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S.I.: OR FOR SUSTAINABILITY IN SUPPLY CHAIN MANAGEMENT

Toward a sustainable supply chain for social credit: learning by experience using single-valued neutrosophic sets and fuzzy cognitive maps

Fernando A. F. Ferreira[1,2] · **Ieva Meidutė-Kavaliauskienė**[1,3]

Abstract
Social credit's goal of fighting poverty and social inequality has meant that this concept has attracted increasing interest, particularly after Muhammad Yunus was awarded the 2006 Nobel Peace Prize. However, studies that have analyzed the supply chain and socio-economic impacts of this type of micro-credit are still extremely rare. Social credit is an issue that needs to be taken seriously because its objectives differ from those of other types of credit, that is, its main goals go beyond profit to embrace additional social concerns. Adopting a process-oriented stance that used single-valued neutrosophic sets and fuzzy cognitive maps, this study sought to develop a cognitive structure that facilitates a deeper understanding of social credit's supply chain. Group meetings were held with a panel of professional credit analysts. The resulting framework shows that the socio-technical approach applied provides value for those analyzing the cause-and-effect relationships between the supply chain components of social credit. The results thus contribute to fulfilling social credit's goals of promoting sustainability and improving human lives. The advantages, managerial implications, and limitations of this research are also discussed.

Keywords Social credit · Sustainable supply chain (SSC) · Fuzzy cognitive mapping · Single-valued neutrosophic sets (SVNSs)

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1 Introduction

The 2008 financial crisis and its aftermath have affected the financial stability of individuals, companies, and countries (Ferreira et al. 2018). According to Yu et al. (2015), this turmoil has reduced individuals' economic freedom and, consequently, increased social inequality, poverty, and unemployment rates in different parts of the world.

Social credit is historically rooted in the fight against social inequality and poverty (*cf.* Douglas 1935) as a micro-credit that allows unemployed people to create and run their own businesses. This helps improve these individuals' economic situation and promote countries' socio-economic development. This type of micro-credit thus has both a clear social mission to alleviate poverty and a social impact on communities. Martin-Nielsen (2007), Ferreira et al. (2018) and Xavier et al. (2018) report that many societies' growth and development would be slower or even nonexistent without social credit.

Banks play an important role in financing social credit (Berger and Black 2011; Blanco et al. 2013; Bravo et al. 2013; Cornée and Szafarz 2014; Yu et al. 2015). For instance, they can help buyers and suppliers develop a more holistic understanding of this credit's supply chain, thereby improving its integration and optimizing resources (Silvestro and Lustrato 2014; Pramanik et al. 2017). Although social credit can serve as an engine of socio-economic development (Hutchinson and Burkitf 1997), social credit's main objectives go beyond profit to embrace additional social concerns (*cf.* Douglas 1935; Martin-Nielsen 2007; Cooney and Lynch-Cerullo 2014; Ferreira et al. 2018; Xavier et al. 2018). This means its supply chain needs to be sustainable, which, in turn, requires a thorough understanding of social credit's determinants. Pramanik et al. (2017, p. 205) argue that sustainability is particularly important because *"all players of a coordinated supply chain get better shares of benefit*[s] *which cannot be obtained when* [each] *one optimizes its own decision individually"*. Given this context, two interlinked questions need to be addressed:

- How can the determinants of social credit be identified?
- What are these determinants' impacts on the sustainability of social credit's supply chain?

Identifying and understanding the conditions that underpin social credit, as well as acknowledging and clarifying the links between them, is a crucial part of enhancing value creation and achieving the desired sustainability goals.

The present study adopted a constructivist, process-oriented stance and sought to answer the above questions through the integrated use of single-valued neutrosophic sets (SVNSs) and fuzzy cognitive maps (FCMs). The resulting framework can be used to highlight imprecise and incomplete information and increase the efficiency and quality of the information used. Accurate and reliable information can increase the efficiency of social credit by making the decision-making process more logical and realistic.

Introduced as a variation of fuzzy and intuitionistic fuzzy sets, neutrosophic sets (NS) have been incorporated into decision-making processes to represent incomplete, imprecise, uncertain, and inconsistent information that exists in real-world decision situations (Peng et al. 2014a). FCMs, in turn, are a well-established problem-structuring tool that facilitates the representation of knowledge, supports the identification and interpretation of information, and stimulates mental associations (Kosko 1986; Ferreira 2016; Ribeiro et al. 2017). The integrated use of these methodological tools (i.e., NS and FCMs) facilitates the identification of the different criteria related to the decision problem at hand, as well as a better understanding of their cause-and-effect relationships (Yaman and Polat 2009; Salmeron 2012).

Although this methodological approach is not new in banking contexts (e.g., Ferreira et al. 2016, 2017; Azevedo and Ferreira 2017; Carlucci et al. 2018; Santos et al. 2018),

a review of the relevant literature found no prior studies reporting the use of SVSNs and FCMs to analyze social credit's supply chain. The proposed methodology thus contributes to the extant literature on finance, sustainability, supply chain management, and operational research/management science (OR/MS).

This paper is organized as follows. The study's theoretical foundation and literature review of research on social credit and its supply chain are presented in section two. Section three presents the methodological background of the techniques applied. Section four describes the methodological processes followed during the group meetings with a panel of professional credit analysts. Section five concludes the paper by highlighting the study's main contributions and presenting a roadmap for future research.

2 Background on social credit and its supply chain

Although social credit's roots date back to the 1930s (Douglas 1935), interest in this type of credit increased significantly only after Muhammad Yunus was awarded the 2006 Nobel Peace Prize. More in-depth discussions of social credit's origins and baseline principles can be found in Hutchinson and Burkitf (1997), Martin-Nielsen (2007), Ferreira et al. (2018) and Xavier et al.'s (2018) work. According to Douglas (1935), a fear of poverty is seen as the least efficient way to achieve economic development, so, instead of allocating direct subsidy funds to economic agents, governments need to create credit lines. In this way, they can provide support to those who seek to achieve financial stability by running their own businesses.

No consensus has yet been reached on how to conceptualize social credit. However, it is broadly understood as a type of micro-credit that focuses on fighting social inequality and poverty (*cf.* Douglas 1935; Martin-Nielsen 2007; Yu et al. 2015; Ferreira et al. 2018). Because this credit is not backed by collateral—that is, no guarantee of reimbursement is required—Yu et al. (2015) note that social credit can be an extremely important way to reduce levels of poverty and crime or even the likelihood of war. Consequently, social credit increases individuals' economic stability and strengthens socio-economic sustainability. Banks and other credit institutions have realized that their stakeholders' poor environmental and social performance, especially that of clients, can represent a threat to these institutions' profitability.

However, according to Carlucci et al. (2018), a challenge arises from the considerable number of stakeholders potentially involved, who do not necessarily share the same interests and priorities. Gómez-Luciano et al. (2018, p. 311) note that *"intermediary stakeholders' organizations in the supply chain play a key role in the development of a sustainable supply chain* [SSC]*"*. These stakeholders' social and ethical values contribute to the supply chain's social sustainability through successful collaboration and ethical sourcing (Railienė and Sinevičienė 2015; Gómez-Luciano et al. 2018). Figure 1 presents the stakeholders who can influence the sustainability of social credit's supply chain.

The specific characteristics of this type of micro-credit—whose objectives, as mentioned previously, go beyond profit—need to be highlighted since these mean that the provision of social credit cannot be analyzed in the same way as other types of credit are. Carlucci et al. (2018, p. 1304) state that *"recent analyses have shown that sustainable, values-based banks, which try to base their decisions taking into account the triple bottom line* […] *thus considering the needs of people and the environment, in addition to profit, are often outperforming traditional mainstream banks in terms of financial indicators"*. Figure 2 diagrams the influence of social concerns on the supply chain of social credit.

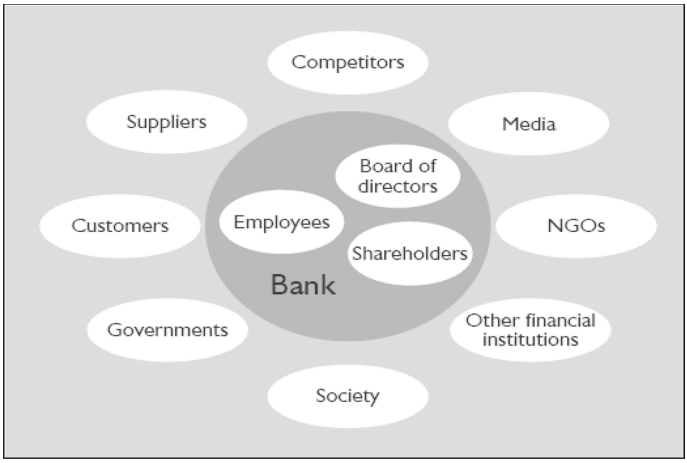

Fig. 1 Internal and external stakeholders of social credit's supply chain. *Source*: Jeucken and Bouma (1999)

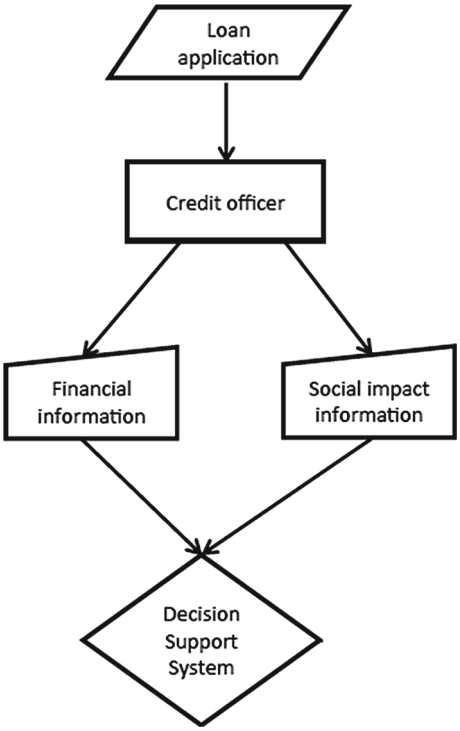

Fig. 2 Influence of social concerns on social credit's supply chain. *Source*: Adapted from Serrano-Cinca et al. (2016, p. 3507)

Due to the difficulty of identifying who truly is on or below the poverty line, Silvestro and Lustrato (2014) and Serrano-Cinca et al. (2016) point out that social credit's supply chain must be carefully analyzed. According to Martin-Nielsen (2007), Zhang et al. (2016), Ferreira et al. (2018) and Xavier et al. (2018), this supply chain is not without its limitations, most of which are related to the selection and operationalization of evaluation criteria for assessing social credit applications and their respective socio-economic impacts. Calculating

financial and non-financial returns cannot follow the same procedures, and the latter needs to consider the social impacts that the credit will have (*cf.* Abdou and Pointon 2011; Cooney and Lynch-Cerullo 2014; Cornée and Szafarz 2014; Serrano-Cinca et al. 2016).

These aspects are important when the specific nature of social credit is considered, given that evaluators (i.e., banks or credit institutions), as discussed earlier, should be open to subjective factors and sensemaking processes. Concurrently, this allows the United Nations' (2015) first principle of responsible investment to be respected by incorporating environmental, social, and governance issues into investment analyses and decision-making processes. In this way, the social dimension and sustainability objectives of social credit can be emphasized.

However, Serrano-Cinca et al. (2016, p. 3505) report that, *"when incorporating social* […] *aspects* […], *many conceptual problems arise. The lack of sufficient social* […] *data makes it difficult to use conventional statistical tools"*. Thus, the first research question addressed in the present study pertained to the key determinants of social credit and the ways they interrelate with each other. Identifying and understanding these determinants and clarifying the links between them is crucial to enhancing value creation because this analysis helps introduce social issues into the entire micro-finance value chain. By improving the current understanding of these determinants, the present research's results are expected to contribute to better credit granting decisions and thus to an SSC in social credit contexts. As Tang (2018, p. 1) points out, this is a matter that needs to be taken seriously primarily because *"the area of socially responsible supply chain*[s] *is not well understood"*.

The current study's second research question sought to determine whether an experience-based representation of social credit can be developed and whether this framework can enhance value creation and contribute to an SSC. While sustainability in supply chain management has been heavily researched (*cf.* Gómez-Luciano et al. 2018; Tang 2018), little theoretical and empirical research has focused on social credit's supply chain. Thus, a fuller understanding of this hitherto largely underdeveloped topic is not only of academic interest but also of great utility to the decision makers involved. This study proposed the combined use of SVNSs and FCMs specifically to identify the determinants of social credit and their cause-and-effect relationships.

3 Methodology

3.1 Principles of neutrosophic sets

Social credit's objectives go far beyond profit by including additional social concerns. In real life situations, however, the information available for analyses of social credit applications is imprecise, uncertain, or incomplete, thereby decreasing social credit's efficiency. Because the traditional methods of probabilities cannot deal with vague, uncertain, and incomplete information, Smarandache (1999) introduced the neutrosophic logic. This is a powerful, general, and formal framework that generalizes the concepts of classic, fuzzy, and intuitionistic fuzzy sets in order to measure truth, indeterminacy, and falsehood (Lupiáñez 2017; Zavadskas et al. 2017; Abdel-Basset and Mohamed 2018).

In broad terms, Neutrosophy is an epistemological approach that studies the origin, nature, and scope of neutralities, as well as their interactions with different ideational spectra (*cf.* Smarandache and Pramanik 2016). Therefore, NS are powerful logics designed to facilitate understanding of indeterminate or inconsistent information (Peng et al. 2014a). Although each set theory has advantages and disadvantages, by applying neutrosophic operators (i.e.,

union, intersection, etc.), uncertainty and indeterminacy are taken into consideration in the decision-making process.

According to Smarandache (1999) and Ye (2013), a neutrosophic set N in X is defined on a universe of discourse U and specified by truth $TN(x)$, indeterminacy $IN(x)$, and falsity $FN(x)$ membership functions. In this definition, $x \in X$ and $TN(x)$, $IN(x)$, and $FN(x)$ are real standard or non-standard subsets of $]-0, 1+[$ (*i.e.*, $TN(x)$: $X \rightarrow]-0, 1+[$; $IN(x)$: $X \rightarrow]-0, 1+[$; and $FN(x)$: $X \rightarrow]-0, 1+[$). No constraints exist on the sum of $TN(x)$, $IN(x)$, and $FN(x)$, so $-0 \leq \sup TN(x) + \sup IN(x) + \sup FN(x) \leq 3+$ (*cf.* Ji et al. 2018). In practice, if an expert is asked his or her opinion about a certain statement, he or she may say that the probability that the statement is true is 0.5, 0.6 that it is false, and that the degree to which he or she is not sure is 0.2. In neutrosophic notation, this can be expressed as $x(0.5, 0.2, 0.6)$ (Ye 2013; Peng et al. 2014b).

Because neutrosophic set and set-theoretic operators need to be specified to be used in real-life applications (*cf.* Ye 2013; Abdel-Basset and Mohamed 2018), Wang et al. (2010) proposed the concept of SVNSs. This is an instance of NS that allows the ambiguous nature of subjective judgments to be modeled, capturing imprecise, uncertain, and inconsistent information in multiple-criteria decision situations. Mathematically, an SVNS N in X takes the form $N = \{\langle x, TN(x), IN(x), FN(x)\rangle : x \in X\}$, in which $TN(x)$: $X \rightarrow [0, 1]$, $IN(x)$: $X \rightarrow [0, 1]$, and $FN(x)$: $X \rightarrow [0, 1]$ with $0 \leq TN(x) + IN(x) + FN(x) \leq 3$ for all $x \in X$. For simplification, a SVNS number is exemplified by $N = (a_1, a_2, a_3)$, in which $a_1, a_2, a_3 \in [0, 1]$ and $a_1 + a_2 + a_3 \leq 3$.

The mathematical foundations of SVNS are thoroughly discussed by Wang et al. (2010), Peng et al. (2014b), Abdel-Basset and Mohamed (2018), Ji et al. (2018) and Vafadarnikjoo et al. (2018). The present study, however, used Ye's (2013, p. 391) definition, namely, that *"an SVNS is a generalization of classic set, fuzzy set, intuitionistic fuzzy set, and paraconsistent set* […]*, and* [SVNSs] *can handle not only incomplete information but also the indeterminate* […] *and inconsistent information which exist*[s] *commonly in real situations"*. This approach is considered extremely useful in the context of social credit, in which most of the available information is inaccurate, fuzzy, or incomplete.

Following this, the reasons of our methodological option should be highlighted. First, as explained by Smarandache and Pramanik (2016, p. 9), *"NS approaches are suitable to modeling problems with uncertainty, indeterminacy and inconsistent information in which human knowledge is necessary, and human evaluation is needed"*, which seems to be the case of social credit evaluations. Second, social credit's main objectives go beyond profit to embrace additional social concerns. This aspect is important when the specific nature of social credit is considered, given that evaluators (*i.e.*, banks or credit institutions) should be open to subjective factors and sensemaking processes. Last, because the results obtained by NS allow uncertainty and indeterminacy to be taken into consideration in the decision-making process, their use to address the evaluation of social credit applications seems to be a very promising line of research. As pointed out earlier, accurate and reliable information can increase the efficiency of social credit by making the decision-making process more logical and realistic.

3.2 Cognitive and fuzzy cognitive mapping

Humans' information-processing capacity is widely acknowledged to be severely bounded by individuals' limited cognitive capacity to store information and pursue multiple objectives at the same time. The list of limitations in this area is quite long, and they are often

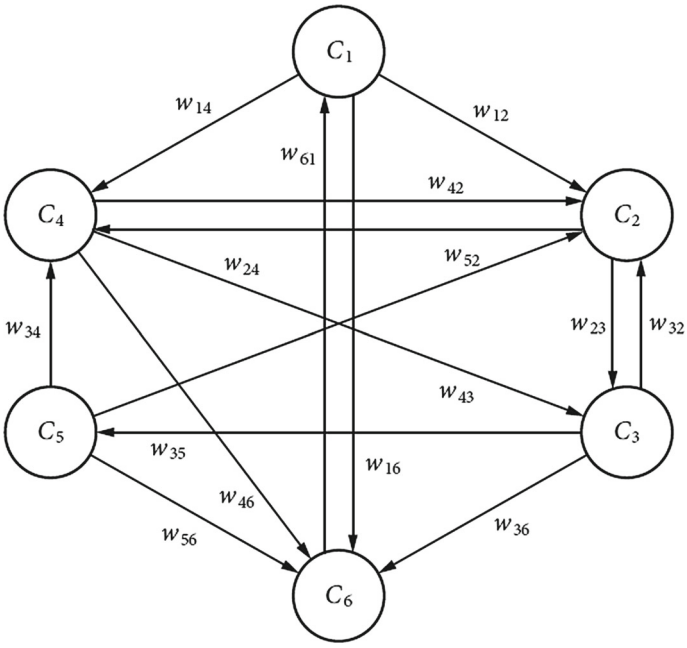

Fig. 3 Example of an FCM. *Source*: Kang et al. (2012, p. 78)

suspected of being the culprit behind lapses in reasoning (Kahneman and Tversky 1982). While attempting to address this issue, Ackermann and Eden (2001), Montibeller and Belton (2006) and Carayannis et al. (2018), among many other authors, note that cognitive mapping can be useful as a way both to reduce the number of omitted criteria in decision-making frameworks and to increase people's understanding of the cause-and-effect linkages between variables and/or concepts. Cognitive maps can also be seen as knowledge-sharing tools, which Eden (2004) defines as representations, schemas, or mental models created by individuals to reveal subjective information they want to provide to others. Thus, these maps allow complex decision problems to be structured and resolved more efficiently.

The efficient use of this methodological tool depends on the decision makers' objectives, type of decision problem to be analyzed, and nature of the decision-making context, but cognitive maps allow different individuals to negotiate the input. This process increases learning through an improved understanding of the decision situation at hand (see Ackermann and Eden 2001; Belton and Stewart 2002; Faria et al. 2018; Fonseca et al. 2018). Despite the practical advantages of cognitive mapping, Stylios and Groumpos (1998), Papageorgiou (2013), Misthos et al. (2017) and Ribeiro et al. (2017) argue that "simple" cognitive maps are incapable of embodying the true dynamics of real decision problems because the intensity of the cause-and-effect relationships between concepts and/or criteria remains unquantified.

In light of this limitation, Kosko (1986) developed the fuzzy cognitive mapping approach, which adds elements from fuzzy logic and artificial neural networks to the cognitive mapping approach to produce FCMs. In these maps, each cause-and-effect relationship is represented by an arrow and a real number w_{ij} that represents the degree of influence that an arrow-tail concept *Ci* has on an arrow-head concept *Cj*. An example of an FCM is provided in Fig. 3.

According to Kosko (1986), the value w_{ij} assumes a real number between -1 and 1 according to the following three conditions. The first is $w_{ij} < 0$, in which an increase (decrease)

in C_i leads to a decrease (increase) in C_j. The second condition is $w_{ij} = 0$, in which no cause-and-effect relationship exists between C_i and C_j. The last is $w_{ij} > 0$, in which an increase (decrease) in C_i leads to an increase (decrease) in C_j.

In algebraic terms, FCMs are grounded on a state vector A and an adjacent matrix W (Stylios and Groumpos 1998; Salmeron 2012). In the state vector A ($[1 \times n]$), n is the number of concepts in the FCM, and the state values a_i are between -1 and 1 (Kosko 1986; Tsadiras 2008). The adjacent matrix W $[n \times n]$, in turn, comprises the degree of intensity w_{ij} of the relationships between concepts (Ferreira 2016) so that the main diagonal only includes zeros because a concept rarely causes itself (Stylios and Groumpos 1998; Tsadiras 2008; Carvalho 2013; Ribeiro et al. 2017). Thus, state values can be predicted by applying Eq. (1) (*cf.* Kosko 1986; Stylios and Groumpos 1998):

$$A_i^{(t+1)} = f\left(\sum_{\substack{j=1 \\ j \neq i}}^{n} A_j^{(t)} \times w_{ji}\right) \tag{1}$$

in which $A_i^{(t+1)}$ is the activation level of concept i at moment t+1, $A_j^{(t)}$ is the activation level of concept j at moment t, w_{ji} is the degree of intensity of the relationship between C_j and C_i, and f is the threshold function that confines the state value to an interval. Tsadiras (2008), Mazlack (2009) and Azevedo and Ferreira (2017) assert that the threshold function can assume different forms: (1) binary (i.e., $f(x) = 0$ or 1), (2) trivalent (i.e., $f(x) = -1,\ 0,$ or 1), (3) sigmoid (i.e., $f(x) \in [0;\ 1]$), or (4) hyperbolic tangent (i.e., $f(x) \in [-\ 1;\ 1]$). This approach enables qualitative comparisons between concepts and allows the researcher to assign them a meaning.

Basically, FCMs are begun by applying a stimulus, namely, the attribution of an activation level to one or more concepts included in the map. The degree of intensity of the relationships between concepts and/or criteria then causes an *"iterative mechanism, which propagates in the network the initial node stimulations and,* [… in] *this way, estimates the direct and indirect effects ending in each concept"* (Kouloutiotis 2004, p. 217). According to Salmeron (2012), this causal propagation results, after a few simulations, in the following three possible system behaviors: (1) equilibrium; (2) cyclic behavior; or (3) chaotic behavior. These results allow decision makers to formulate "what-if" questions and understand more fully the decision problem under study (Yaman and Polat 2009; Carlucci et al. 2018). Because of this feature, the combined use of FCMs with SVNSs has the potential to produce a transparent, well-informed, and logical decision-making framework for use in the assessment of social credit applications, increasing the efficiency and quality of the entire evaluation process.

4 Application and results

The present study sought to analyze the conditions and key determinants of social credit and its supply chain. A better understanding of these determinants and the ways they relate to each other can help bank managers and other decision makers to enhance value creation through more informed decisions. Concurrently, this allows social credit's sustainability objectives to be achieved more efficiently.

4.1 Participants

For the current FCM development process, a panel of decision makers (i.e., experts) involved in credit risk assessment was formed because, according to Yaman and Polat (2009, p. 387), *"using a group of experts has the benefit of improving the reliability of the final model"*. More specifically, the panel consisted of six professional credit risk analysts from the four largest banks operating in Portugal, thereby representing a quite significant proportion of the country's banking system (*cf.* Ferreira and Monteiro-Barata 2011).

These analysts each had from 10 to 30 years of experience evaluating different types of credit applications, including for social credit, but other criteria also supported the selection of specific participants. First, Eden and Ackermann (2001, p. 22) suggest that the facilitator (i.e., researcher) needs to *"relate personally to a small number* [of participants such as] […] *three to ten persons"*. Second, the panel needed to incorporate participants with a high level of expertise in credit risk analysis. Third, panel members should be heterogeneous in terms of gender, age, academic background, and professional experience. Last, the experts had to be available to participate in two 4-h group meetings, for a total of 8 h of group work.

Notably, the goal of this selection process was not to achieve representativeness or to facilitate generalizations but rather to focus strongly on the assessment process of social credit applications. Due to the study's constructivist, process-oriented stance, the primary objective was to bring together the experience and practical know-how of professional credit analysts, thereby gaining new insights and using these to create an evaluation framework. Bell and Morse (2013, p. 13) note that the constructivist stance of this type of approach puts *"less emphasis on outputs* per se *and more focus on process"*. Therefore, although the results are context-specific, the procedures followed, if correctly adjusted, can work well with different panels or in other contexts (see also Belton and Stewart 2002).

4.2 Construction of initial cognitive structure

The first group meeting was held to identify social credit evaluation criteria and organize them into a simple cognitive structure that could be converted into a group FCM. To start the group work, the facilitator—one of the authors of this paper—carefully explained the methodological procedures and respective objectives to avoid possible misunderstandings. The following trigger question was then asked: *"According to your values and professional experience as credit analysts, what are the most important criteria that should be used when deciding whether to grant social credit?"*. According to Ackermann and Eden (2001), Tegarden and Sheetz (2003) and Faria et al. (2018), a well-defined trigger question is vital to stimulating reflection on the decision problem and discussion among the participants.

In broad terms, we followed the fundamentals of the Strategic Options Development and Analysis (SODA) approach. According to Eden and Ackermann (2001), there are no strict rules for the application of the SODA methodology: participants are free to identify criteria and create clusters, as long as the group approves the cognitive structure, based on what is invariably a very dynamic and interactive negotiation process. To facilitate the criteria identification, the "post-its technique" was used (Eden and Ackermann 2001). More specifically, the group was invited to share opinions, values, and experiences that would help identify relevant criteria for the assessment of social credit applications. These criteria were written on post-it notes (i.e., one criterion per post-it) (see Ribeiro et al. 2017), which were subsequently organized into "areas of concern" (i.e., clusters).

Six clusters were identified by the group after intense collective discussion. The first is *external surroundings*, which includes variables related to the business environment such as social policies and demographic and macroeconomic factors. The second is *project*, which incorporates evaluation criteria related to social projects such as purpose, job creation, target market, competitors, potential customers, business plan quality, and financial viability. The third cluster is *customer profile and guarantees*, which includes variables related to the applicants' creditworthiness and their guarantors (i.e., other people responsible for reimbursing the credit in case of default). The fourth cluster is *aspects of profitability and risk for banks*, which covers financial variables, such as rate of indebtedness, level of exposure, and credit volume, and which ensure a balance between projects' profitability and risk. The fifth is *governance*, which includes analyses of clients' organizational model, including their decision-making policies. The last cluster is *deal breakers*, which involves all situations that prevent the granting of social credit such as fraud, money laundering, and the absence of confidence in clients.

In the next stage of the meeting, the criteria were reorganized inside each cluster according to their relative importance so that the most important ones were placed at the top of the respective cluster and the least important at the bottom. After another round of discussion and negotiation, a group consensus was achieved, and an initial cognitive map was generated using the *Decision Explorer* software (www.banxia.com) (see Fig. 4. Size restrictions prevent a better visualization, but an editable version of the map can be obtained from the corresponding author upon request).

As shown in Fig. 4, each arrow stands for a cause-and-effect relationship, thereby visualizing the interactions between criteria and improving the decision makers' understanding of the social credit risk evaluation process. Although subjective in nature, the constructivist stance of the cognitive mapping techniques applied facilitated continuous learning through discussions among the credit analysts. This proved important in terms of the procedures followed and reinforced the process-oriented nature of the proposed methodology (Bell and Morse 2013; Carlucci et al. 2018).

4.3 FCM development

As noted in Sect. 3.2, simple cognitive maps are unable to represent decision situations dynamically. Thus, the second group session was dedicated to developing an FCM, in which the social credit evaluation system's dynamics were represented by fuzzy quantification of the links between criteria, using an interval from − 1 to 1 (Kosko 1986). This exercise was, furthermore, combined with an application of the neutrosophic set method. The panel members were asked to quantify the links between the criteria identified in the first meeting and to specify the probability that the corresponding statements about relationships were true, uncertain, or false (see Sect. 3.1).

The participants engaged in detailed discussions during this exercise, in which all degrees of intensity—related to the FCM—and respective statement possibilities—related to NS—were carefully debated and collectively accepted. Given the heterogeneous experiences reported by the panel members, negotiation was a key component in this phase of the process.

With all the relationships and statement possibilities quantified, an FCM could be created using the *FCMapper* (www.fcmappers.net) and Pajek (www.mrvar.fdv.uni-lj.si/pajek) software packages. Figure 5 presents the cognitive structure of what would become the FCM. To simplify this figure, all labels have been removed, but an editable version with all specifications is available upon request.

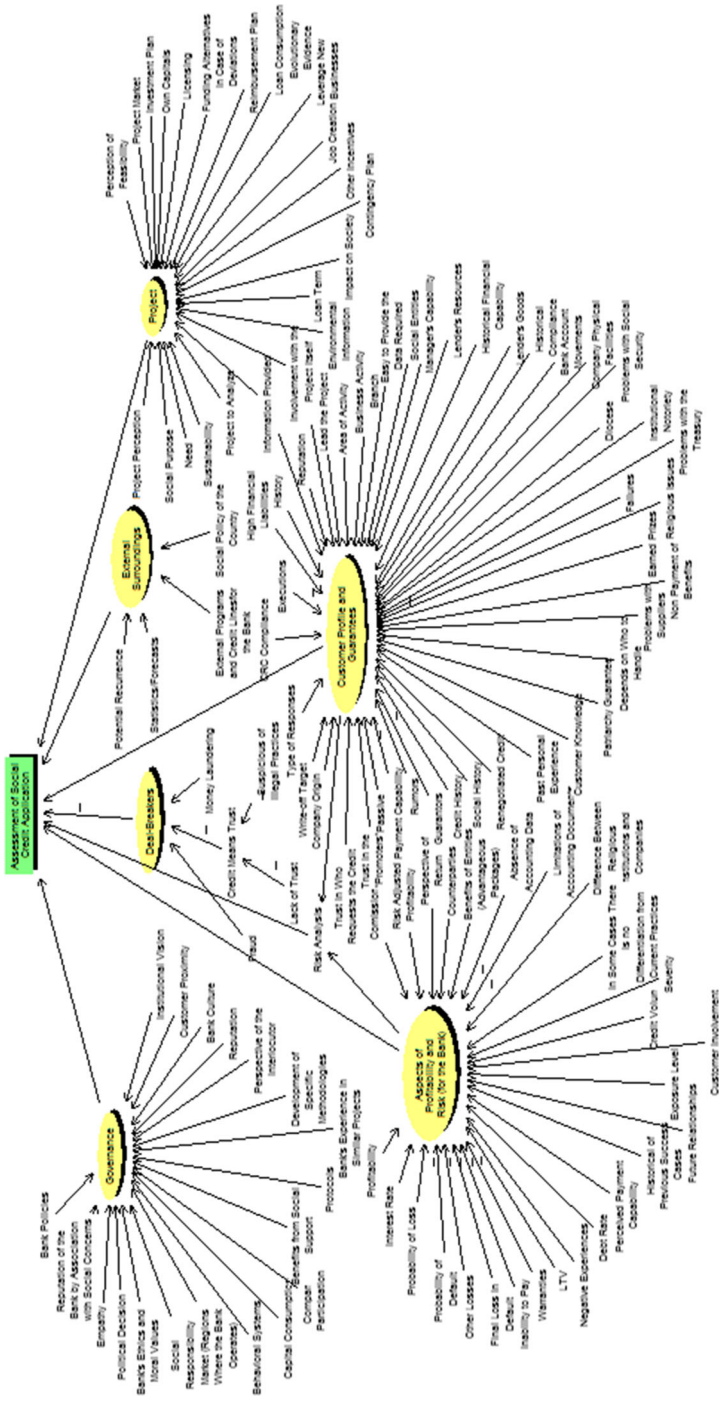

Fig. 4 Initial group cognitive map. *Source:* Adapted from Ferreira et al. (2018)

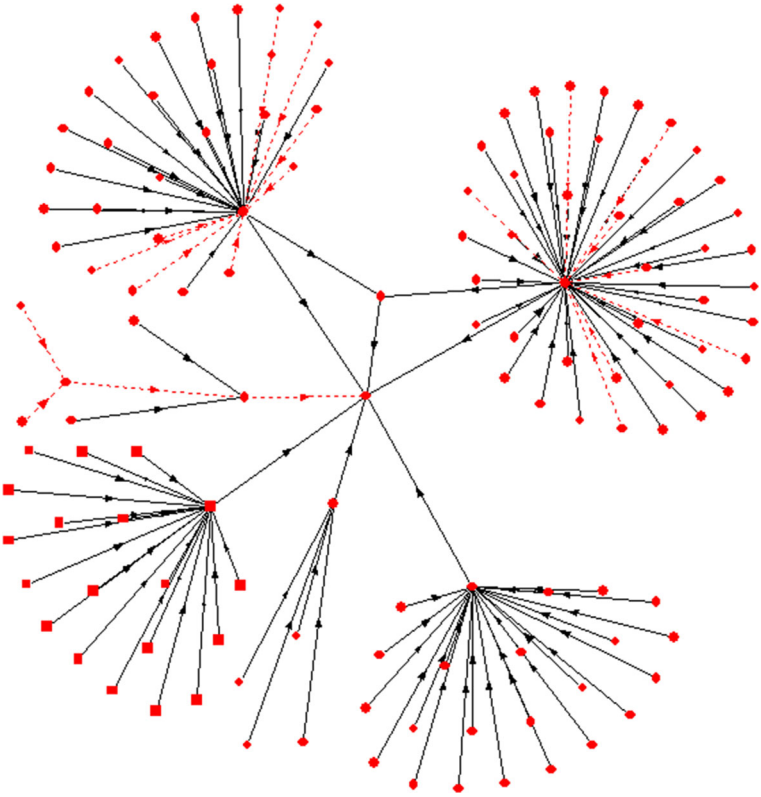

Fig. 5 FCM structure of social credit evaluation

Notably, the values of w_{ij} were directly projected by the panel members during a lengthy negotiation. In this process, the SVNS approach was applied (see Sect. 3.1), and the truth-membership, indeterminacy-membership, and falsity-membership degrees for each element were represented by singleton sub-sets. Figure 6 offers an example of this exercise's results. As required by the FCM approach, the intensities of the cause-and-effect links included in the cognitive structure were inserted into an adjacency matrix W. Size restrictions make the presentation of W in this paper impossible. Table 1 thus provides an example of the matrix used, although a file containing all specifications is available upon request.

Several simulations were carried out at this stage of the process to ensure the social credit evaluation system's stability. The visualization of the FCM's dynamics provided the panel members with a realistic overview of the impact each evaluation criteria could have on social credit risk analyses. According to Carlucci et al. (2013, p. 216), *"once the FCM has been constructed, it can be used to model and simulate the behavior of the system including performance objectives, process performance objectives and knowledge assets"*. The next phase of the present research was the group's analysis of the key criteria influencing social credit risk assessments, which facilitated an enhanced understanding of the supply chain components of social credit.

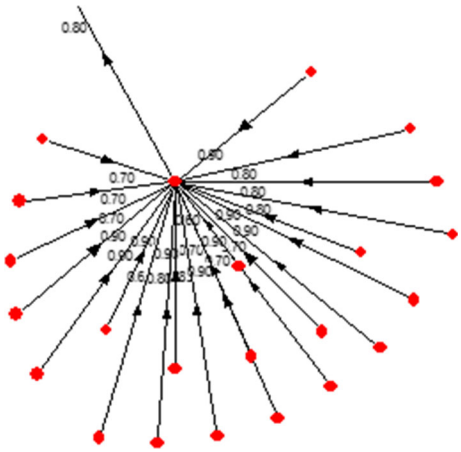

Fig. 6 Intensity degrees for one of the clusters

Table 1 Adjacency matrix example

	C_1	C_2	…	C_{n-1}	C_n
C_1	0	w_{12}	…	w_{1n-1}	w_{1n}
C_2	w_{21}	0	…	w_{2n-1}	w_{2n}
…	…	…	…	…	…
C_{n-1}	w_{n-11}	w_{n-12}	…	0	w_{n-1n}
C_n	w_{n1}	w_{n2}	…	w_{nn-1}	0

4.4 Static and dynamic analyses of results

FCMs are constructed both to facilitate the identification of evaluation criteria and respective cause-and-effect relationships and to predict their behaviors in future scenarios (Tsadiras 2008). Ferreira (2016) classifies these two types of analyses as static and dynamic, respectively. Both were conducted in the current study. In the static analysis, no changes were introduced in the social credit evaluation system's initial values.

4.4.1 Static analysis

Static analysis is based on the concepts' degree of centrality, which allows each criterion's influence on the system in question to be analyzed. Misthos et al. (2017) and Ribeiro et al. (2017) observe that a high degree of centrality indicates that a criterion is extremely important. Table 2 presents only the social credit evaluation criteria that showed the highest degrees of centrality, but the complete list is available upon request.

According to the panel members' collective perception, the most significant concepts and/or criteria of the social credit supply chain are: *customer profile and guarantees* (27.70); *aspects of profitability and risk for the bank* (20.20); *project* (18.30); *governance* (11.90); *external surroundings* (3.50); and *deal breakers* (3.50). These results were compared with Ferreira et al. (2018) and Xavier et al.'s (2018) findings, revealing slight changes in the ranking of the criteria and/or determinants obtained. For instance, *customer profile and guarantees* was ranked in first place in the present study, while in Ferreira et al. (2018) and Xavier et al.'s (2018) work the determinant of *deal breakers* was given greater priority.

Table 2 Degree of centrality of social credit evaluation criteria

Evaluation criterion	Outdegree	Indegree	Centrality
Customer profile and guarantees	1.50	26.20	27.70
Aspects of profitability and risk for the bank	1.40	18.80	20.20
Project	0.80	17.50	18.30
Governance	0.70	11.20	11.90
External surroundings	0.70	2.80	3.50
Deal breakers	0.90	2.60	3.50

Nonetheless, the current findings are consistent with the results of the previously discussed research in this field. In addition, the FCM developed in the present study facilitated the identification of a wide range of factors, components, and criteria in a quite transparent and logical manner. By identifying the most central criteria influencing social credit assessment, these results can help credit analysts evaluate social credit applications based on a transparent, well-informed framework.

4.4.2 Dynamic analysis

Within the FCM approach, dynamic analysis involves the assignment of activation values to criteria, thereby representing plausible scenarios and allowing specific effects to be predicted through simulations (Misthos et al. 2017). This analysis was conducted in the present study using the *Mental Modeler* software (www.mentalmodeler.org), and was divided into two levels: inter- and intra-cluster.

Inter-cluster analysis As previously mentioned, the participating credit analysts collectively identified six clusters as important determinants of social credit's supply chain (see Fig. 4; Table 2). In this study, inter-cluster analysis submitted each of these six cluster to multiple variations (i.e., − 0.50, 0.75, and 1.00) in order to understand their impact on the social credit assessment process. Figures 7, 8 and 9 track the behavior of this determinant (i.e., social credit application evaluation) as each cluster was changed by − 0.50, 0.75, and 1.00, respectively.

As can be seen in Figs. 7, 8 and 9, *deal breakers* is the only cluster with a negative impact on the assessment of social credit applications. As revealed by the initial group cognitive map, this effect occurs because the cluster has a negative cause-and-effect relationship with the system's evaluation purpose. Thus, when deal breakers decrease (increase), this induces an increase (decrease) in favorable assessments of social credit applications.

In general, the clusters' influence on evaluations of social credit applications is uniform for the different variations simulated. The *costumer profile and guarantees* cluster has the strongest influence (0.87 in a 1.00 variation), followed by *aspects of profitability and risk for the bank* (0.85). These insights can help credit analysts rationalize their decisions based on these determinants rather than other factors.

Intra-cluster analysis At the intra-cluster level, various criteria from each cluster were selected and submitted to variations of − 0.50, 0.75, and 1.00. As exemplified in Fig. 10, the objective was to analyze these collectively and discuss the selected criteria's effect on their respective cluster.

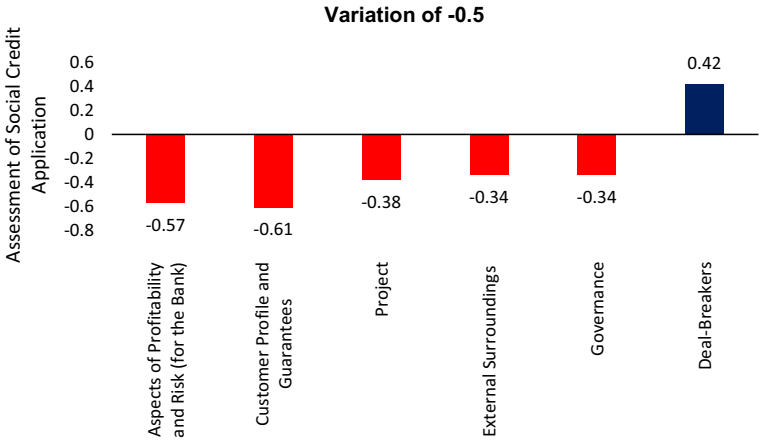

Fig. 7 Impact on social credit assessment of − 0.50 variation in each cluster

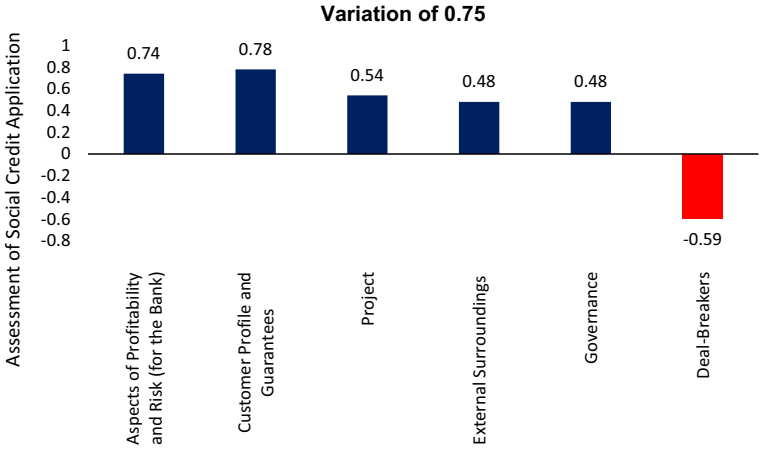

Fig. 8 Impact on social credit assessment of 0.75 variation in each cluster

As shown in Fig. 10, the intra-cluster analysis can provide support for decision making because the results facilitate the identification and understanding of the causes of the clusters' behavior. Similar to cluster level analysis, intra-cluster evaluations facilitate the identification and understanding of key criteria when granting social credits.

In this study, a battery of analyses at this level were carried out for different logical chains in the FCM created, which allowed for a deeper reflection on and fuller understanding of the social credit assessment process. This was considered an extremely positive outcome by the expert panel members. From their perspective, the primary benefit is that the socio-technical approach applied (i.e., a combination of FCMs and SVNSs) provides value for those seeking to analyze the cause-and-effect relationships between the supply chain components of social credit. This, in turn, contributes to the achievement of its sustainability goals. Table 3 presents the impacts found by the dynamic analyses at the intra-cluster level.

As discussed earlier, the granting of social credit is as an engine of social and economic development. However, for this to occur, social credit requires an SSC, which requires a

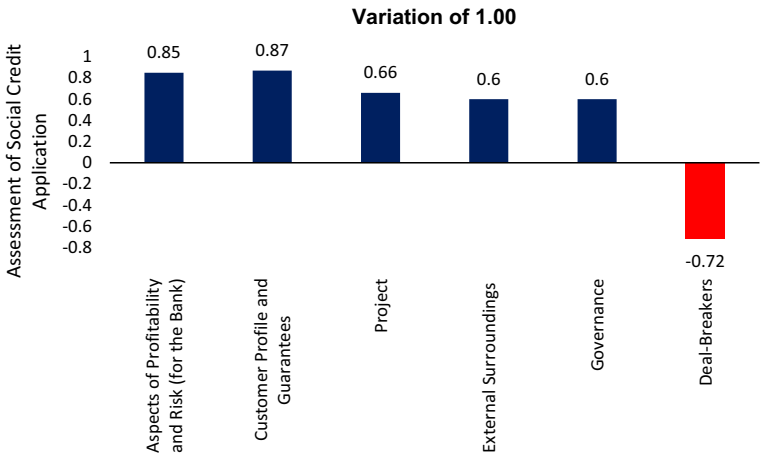

Fig. 9 Impact on social credit assessment of 1.00 variation in each cluster

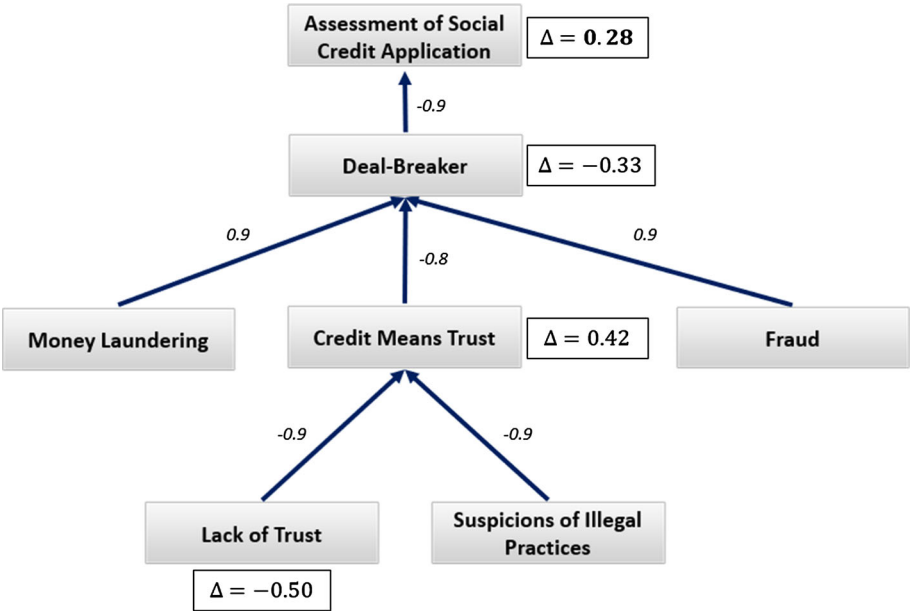

Fig. 10 Example of intra-cluster analysis

thorough understanding of the determinants of this type of micro-credit. This is precisely what the present study accomplished by combining SVNSs and FCMs, thereby contributing to the extant literature on finance, sustainability, supply chain management, and OR/MS.

4.5 Validation, limitations, and recommendations

The determinants of social credit and their cause-and-effect relationships were represented using an SVNS–FCM framework that required the organization of information provided by a

Table 3 Results of intra-cluster analyses

Evaluation criterion	Intensity degree	− 0.50 Variation	0.75 Variation	1.00 Variation
Customer profile and guarantees				
Trust in the person requesting the credit	0.90	− 0.52	0.59	0.72
Trust in the "promoters"	0.90	− 0.52	0.59	0.72
Payment capacity	0.80	− 0.38	0.54	0.66
Previous failures	0.70	− 0.34	0.48	0.60
Aspects of profitability and risk for the bank				
Risk-adjusted profitability	0.80	− 0.38	0.54	0.66
Loan-to-value ratio	0.80	− 0.38	0.54	0.66
Debt rate	− 0.80	0.38	− 0.54	− 0.66
Negative experiences	− 0.90	0.52	− 0.59	− 0.72
Project				
Job creation	0.90	− 0.52	0.59	0.72
Leverage of new businesses	0.90	− 0.52	0.59	0.72
Social purpose	0.90	− 0.52	0.59	0.72
Sustainability	0.80	− 0.38	0.54	0.66
Governance				
Social responsibility	0.90	− 0.52	0.59	0.72
Bank policies	0.80	− 0.38	0.54	0.66
Bank culture	0.70	− 0.34	0.48	0.60
Protocols	0.60	− 0.29	0.42	0.54
External surroundings				
External credit lines	0.80	− 0.38	0.54	0.66
National social policy	0.70	− 0.34	0.48	0.60
Statistics/forecasts	0.70	− 0.34	0.48	0.60
Potential recurrence	0.60	− 0.29	0.42	0.54
Deal breakers				
Fraud	0.90	− 0.52	0.59	0.72
Money laundering	0.90	− 0.52	0.59	0.72
Bad credit history	− 0.80	0.38	− 0.54	− 0.66

panel of professional credit analysts. The results include a clearer understanding of the social credit assessment process, combinations of multiple criteria, and the ability to appraise the evaluation system's behavior when different scenarios are considered. Given these results, the participants agreed that developing an SVNS–FCM framework in social credit concession contexts can contribute to improving their decision making and guaranteeing the sustainability of this type of micro-credit. Because the objectives of social credit go beyond profit, one participant said, *"a structured system in which its* [social credit's] *determinants are clearly identified facilitates well-informed, consistent loan-granting decisions"*.

The proposed framework is not without limitations, most of which are related to the idiosyncratic nature of the procedures followed. This means that any change in the elements of the panel sessions (e.g., decision makers, facilitators, and techniques) would probably result

in different representations of the social credit evaluation system (Pires et al. 2018), requiring adaptations and adjustments whenever necessary. The constructivist, process-oriented nature of the present methodological proposal needs to be highlighted again, especially since the cognitive structure developed is extremely flexible and allows for updates focused on continuously improving the system's outputs (Bell and Morse 2013).

5 Conclusion

Because social credit's objectives go beyond profit to embrace additional social concerns, the assessment of social credit applications is a complex endeavor. Given that the assessment of something as intangible as social concerns often suffers from overvaluation or undervaluation, evaluating a project's future intangible social impacts cannot be an exact science (Serrano-Cinca et al. 2016; Lamata et al. 2018). Thus, statistical methods alone cannot capture the basic data that allow for a proper analysis of social credit's relevant social impacts, and, for this reason, a methodology combining SVNSs and FCMs and based on an expert panel's judgment was chosen.

The proposed approach is comprehensive in that it covers a wide range of possible criteria used in social credit analyses, including qualitative and quantitative data and social and financial elements, as well as indicators that measure different dimensions of social credit's supply chain. The framework developed is also extremely flexible and allows criteria to be added or replaced in accordance with the social credit's mission.

When compared to the existing literature on social credit, this study corroborates some previous findings, including that six major groups of factors or determinants exist. The first of these is *external surroundings*, which includes criteria related to the business environment such as social policies and demographic and macroeconomic factors. The second determinant is *project*, which incorporates evaluation criteria related to the social projects in question, such as purpose, job creation, target market, competitors, potential customers, quality of the business plan, and financial viability. The third factor is *customer profile and guarantees*, which includes variables related to the applicants' creditworthiness and their guarantors (i.e., other people responsible for reimbursing the credit in case of default). The fourth is *aspects of profitability and risk for banks*, which covers financial variables, such as rate of indebtedness, level of exposure, and credit volume, that ensure a balance between the projects' profitability and risk. The fifth determinant is *governance*, which analyzes clients' organizational model, including decision-making policies. The last factor is *deal breakers*, which involves all situations that prevent the granting of social credit, such as fraud, money laundering, and a lack of confidence in the applicants.

However, the present results include slight changes in the ranking of these groups of criteria compared with Ferreira et al. (2018) and Xavier et al.'s (2018) findings. For instance, *customer profile and guarantees* was ranked in first place in the present study, while *deal breakers* was given higher priority in the cited studies. In addition, the FCM developed facilitated the identification of a wide range of factors, components, and criteria in a quite transparent, logical manner. The proposed methodology identified the most central criteria influencing social credit assessments by measuring the intensity of their cause-and-effect relationships using SVNSs and performing static and dynamic analyses, including inter- and intra-cluster analyses.

This approach further fosters greater transparency in the way these criteria interact with each other, thereby helping credit analysts to understand social credit based on a well-

informed evaluation framework. No evidence of the combined use of SVNSs and FCMs in this research context was found in the existing literature, so the proposed methodology adds to the body of knowledge in the fields of finance, sustainability, supply change management, and OR/MS.

As mentioned previously, these results are idiosyncratic, which means they cannot be extrapolated to other contexts without procedural adjustments. Nonetheless, the present findings can serve as an important starting point for other researchers and credit analysts seeking to examine the foundations of social credit. The process-oriented nature of the applied approach also needs to be emphasized especially because the procedures followed can be easily replicated in other contexts or with different participants (*cf.* Bell and Morse 2013; Ferreira and Santos 2016; Gonçalves et al. 2016; Pereira et al. 2017; Ferreira et al. 2019).

Research on SSCs can influence private and public policies (Tang 2018), creating value for banks and society at large in social credit contexts. Because of social credit's underlying contexts and objectives, as well as the multiple stakeholders involved, research in this area is fundamentally different from traditional research on credit analyses and supply chains. The proposed methodology should thus be viewed as complementary rather than contrastive.

Future investigations may want to consider replicating the SVSN and FCM procedures followed in this study with different panel participants. Researchers could also combine this approach with different methods (see, for example, Belton and Stewart 2002; Zavadskas et al. 2014) to make analyses more robust and contribute to a fuller understanding of social credit assessments. Another line of research could focus on the relationship between social outreach and the probability of default, as previously suggested by Serrano-Cinca et al. (2016). Any further advancements in research on social credit assessment practices and supply chain management would be welcomed, especially those strengthening social credit's sustainability.

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