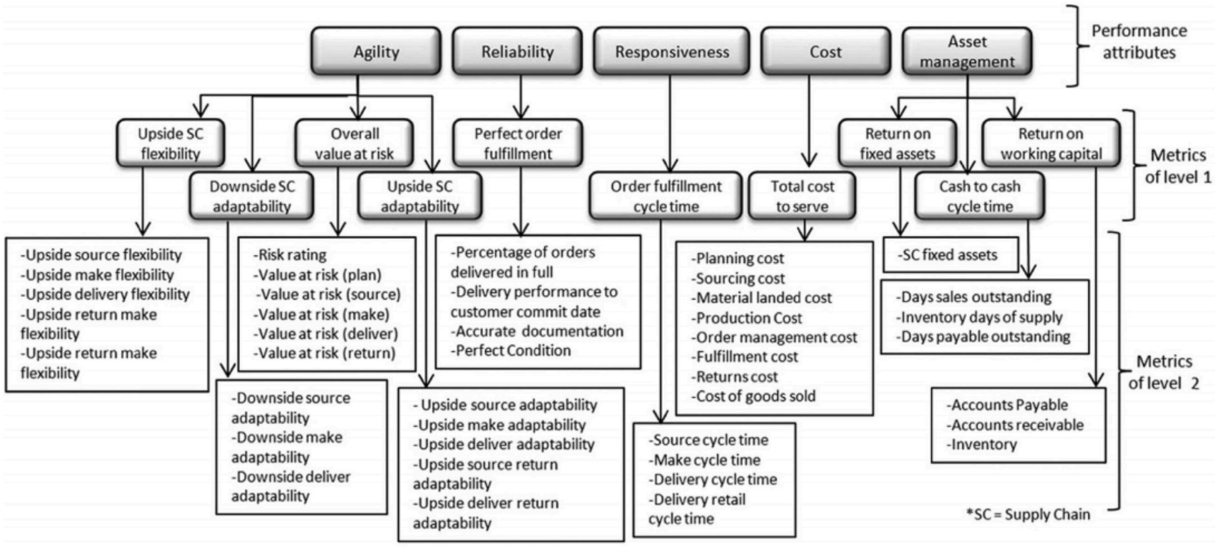

Fig. 2. Performance attributes and indicators of the SCOR® model (Ganga and Carpinetti, 2011).

Table 3
Fuzzy inference applications in the supply chain context.

Authors	Field	Journal	Year	Proposition	Technique
Ghadimi (2017)	Sustainable supplier performance	Computers & Industrial Engineering	2017	Decision making approach to evaluate and select the most sustainable suppliers	FIS
Ghadimi et al. (2017)	Sustainable supplier selection	European Journal of Operational Research	2018	Automate the process of sustainable supplier selection and order allocation	FIS
Khan et al. (2018)	Sustainable supplier performance	Journal of Cleaner Production	2018	Supplier sustainability performance evaluation framework	FIS AND Fuzzy Shannon Entropy
Aqlan and Lam (2015)	Supply Chain Risk Assessment	International Journal of Production Economics	2015	Integrated framework for supply chain risk assessment	FIS
Pourjavad and Shahin (2018a)	Sustainable supply chain performance	Intelligent Systems in Accounting, Finance and Management	2018	Framework for measuring the performance of sustainable services	FIS AND Fuzzy DEMATEL
Amindoust (2018)	Sustainable supplier selection	Computers & Industrial Engineering	2018	A resilient-sustainable framework based on supplier selection indicators	FIS AND DEA
Amindoust et al. (2012)	Sustainable supplier selection	Applied Soft Computing	2012	A method for evaluating and ranking a set of suppliers based on sustainable indicators	FIS
Pourjavad and Shahin (2018a), Pourjavad and Shahin (2018b)	Green Supply Chain Performance Management	International Journal of Fuzzy Systems	2017	To decrease the uncertainty of green supply chain performance evaluation	FIS
Tahriri et al. (2014)	Supplier ranking and selection	Journal of Industrial Engineering International	2014	A method for ranking and selecting suppliers	FIS AND Fuzzy Delphi
Amindoust and Saghafinia (2017)	Sustainable supplier selection	The Journal of the Textile Institute	2017	A framework for textile suppliers' sustainability evaluation and ranking	FIS

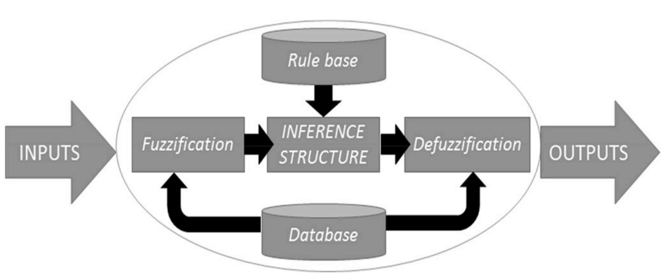

Fig. 3. Main elements of a Fuzzy Inference System.

method corresponds to a special inference structure, which has its own meanings and applications. The Max-Min operator presented in equation (4) was used by Zadeh in the approximate reasoning based on if-then linguistic rules (Jamshidi et al., 1993).

$$S \circ R(x,\ y) = Max\ \{Min\ (\mu_A(x,y),\ \mu_B(y,z)\} \quad (4)$$

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 (5) is used when compensation between input variables is preferred (Von Altrock, 1997).

$$AG(.) = Max\ (\ \mu_{R1}(x),\ \mu_{R2}(x)\ldots\ \mu_{Rn}(x)) \quad (5)$$

Finally, the defuzzification interface converts the output fuzzy numbers 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 (6).

$$CoA = \frac{\sum_{k=1}^{n} \mu_A\ (X_K)\ X_K}{\sum_{k=1}^{n} \mu_A (X_K)} \quad (6)$$

4. Decision making model for supply chain improvement based on customer perceived value

Fig. 4 presents the proposed decision making model to aid decision makers to understand the impact of supply chain dimensions of performance on customer perceived value. It consists of a cyclical structure composed by three steps that aim to improve continuously the SCOR® performance indicators by internalizing customer perception of value creation. This integration between value and performance brings to the decision makers a holistic vision about the gaps that should be addressed and how to address them. Also, the simulation of multiple scenarios helps to identify which performance attribute most impact customer perceived value so as to develop more effective action plans. The steps of the proposed approach are described next.

Step 1: Customer-focused indicators determination.

The first step consists in gathering information about the proposed indicators, as presented in Table 4. It is important to note that only SCOR® customer-focused attributes were considered in the model, not including the internal-focused ones (cost and asset management). This is because it cannot be stated that an efficient management of those indicators will uniquely determine the price of a product or service which can also be impacted by marketing strategies such as dynamic pricing (Tang, 2006). Therefore, the choice for customer-focused attributes is justified by the fact that this study proposes a supply chain CPV perspective. In this regard, the perception of value comes from the level of service that the supply chain is capable to provide to the customers. If a product perspective had been adopted, its quality aspect would have to be assessed by attributes such as product conformance to the specifications, durability or aesthetics. Considering the supply chain perspective, quality of conformance is perceived by elements such as the responsiveness and reliability of the supply chain, which are the main criteria for assessing value delivery to customers (Lapierre, 2000).

Step 2: Fuzzy inference.

The second step consists mainly of inferring the customer perceived value as a consequence of performance on the considered SCOR® level 1 indicators. It is composed by two FIS as illustrated in Fig. 4 and described next:

Table 4
Proposed performance attributes and level 1 indicators (Supply Chain Council (SCC), 2017).

Attribute	Indicator	Description
Agility	Upside SC flexibility	The number of days required to achieve an unplanned sustainable 20% increase in quantities delivered.
	Downside SC adaptability	The reduction in quantities ordered sustainable at 30 days prior to delivery with no inventory or cost penalties.
	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.
	Upside SC adaptability	The maximum sustainable percentage increase in quantity delivered than can be achieved in 30 days.
Reliability	Perfect order fulfilment	The percentage of orders meeting delivery performance with complete and accurate documentation and no delivery damage.
Responsiveness	Order fulfilment cycle time	The average actual cycle time consistently achieved to fulfill customers orders.

- FIS 1 computes agility (the consequent), from its respective indicators (the antecedents), as presented in Table 4. The rule base and membership functions of this first FIS are parameterized according to the expert perception about the supply chain;
- FIS 2 computes the customer perceived value (the consequent) based on three inputs: agility, the consequent of the FIS 1, perfect order fulfillment and order fulfillment cycle time, the level 1 indicators of respectively reliability and responsiveness. It is important to note that for this second FIS, the expert should parameterize the rule base considering the customer value perspective.

In this step, the linguistic terms and corresponding fuzzy numbers of

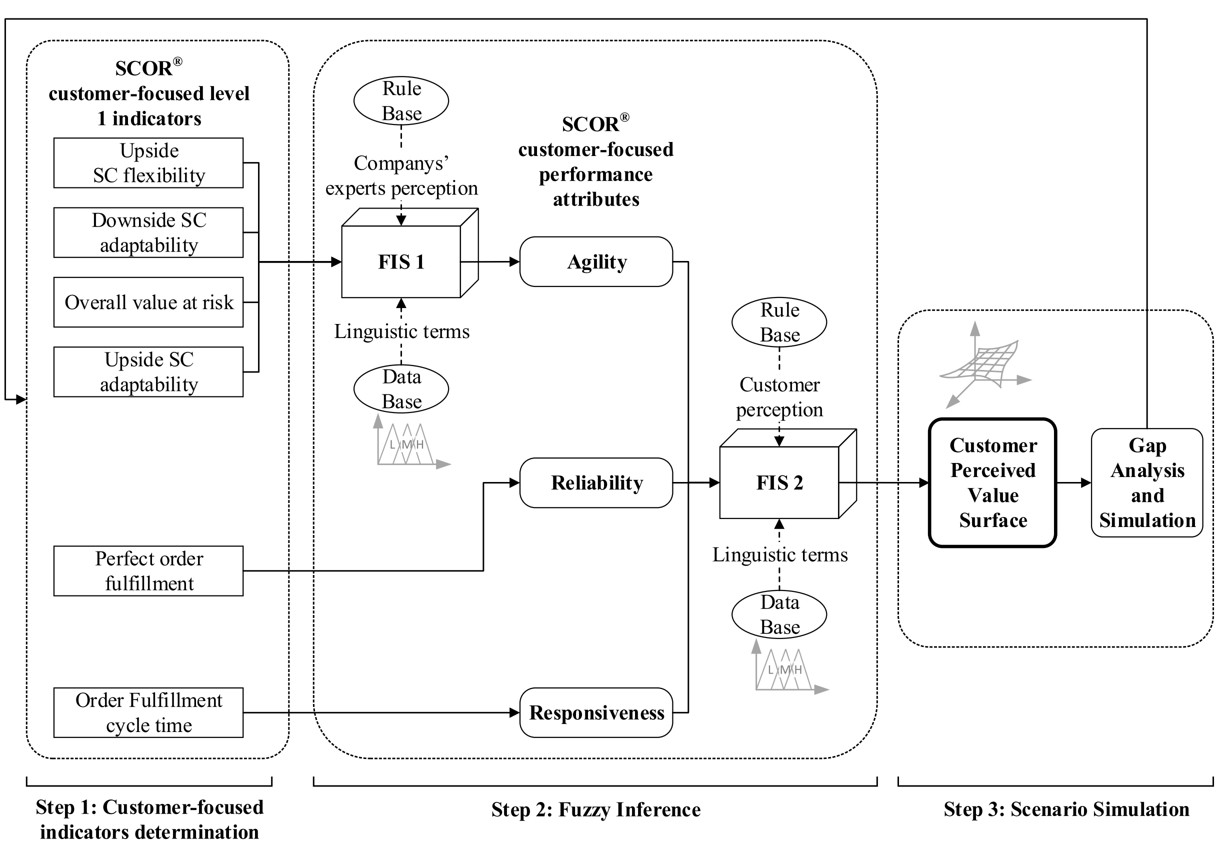

Fig. 4. Proposed decision making model for supply chain improvement based on customer perceived value.

the input and output variables should be defined. Triangular fuzzy numbers are usually adopted for this kind of application (Kaushal and Basak, 2018). In addition, based on literature of fuzzy logic, the chosen fuzzy logic operators are:

- The "Minimum", to operationalize the connective "AND" and to generate the implication relations between the antecedents and consequents;
- The "max-min" operator, to compute the composition between the implication relations and the singleton sets for each activated rule;
- The "maximum" operator, to aggregate the outputs of the activated fuzzy rules;
- The "center of area" operator, to defuzzify the aggregated fuzzy set and generates the final output value.

Step 3: Scenario simulation.

Finally, in the third step, scenario simulation is carried out based on the response surfaces as a result of the second FIS. This step occurs after defuzzification, which provides the perceived value rating, in crisp representation, and corresponding response surfaces. The crisp output rating varies in a range of 1–10 and represents the perceived value diagnosis, the present perceived value state, resultant from the inputted SCOR® performance values in the FIS. The perceived value surfaces consist of the surface plot of customer perceived value as a function of the SCOR® customer-focused attributes: agility, reliability and responsiveness.

Each surface shows the customer perceived value as a function of the combination of two attributes. Therefore, three surfaces are generated: agility vs. reliability, agility vs. responsiveness and reliability vs. responsiveness. Note that these three surfaces were generated due to the number of attributes selected. For instance, if another attribute was added, three more surfaces would be generated to cover all the combinations with the other three attributes.

The computational routines for the proposed approach were implemented in MATLAB®. An illustrative case of application of the proposed method is presented in the next section.

5. Illustrative application case

An illustrative application of this proposal was developed based on the context of a company in the fast moving consumer goods sector. The company produces and distributes beverages and its competitive strategy is based on low cost, high operational performance and supply chain reliability. The application of this proposal focused on the distribution of beverages to retailers, in the very end of the chain and close to the final customers. Consequently, people in charge of this operation had a clear perception of the impact of the supply chain operations on customer perceived value. The application of the proposed model has focused on a particular product line with high inventory turnover and a large contribution to gross income and market share. The production programming, storage and delivery of this product line was in accordance with the sales curve, based on historical data.

The application followed the steps presented in section 4 and described next. The necessary information to parameterize the two FIS was collected through personal interviews with an academic with previous experience in the company. This expert has an in-depth knowledge of both the SCOR® level 1 indicators and the customer experience management in that particular company.

Step 1: Customer-focused indicators determination.

In this first step, the company level of performance in relation to each of the SCOR® customer-focused level 1 indicators was obtained from its enterprise resource planning systems. This information is presented in Table 5. It is important to note that the considered SCOR® level 1 indicators were already used by the focus company of this application but with proprietary denominations. The overall value at risk indicator in the illustrative company is measured by the probability of stock inaccuracy in monetary figures. For this illustrative application, stock inaccuracy was measured by the difference between what is physically in the warehouse and what the information system indicates. The monetary figure was obtained based on an estimation of the product line price, since the price policy defined by the company varies according to several factors such as competition and season of the year.

Table 5 presents the indicator values in their original units and the corresponding values into a converted uniform range from zero to ten, so as to make feasible future internal and external benchmarking. To calculate the converted figures, what should be observed first is whether the indicator is of direct or inverse proportion. An indicator such as downside SC adaptability, for example, shows a direct proportion, that is, the higher its value, the better the performance. However, an indicator such as overall value at risk presents an inverse proportion, that is, the higher its value, the worse the performance. Table 5 shows the reference and current figures, the type of proportion relation of each indicator and its converted figure according to equations (7) and (8), respectively for direct and inverse proportions.

$$Converted\ Figure = Current\ Figure/_{Reference\ Figure} \tag{7}$$

$$Converted\ Figure = Reference\ Figure/_{Current\ Figure} \tag{8}$$

Step 2: Fuzzy inference.

For each antecedent variable of both FIS, three linguistic terms are proposed for this application, named "low", "medium" and "high". For the consequents, five terms are proposed: "very low", "low", "medium", "high" and "very high". The corresponding fuzzy numbers for these linguistic terms are presented in Tables 6 and 7. As presented in Figs. 5 and 6, superposed triangular membership functions are stablished for antecedent and consequent variables due to their suitability to this kind of application (Osiro et al., 2014).

For the first FIS, the rule base consists of 81 if-then rules and is presented in Table 8(in Appendix A). The linguistic terms of the consequent for each rule were defined based on interviews with an academic with previous experience in the company and in-depth knowledge of the interactions between the antecedents (Upside SC Flexibility,

Table 6
Linguistic terms to evaluate the antecedents.

Linguistic terms	Fuzzy triangular number
Low	(0, 0, 5)
Medium	(0, 5, 10)
High	(5, 10, 10)

Table 5
Step 1: converted figures of the SCOR® level 1 indicators.

SCOR® level 1 indicator	Indicator name in the company	Unit	Current figure	Reference figure	Proportion relation	Converted figure (0–10 range)
Upside SC flexibility	Delivery flexibility	Days	4,3	3	Inverse	7
Downside SC adaptability	Order adaptability	Percentage	40	100	Direct	4
Overall value at risk	Stock inaccuracy	Monetary	6,25M	5M	Inverse	8
Upside SC adaptability	Delivery adaptability	Percentage	90	100	Direct	9
Perfect order fulfilment	Current Delivery Performance (CDP)	Percentage	80	100	Direct	8
Order fulfilment cycle time	Cycle time	Days	5	2	Inverse	4

Table 7
Linguistic terms to evaluate the consequent.

Linguistic terms	Fuzzy triangular number
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)

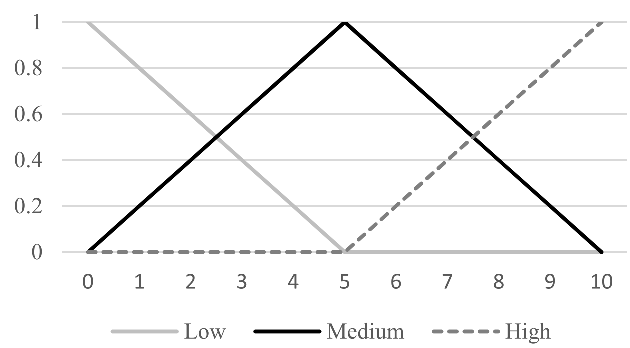

Fig. 5. Membership functions of the antecedent linguistic terms.

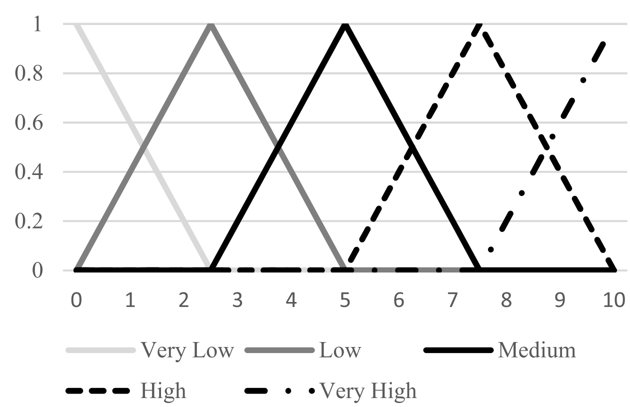

Fig. 6. Membership functions of the consequent linguistic terms.

Downside SC Adaptability, Overall value at Risk and Upside SC Adaptability) to compose the consequent (Agility).

For the second FIS, the rule base with 27 if-then rules is presented in Table 9 (in Appendix A). Analogous to FIS 1, the linguistic terms from Tables 6 and 7 are used to define the rules. For this FIS, the construction of the rule base is based on attributes which affect customer value creation. Therefore, the rule base should reflect the customer's perceptions concerning the interactions between the antecedents (Agility, Reliability and Responsiveness) to define the consequent (Perceived Value). For this particular illustrative application, the rule base was set based on the perceptions of the same expert that defined the rule base of FIS 1. It is justified since this person, with previous experience in the very end of the supply chain and close to the final customers, had a quite clear perception of the impact of the antecedents on customer perceived value, the consequent.

For the first FIS, the converted values of the antecedents (Table 5), upside SC flexibility, downside SC adaptability, overall value at risk and upside SC adaptability, are, respectively, 7, 4, 8 and 9. After defuzzification, the output for agility was 6.66. The inputs for the antecedents of the second FIS were 6.66 for agility (the output of the first FIS), 8 for reliability and 4 for responsiveness. After defuzzification, the customer perceived value index obtained was 5.94. How to improve this perceived value figure, according to this proposed model, is explored in step 3, scenario simulation.

Step 3: Scenario simulation.

Three response surfaces were generated as result of the second FIS, represented on Figs. 7–9. The response surface analysis consists in identifying the shortest path to maximize the customer perceived value index.

6. Discussion

6.1. Directives for action plans

Observing Fig. 7 it is possible to see how different values for agility and reliability impact the customer perceived value index. Assuming that the company's current scenario corresponds to agility and reliability levels of 6.66 and 8 respectively, the red dot on the surface indicates the present customer value index. The red arrow indicates the path for theoretically improving the perception of value. After analyzing the response surface of Fig. 7, it is clear that agility has greater impact on perceived value than reliability. Following the same reasoning, Fig. 8 shows that responsiveness has greater impact on perceived value than reliability. Finally, in Fig. 9, it is possible to realize that the contribution of agility to increase perceived value is greater than the contribution of responsiveness.

By the analysis of these three response surfaces, it is possible to infer that improving agility should be prioritized, since it has a greater impact on customer perceived value. For a deeper understanding about how to improve agility, it is possible to use the same approach of response surface analysis, since it is also the result of an inference system. Six response surfaces were generated in the first FIS. Considering this illustrative case, it is possible to realize that downside supply chain adaptability contributes mostly to agility as shown in Figs. 10–12.

These surfaces provide to decision makers the ability to visualize and understand the impact of supply chain dimensions of performance on the customer perceived value. Therefore, the major contribution of this surface analysis is that an improvement path can be traced connecting the crisp output of FIS 2 to an optimal point which the company desires to achieve so as to improve the current status. With this information, directives for action plans can be defined to aid managers in the value improvement process.

6.2. Sensitivity analysis

To validate the proposed model, a sensitivity analysis is conducted. In order to analyze the consistency and sensitivity of the inference systems, the full 3^k factorial design technique (Montgomery, 2017) was used to assess the interaction effects between the input and the output variables and to evaluate the relative importance of the input variables based on the rule-bases of both FISs (Osiro et al., 2014; Lima-Junior et al., 2013).

The first FIS includes four input variables (UpSc-flex, DownSC-ad, OvRISK-ad and UpSC-ad) that have to be tested in three levels (low, medium and high), leading to 3^4 (81) combinations of levels of the input variables have to be tested. For the second FIS, 3^4, 27 combinations of levels of the three factors (agility, reliability and responsiveness) have to be tested. Since all input variables were defined in the range from 0 to 10, the input variables were set to values 0, 5 and 10. Tables 10 and 11 in Appendix B present the designed experiments and corresponding defuzzified FIS outputs. The designed experiments were tested in a random sequence. The outputs given by each FIS (presented in the last column of Tables 10 and 11) were analyzed using Minitab 17®.

Figs. 13 and 14 present the interaction effect graphs of respectively the input variables of the first FIS for agility measurement and of the second FIS for CPV measurement. The output of each FIS is represented

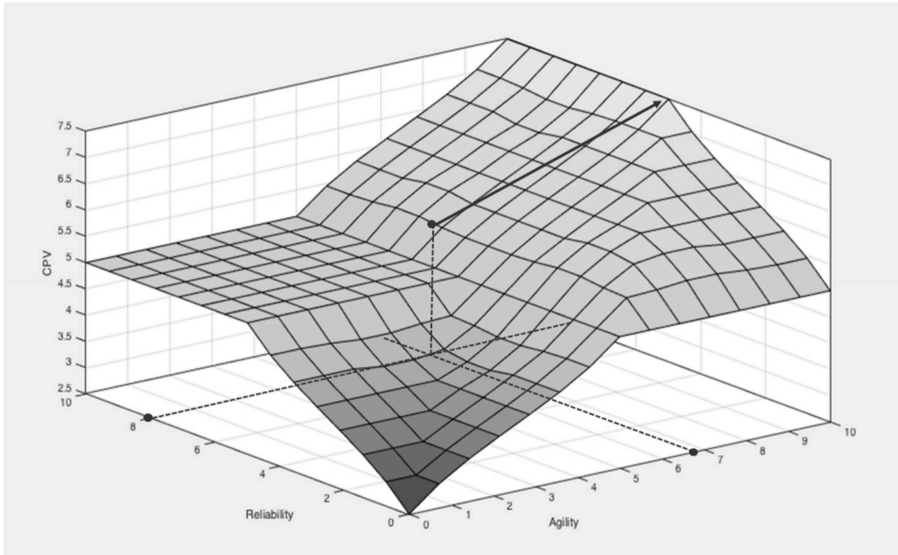

Fig. 7. Perceived value as a function of agility and reliability.

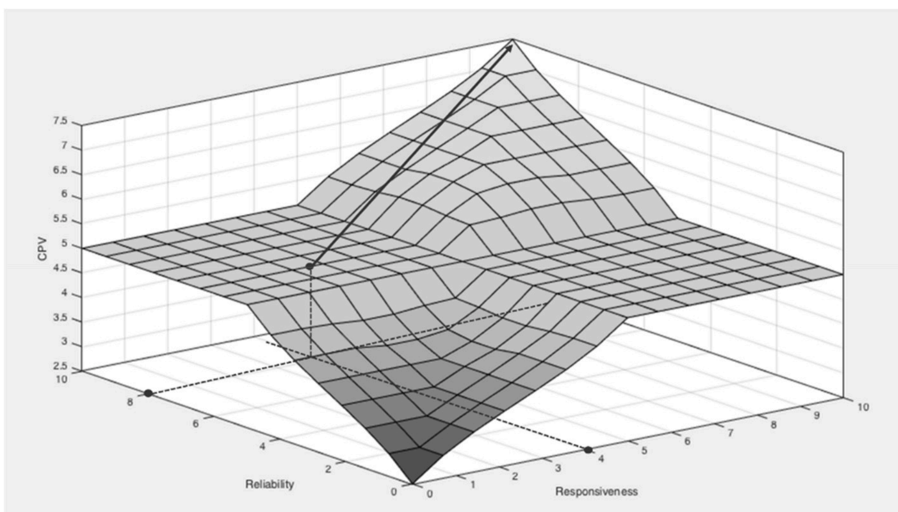

Fig. 8. Perceived value as a function of reliability and responsiveness.

by the y-axis of the graphs and the linguistic terms of the tested factor are indicated by the x-axis. The graphs present the outputs according to the interacting input variables. In this analysis, if the lines are not parallel at all, it indicates an interaction between the variables. On the other hand, if the lines are nearly parallel, it indicates that there is no interaction between the variables. Analyzing the graphs in Fig. 13, it is possible to conclude that there is not a significant interaction effect between the input variables in the first FIS, indicating that there is no trade-off relationship among them. In addition, the graphs and the response surfaces show that the criteria UpSC(ad) and DownSC (ad) have higher impact on agility than over the other two input variables, meaning that the defined FIS rule base is leading to a prevalence of these two input variables over the others. Likewise, it can be seen in Fig. 14 that there is no interaction effects among the input variables of the second FIS for CPV assessment. Therefore, it can also be concluded that there is no trade-off relationship between the variables.

7. Conclusion

This paper presented a decision making model based on fuzzy inference and the SCOR® model to predict the impact of supply chain dimensions of performance on customer perceived value. The central idea is to enable scenario simulation so as decision makers can gain a better understanding of the contribution of the supply chain attributes of performance to customer value creation. The SCOR® level 1 indicators were applied as a mean to assess customer perceived value in a multi-dimensional way. Also, adopting SCOR® indicators enables benchmarking with other supply chains as well as facilitates the communication with suppliers and stakeholders. Although widely recognized, the SCOR® model was never applied to quantify perceived value in association with soft computing techniques. The use of fuzzy inference in this proposed decision model allows human reasoning to model the subjective cause and effect relationships between SCOR® indicators and customer value creation.

The results of the application case, in a company within a supply chain of fast moving consumer goods, illustrated the expected benefits of the proposed model. It showed that improvement of agility should be prioritized as it has a greater impact on customer perceived value. In turn, the application showed that downside supply chain adaptability contributes mostly to improvement on agility. Therefore, in general, the

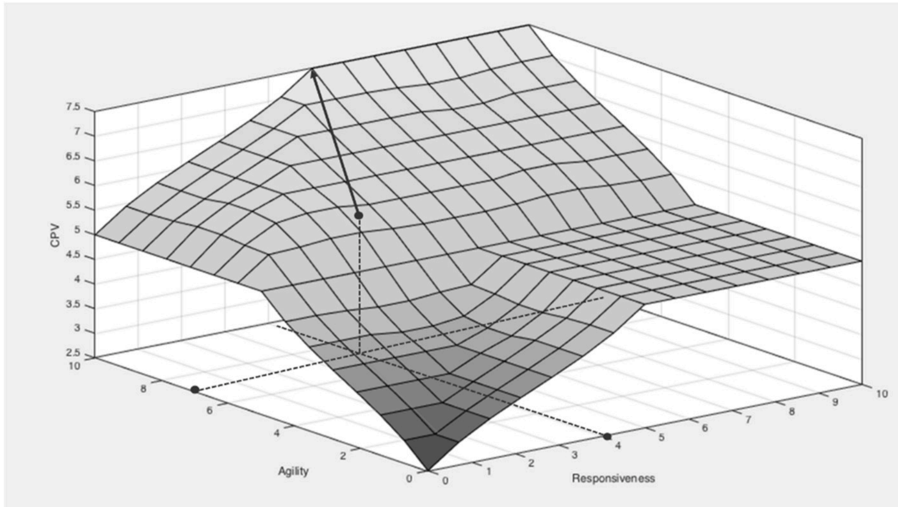

Fig. 9. Perceived value as a function of agility and responsiveness.

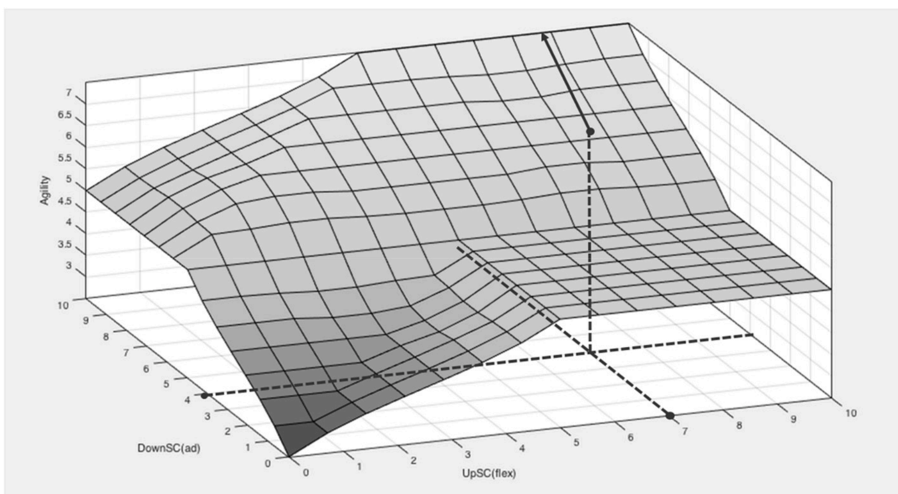

Fig. 10. Agility as a function of downside supply chain adaptability and upside supply chain flexibility.

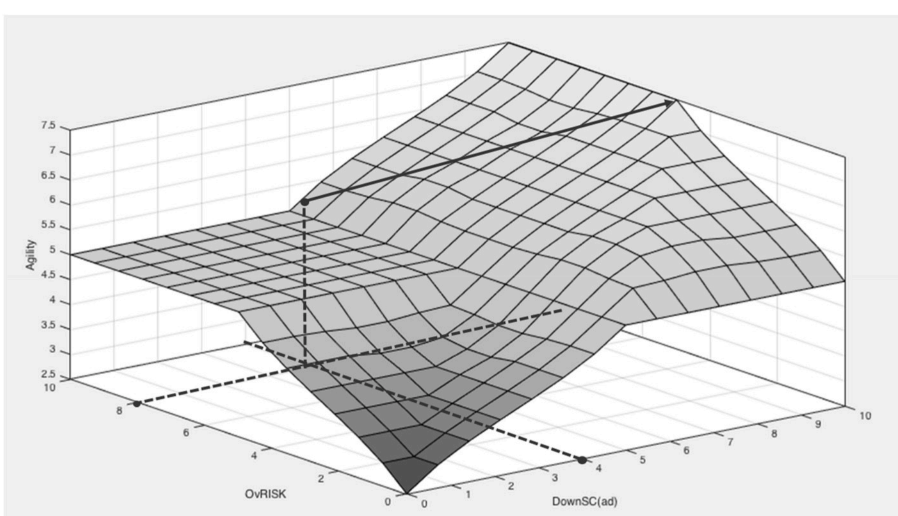

Fig. 11. Agility as a function of downside supply chain adaptability and overall value at risk.

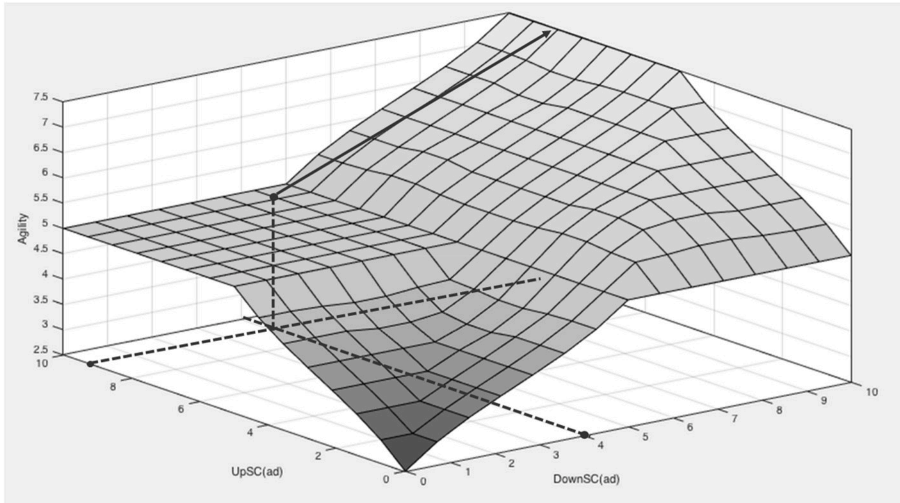

Fig. 12. Agility as a function of downside supply chain adaptability and upside supply chain adaptability.

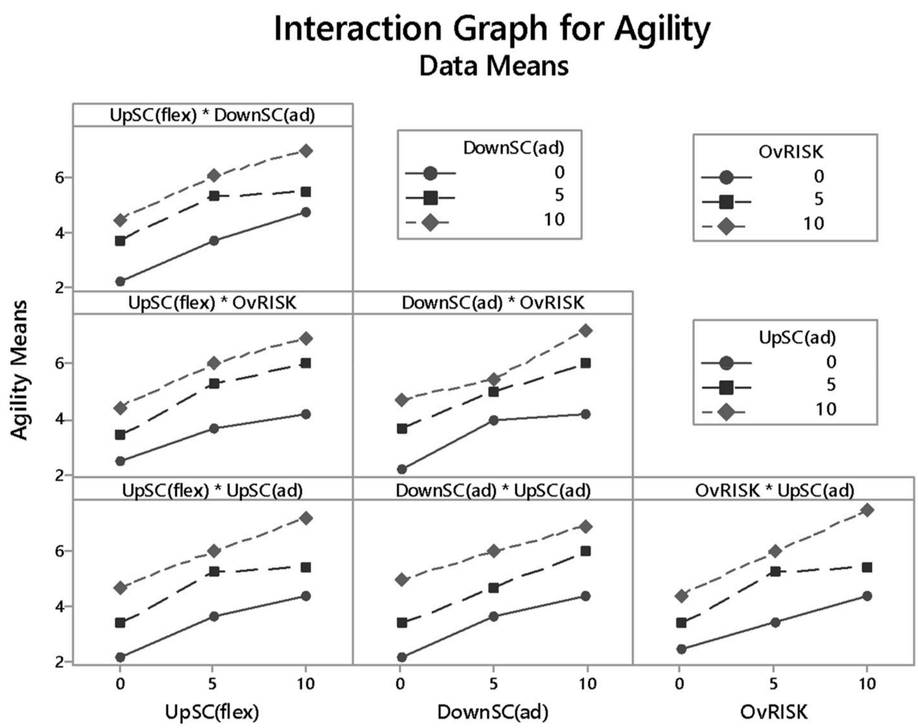

Fig. 13. Graphs of the interaction effects of the input variables of the FIS-1 for agility measurement.

proposed approach makes feasible the identification of crucial supply chain attributes of performance that significantly impact perceived value creation, providing the possibility of prioritization and anticipation, which can save resources and efforts.

However, it is important to note that the conclusions derived from scenario simulation are dependent on the design of the rule bases. On that, the first point is that the rule base of FIS 2 should be built based on the customer perspective, so as to internalize customer value creation as a driver for supply chain continuous improvement initiatives. As a second point, the rule bases used in the application case were also illustrative, in a sense that they need to be redesigned, refined and further improved over use. In addition, for different supply chain configurations (for instance, lean, agile and demand driven), the interplay between SCOR® indicators and customer perceived value changes. Therefore, the experts' knowledge is very important to capture these supply chain particularities and built those into the rule bases. Hence, the proposed decision model is adaptable to various supply chain configurations.

On the other hand, the drawback associated with the use of FIS refers mostly to the difficulty of defining suitable linguistic terms and corresponding fuzzy numbers. In addition, depending on the number of indicators and linguistic terms, the base of rules can grow exponentially which adds complexity to the rule base design. Also, the final defuzzified output changes according to variations in the inference operators, such as t-norms, s-norms and different deffuzification operators. Thus, adjusting the inference system is a learning process, which in a real application should involve a team of experts on supply chain performance and fuzzy inference.

Finally, the proposed decision model can be further improved. In this regard, consensus techniques could be applied to increase the robustness of the rule base design by a group of experts. In addition, the application

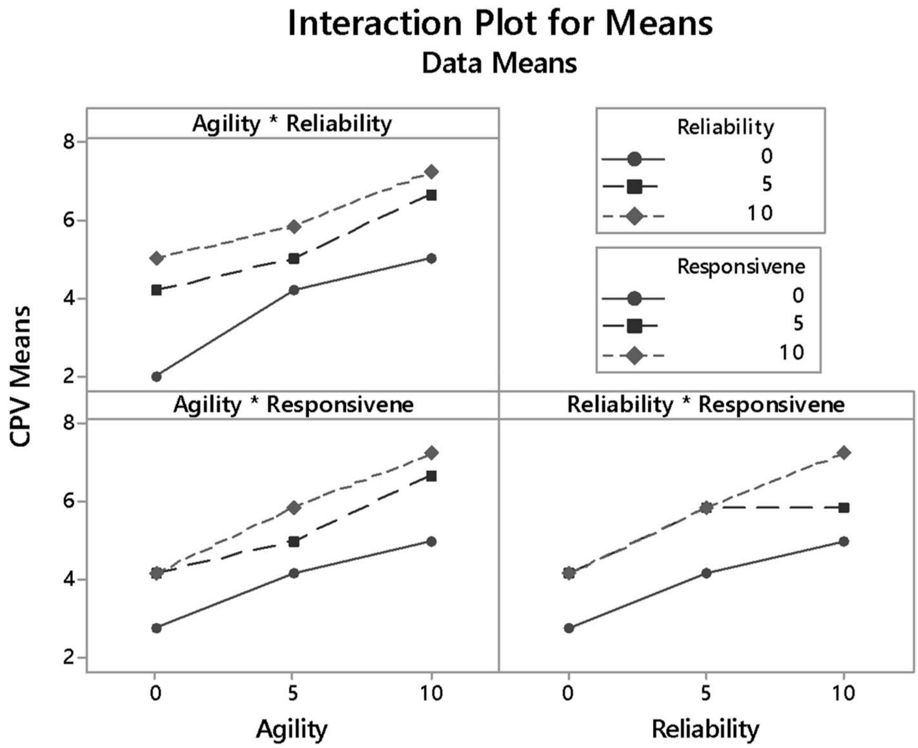

Fig. 14. Graphs of the interaction effects of the input variables of the FIS-2 for CPV measurement.

of neuro-fuzzy approaches can be explored if there is data available for training the system.

Acknowledgements

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Appendix A. Inference rules for FIS 1 and FIS 2

Table 8
Inference rules for agility determination.

Rule	*If*							*Then*
	Up SC Flex	Op	Down SC Ad	Op	Ov risk	Op	Up SC Ad	Agility
1	Low	AND	Low	AND	Low	AND	Low	Very Low
2	Low	AND	Low	AND	Low	AND	Medium	Very Low
3	Low	AND	Low	AND	Low	AND	High	Low
4	Low	AND	Low	AND	Medium	AND	Low	Very Low
5	Low	AND	Low	AND	Medium	AND	Medium	Low
6	Low	AND	Low	AND	Medium	AND	High	Low
7	Low	AND	Low	AND	High	AND	Low	Low
8	Low	AND	Low	AND	High	AND	Medium	Low
9	Low	AND	Low	AND	High	AND	High	Medium
10	Low	AND	Medium	AND	Low	AND	Low	Very Low
11	Low	AND	Medium	AND	Low	AND	Medium	Low
12	Low	AND	Medium	AND	Low	AND	High	Low
13	Low	AND	Medium	AND	Medium	AND	Low	Low
14	Low	AND	Medium	AND	Medium	AND	Medium	Medium
15	Low	AND	Medium	AND	Medium	AND	High	Medium
16	Low	AND	Medium	AND	High	AND	Low	Low
17	Low	AND	Medium	AND	High	AND	Medium	Medium
18	Low	AND	Medium	AND	High	AND	High	Medium
19	Low	AND	High	AND	Low	AND	Low	Low
20	Low	AND	High	AND	Low	AND	Medium	Low
21	Low	AND	High	AND	Low	AND	High	Medium
22	Low	AND	High	AND	Medium	AND	Low	Low
23	Low	AND	High	AND	Medium	AND	Medium	Medium
24	Low	AND	High	AND	Medium	AND	High	Medium
25	Low	AND	High	AND	High	AND	Low	Medium

(*continued on next page*)

Table 8 (*continued*)

Rule	*If*							*Then*
	Up SC Flex	Op	Down SC Ad	Op	Ov risk	Op	Up SC Ad	Agility
26	Low	AND	High	AND	High	AND	Medium	Medium
27	Low	AND	High	AND	High	AND	High	High
28	Medium	AND	Low	AND	Low	AND	Low	Very Low
29	Medium	AND	Low	AND	Low	AND	Medium	Low
30	Medium	AND	Low	AND	Low	AND	High	Low
31	Medium	AND	Low	AND	Medium	AND	Low	Low
32	Medium	AND	Low	AND	Medium	AND	Medium	Medium
33	Medium	AND	Low	AND	Medium	AND	High	Medium
34	Medium	AND	Low	AND	High	AND	Low	Low
35	Medium	AND	Low	AND	High	AND	Medium	Medium
36	Medium	AND	Low	AND	High	AND	High	High
37	Medium	AND	Medium	AND	Low	AND	Low	Medium
38	Medium	AND	Medium	AND	Low	AND	Medium	Medium
39	Medium	AND	Medium	AND	Low	AND	High	Medium
40	Medium	AND	Medium	AND	Medium	AND	Low	Medium
41	Medium	AND	Medium	AND	Medium	AND	Medium	Medium
42	Medium	AND	Medium	AND	Medium	AND	High	Medium
43	Medium	AND	Medium	AND	High	AND	Low	Medium
44	Medium	AND	Medium	AND	High	AND	Medium	Medium
45	Medium	AND	Medium	AND	High	AND	High	High
46	Medium	AND	High	AND	Low	AND	Low	Low
47	Medium	AND	High	AND	Low	AND	Medium	Medium
48	Medium	AND	High	AND	Low	AND	High	Medium
49	Medium	AND	High	AND	Medium	AND	Low	Medium
50	Medium	AND	High	AND	Medium	AND	Medium	High
51	Medium	AND	High	AND	Medium	AND	High	High
52	Medium	AND	High	AND	High	AND	Low	Medium
53	Medium	AND	High	AND	High	AND	Medium	High
54	Medium	AND	High	AND	High	AND	High	Very High
55	High	AND	Low	AND	Low	AND	Low	Low
56	High	AND	Low	AND	Low	AND	Medium	Low
57	High	AND	Low	AND	Low	AND	High	Medium
58	High	AND	Low	AND	Medium	AND	Low	Low
59	High	AND	Low	AND	Medium	AND	Medium	Medium
60	High	AND	Low	AND	Medium	AND	High	High
61	High	AND	Low	AND	High	AND	Low	Medium
62	High	AND	Low	AND	High	AND	Medium	Medium
63	High	AND	Low	AND	High	AND	High	High
64	High	AND	Medium	AND	Low	AND	Low	Low
65	High	AND	Medium	AND	Low	AND	Medium	Medium
66	High	AND	Medium	AND	Low	AND	High	High
67	High	AND	Medium	AND	Medium	AND	Low	Medium
68	High	AND	Medium	AND	Medium	AND	Medium	Medium
69	High	AND	Medium	AND	Medium	AND	High	High
70	High	AND	Medium	AND	High	AND	Low	Medium
71	High	AND	Medium	AND	High	AND	Medium	Medium
72	High	AND	Medium	AND	High	AND	High	Very High
73	High	AND	High	AND	Low	AND	Low	Medium
74	High	AND	High	AND	Low	AND	Medium	Medium
75	High	AND	High	AND	Low	AND	High	Medium
76	High	AND	High	AND	Medium	AND	Low	Medium
77	High	AND	High	AND	Medium	AND	Medium	High
78	High	AND	High	AND	Medium	AND	High	Very High
79	High	AND	High	AND	High	AND	Low	High
80	High	AND	High	AND	High	AND	Medium	Very High
81	High	AND	High	AND	High	AND	High	Very High

Table 9
Inference rules for customer perceived value determination.

Rule	*If*					*Then*
	Agility	Op	Reliability	Op	Responsiveness	CPV
1	Low	AND	Low	AND	Low	Very Low
2	Low	AND	Low	AND	Medium	Low
3	Low	AND	Low	AND	High	Low
4	Low	AND	Medium	AND	Low	Low
5	Low	AND	Medium	AND	Medium	Medium
6	Low	AND	Medium	AND	High	Medium
7	Low	AND	High	AND	Low	Medium
8	Low	AND	High	AND	Medium	Medium
9	Low	AND	High	AND	High	Medium
10	Medium	AND	Low	AND	Low	Low

(*continued on next page*)

Table 9 (*continued*)

Rule	*If*					*Then*
	Agility	Op	Reliability	Op	Responsiveness	CPV
11	Medium	AND	Low	AND	Medium	Medium
12	Medium	AND	Low	AND	High	Medium
13	Medium	AND	Medium	AND	Low	Medium
14	Medium	AND	Medium	AND	Medium	Medium
15	Medium	AND	Medium	AND	High	Medium
16	Medium	AND	High	AND	Low	Medium
17	Medium	AND	High	AND	Medium	Medium
18	Medium	AND	High	AND	High	High
19	High	AND	Low	AND	Low	Medium
20	High	AND	Low	AND	Medium	Medium
21	High	AND	Low	AND	High	Medium
22	High	AND	Medium	AND	Low	Medium
23	High	AND	Medium	AND	Medium	High
24	High	AND	Medium	AND	High	High
25	High	AND	High	AND	Low	Medium
26	High	AND	High	AND	Medium	High
27	High	AND	High	AND	High	Very High

Appendix B. Sensitivity analysis tests for FIS 1 and FIS 2

Table 10
Tests of input and output variables for agility – FIS 1.

FIS 1 tests	Tested Criteria				Agility
	UpSC(flex)	DownSC(ad)	OvRISK	UpSC(ad)	
1	10	5	0	5	5000
2	0	5	5	5	5000
3	5	0	5	5	5000
4	10	5	5	0	5000
5	10	0	10	5	5000
6	10	10	5	10	9180
7	5	5	5	0	5000
8	0	10	0	5	2500
9	5	10	10	0	5000
10	5	0	10	5	5000
11	10	10	10	10	9180
12	10	0	10	0	5000
13	0	10	5	5	5000
14	5	10	5	10	7500
15	10	10	0	0	5000
16	10	10	10	0	7500
17	10	0	0	5	2500
18	10	0	0	0	2500
19	10	5	5	5	5000
20	0	10	5	10	5000
21	5	10	0	0	2500
22	0	0	10	10	5000
23	0	0	5	0	0,817
24	0	0	10	0	2500
25	10	0	5	0	2500
26	0	10	0	10	5000
27	10	5	5	10	7500
28	5	5	5	10	5000
29	0	0	0	5	0,817
30	0	10	10	10	7500
31	5	5	10	5	5000
32	10	0	5	5	5000
33	0	10	0	0	2500
34	5	0	10	0	2500
35	5	0	0	10	2500
36	10	5	0	10	5000
37	5	10	10	10	9180
38	10	10	0	5	5000
39	0	10	5	0	2500
40	5	5	0	0	5000
41	0	0	10	5	2500
42	0	5	10	0	2500
43	10	0	10	10	7500
44	5	10	5	0	5000
45	5	0	10	10	7500

(*continued on next page*)

Table 10 (*continued*)

FIS 1 tests	Tested Criteria				Agility
	UpSC(flex)	DownSC(ad)	OvRISK	UpSC(ad)	
46	5	10	0	5	5000
47	5	10	10	5	7500
48	10	10	5	0	5000
49	5	5	10	10	7500
50	10	0	5	10	7500
51	10	5	10	10	9180
52	0	0	5	5	2500
53	10	10	5	5	7500
54	5	10	0	10	5000
55	0	10	10	0	5000
56	5	0	0	0	0,817
57	0	5	0	5	2500
58	0	5	10	10	5000
59	10	0	0	10	5000
60	10	10	0	10	5000
61	5	5	0	10	5000
62	10	5	0	0	2500
63	5	0	5	0	2500
64	0	5	5	10	5000
65	10	5	10	0	5000
66	5	5	5	5	5000
67	10	5	10	5	5000
68	5	0	0	5	2500
69	5	10	5	5	7500
70	5	5	10	0	5000
71	0	5	5	0	2500
72	0	0	0	10	2500
73	0	10	10	5	5000
74	5	5	0	5	5000
75	0	5	0	0	0,817
76	10	10	10	5	9180
77	0	0	5	10	2500
78	5	0	5	10	5000
79	0	5	10	5	5000
80	0	5	0	10	5000
81	0	0	0	0	0,817

Table 11
Tests of input and output variables for CPV – FIS 2.

FIS 2 tests	Tested Criteria	CPV		
	Agility	Reliability	Responsiveness	
1	5	0	0	2.500
2	0	0	0	0.817
3	5	0	10	5.000
4	10	10	10	9.180
5	0	5	0	2.500
6	0	0	10	2.500
7	10	0	0	5.000
8	10	5	10	7.500
9	5	0	5	5.000
10	0	10	5	5.000
11	10	10	0	5.000
12	10	10	5	7.500
13	0	10	10	5.000
14	10	5	5	7.500
15	5	10	10	7.500
16	0	10	0	5.000
17	10	0	5	5.000
18	0	5	10	5.000
19	5	5	5	5.000
20	5	10	5	5.000
21	0	5	5	5.000
22	10	5	0	5.000
23	0	0	5	2.500
24	10	0	10	5.000
25	5	5	10	5.000
26	5	5	0	5.000
27	5	10	0	5.000

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijpe.2019.107520.

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