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A CONSTRUCTIVIST MODEL OF BANK BRANCH FRONT-OFFICE EMPLOYEE EVALUATION: AN FCM-SD-BASED APPROACH

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Abstract. The banking sector is one of the primary drivers of economic development. This sector has been affected by various crises throughout its history – most recently, the 2008 financial and economic crisis. In response, banking institutions have had to make diverse changes to their procedures and deal with new concerns related to changes within markets. One of the main recent developments in this sector is the new commercial function assigned to bank branch front-office employees, who have become responsible for selling financial products and services, as well as recruiting and retaining clients. As a result, the sector needs new employee performance evaluation methods in line with banks and staff members' requirements. This study combined fuzzy cognitive mapping techniques and the system dynamics (SD) approach to develop a well-informed performance analysis system for assessing bank branch front-office employees. The proposed system was validated by the Business Process Management Competence Center director at Millennium BCP – a Portuguese private banking corporation. The main difference between the model constructed in the present research and current evaluation practices is that the criteria were collected directly from multiple specialists working at different commercial banks, who deal daily with this decision problem. The model's theoretical and practical implications are also discussed.

Keywords: bank branch front-office employee, fuzzy cognitive map (FCM), performance evaluation, problem structuring methods (PSMs), system dynamics (SD).

JEL Classification: C44, C45, M10.

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Introduction

The banking sector, which is part of the financial sector, is one of the main forces behind economic development (Ferreira et al., 2015). This impact has become more evident since the most recent economic and financial crisis, which significantly increased competition between banks. Between July 2007 and December 2008, the banking sector's overall performance was the worst since the Great Depression, with many financial institutions losing most of their assets (Beltratti & Stulz, 2012). In response, banks have undertaken a deep restructuring of their *modus operandi* (García-Alcober et al., 2019), which has resulted in greater resilience and impermeability to market oscillations and made banks even more powerful, innovative economic agents. According to Ferreira et al. (2014, p. 709), *"the increased intensity of competition has direct implications* [… for] *the way that banks approach costumers and how they define and apply their business strategy"*.

To ensure their survival in the face of new market conditions, banks have focused on attracting and retaining customers. To this end, innovative forms of service have been introduced using multichannel distribution as a strategy to reach a larger number of customers through technological channels such as the Internet and smartphones. Nonetheless, the most important form of interaction continues to be through services provided by bank branches, which provide the foundation for unique relationships between clients and banking institutions through front-office employees. These branches are the strategic core of the image that banks seek to project, as well as the quality of the services provided. In this context, front-office employees play a fundamental role as they, first, represent the institutions' values in relation to clients and, second, function as the key element of sales channels through these employees' new commercial role.

In view of the above changes, bank branches need to have access to an analytical model facilitating performance evaluations of front-office employees. The model should take into consideration the dynamics of the system surrounding these workers in order to facilitate strategic decision making. The model needs to help bank managers assess whether their banks' strategy and proposed objectives are being properly implemented by front-office employees. Given this context, the present study sought to apply problem structuring methods (PSMs), namely, techniques for structuring and modeling decision problems within dynamic and complex systems in abstract and fuzzy domains. These methods have been described in the literature as tools with great potential for clarifying issues based on an understanding of the dynamics of the systems involved (Sterman et al., 2015; Christoforou & Andreou, 2017; Ladeira et al., 2019). The current research thus opted to apply PSMs to the evaluation of bank branch employees.

More specifically, cognitive mapping is widely acknowledged to be an important instrument for structuring and clarifying highly complex situations in order to support decision making. This tool facilitates the development of more transparent and coherent solutions that incorporate both objective and subjective aspects (Ferreira et al., 2017; Carayannis et al., 2018). Fuzzy cognitive maps (FCMs), in particular, are used to represent complex systems' behavior through the representation and quantification of the intensity of cause-and-effect relationships between the systems' components. According to Olazabal and Pascual (2016, p. 21), this method *"is considered a useful tool for setting management objectives*, [and] *communicating and learning, especially in the context of scenario planning applications driven by uncertainty and complexity"*. The system dynamics (SD) approach, in turn, prevents management evaluations from being conducted only on an *ad hoc* basis. This approach ensures assessment models are more transparent, gives them a holistic view of the relevant systems, and measures what managers should focus on most closely (Santos et al., 2002). Thus, a good understanding of cause-and-effect relationships within systems makes identifying the most important evaluation measures possible so that interventions can lead to the desired results (Santos et al., 2002). A significant feature of the SD process is that it involves stakeholders, which is considered an added value in the literature (Santos et al., 2002; Torres et al., 2017).

Based on these complementary quantitative and qualitative methods, the present study sought to identify determinants of bank branch front-office employee performance through the integrated use of fuzzy cognitive mapping and the SD approach. A review of the relevant literature confirmed that no previous study has applied this dual methodology in this research context. The proposed approach, therefore, constitutes a significant contribution to the existing literature on employee performance evaluation, behavioral modeling, and operational research and/or management science.

The rest of this paper is organized as follows. The next section offers an overview of the literature on the banking sector and bank branch front-office employee evaluation. The third section introduces the methodology and some epistemological aspects. Section four describes the procedures followed to construct the proposed framework. The final section provides the study's conclusions and presents some guidelines for further research.

1. Related literature

Banks' survival depends essentially on their capability to respond to the needs of the market in which they operate, on the creation of a distinctive brand associated with quality, and on a constant search for new strategies and innovations (Jackson III et al., 2003). In this context, the multichannel distribution strategy consists of the use of various channels or different combinations of channels to deliver products and/or services to the final consumer. This can be done either through direct distributors such as stores, sales people, or the Internet or through indirect distributors such as brand representatives and distributors (Wilson & Daniel, 2007; Bellou et al., 2015). In particular, this strategy in the banking sector is based on using multiple channels for banking activities, which has become banks' most popular business model (Ho & Wu, 2009). To avoid losing major clients, banks choose to use digitalization to create superior experiences and thus avoid the erosion of these institutions' client base (Reydet & Carsana, 2017).

After bank branches appeared and the client manager role was created, the first signs of innovation in these facilities were the emergence of automatic teller machines that provide safe access to bank accounts. Subsequently, the banking sector invested heavily in telephone services with two main purposes: (1) to ease the flow of information to clients and provide options for conducting some operations through call centers; and (2) to conduct telemarketing. Following the Internet's rise, websites were launched as a new channel for clients to carry out operations without needing to go to physical customer service providers, regardless of whether these services were financial operations (Ramos et al., 2011; Hoehle et al., 2012; Reis et al., 2019). In the new millennium, clients are much more connected to technology through their smartphones, and this has compelled banks to structure banking applications that allow clients to consult and manage their accounts, cards, and balance in real time. Customers can also make transfers or other payments through their telephones (Hoehle et al., 2012). In this context, comparisons need to be made of the pros and cons of bank branch presence in this multi-channel strategy. Since bank branches represent the way that banks define their market strategy and manage their service quality, branches clearly play an important role in banks' sustainability (Ferreira et al., 2016). Bank branches' physical spaces also have a commercial function, with employees seeking to attract new clients and sell financial products and/or services (Eskelinen & Kuosmanem, 2013). These branches are also an extremely important connection between banks and elderly clients who are unable to use other distribution channels (Szopiński, 2016).

In general, bank branches are the main link between clients and their bank, disseminating these institutions' values and commitment to clients, as well as requiring quality standards fulfillment since branches are the banks' public image (Athanassopoulos, 1997; Quaranta et al., 2018). Because bank branch front-office employees play such an important role, their performance is clearly fundamental to banks' success as these workers must participate in all processes related directly to clients. Front-office employees are also responsible for commercial aspects since these staff members are in the forefront of efforts to contact the public (Eskelinen & Kuosmanen, 2013; Bellou et al., 2015; Kearney et al., 2017). Overall, these employees are the "face of the company (*i.e.*, bank)" and the agents who directly ensure service quality (Pimpakorn & Patterson, 2010).

The need to evaluate front-office employees' performance is urgent, including the quality of services they provide to clients, primarily because these workers convey banks' objectives and provide the main commercial contact with customers (Lee et al., 2011; Eskelinen & Kuosmanen, 2013). They have to accomplish their banks' proposed quantitative or qualitative goals (Arbore & Busacca, 2009; Ferreira et al., 2012). Employees can generate competitive advantages for their organization (Małachowski & Korytkowski, 2016) by providing unique resources. Thus, front-office employee performance evaluations allow top managers to conduct accurate analyses of service processes by identifying errors in service provision and to set new goals and guidelines for creating and implementing new strategies at this level. This process culminates in the elimination of inefficiencies and development of competitive advantages (Santos et al., 2008; Yang, 2009; Herrera-Restrepo et al., 2016).

To simplify the information obtained from measurements that are part of performance management processes, models based on different techniques have been created, offering distinct insights into the same problems and providing valuable findings to researchers. However, none of these systems is without limitations. Various authors have attracted attention over the years by using innovative methods that seek to eliminate flaws in previous studies. Table 1 presents some of the major contributions to the knowledge about this topic.

As previously mentioned, perfect approaches or models do not exist. This problem becomes even more significant when applied to an area as complex as the banking sector. When front-office employee evaluations are conducted, an additional layer of subjectivity can be verified. Thus, some limitations are highlighted in Table 1, which fall into two major categories. The first is sample limitations, including numerical or geographical restrictions, a reduced number of banks covered by the study, or the unclear definition of the criteria used to evaluate bank branch front-office employees. The second category is the absence of dynamic analyses of variables considered in the research. Acknowledging the existing models' general limitations is a fundamental step toward adopting new complementary approaches to overcome these problems.

Table 1. Evaluation models of bank branches and/or front-office collaborators: contributions and limitations

Author	Method	Contributions	Limitations
Athanassopoulos (1997)	Data Envelopment Analysis (DEA)	– Model developed to evaluate bank branch production efficiency with reference to managers' efforts to achieve corporate objectives. – Use of data on 68 Greek commercial bank branches to assess the model's results. – Important discoveries at the level of previously unknown interactions between quality of service dimensions and bank branches' ability to increase service quality. – Incorporation of the intangible concept of service quality.	Limitations arising from the DEA method acknowledged.
Berger et al. (1997)	X-efficiency approach applied to bank-branch efficiency	– Study evaluating the efficiency of more than 760 bank branches of a large North American commercial bank. – Use of different approaches to allow comparisons (*i.e.*, distribution-free and thick frontier). – Intermediation and comparison applied as approaches to definitions of bank-branch costs and outputs. – Conclusion that local managers are important to bank branch process efficiency.	Data from only one banking institution. Errors resulting from the model's application since no specific rules established for all spaces, namely, outliers need truncating.
Dekker and Post (2001)	Quasi-concave DEA	– Study using DEA model that replaces assumptions and concavity at production frontier with a less restrictive microeconomic model that assumes almost concavity. – Provision of more consistent estimators. – Possibility of successfully combining the methodology with methods that mitigate DEA models' limitations.	Subject to assumptions about the DEA model's performance in which all relevant variants are considered to be included, thereby excluding effects resulting from measurement errors and omitted variables that cause stochastic disturbances.
Manandhar and Tang (2002)	DEA	– Use of a DEA model incorporating an intangible aspect not yet considered related to resource inputs.	Limitations inherent to the DEA approach.
Jackson III et al. (2003)	Game theoretic model	– Study of different market structures or competitive conditions' influence on banks' decision to increase their services and products' quality. – Market structure with a strong influence on service quality, moderated by the level of imitation and interaction of demand and supply.	Limited to the application of a game theory.

Continue of Table 1

Author	Method	Contributions	Limitations
Karatepe et al. (2005)	Multi-stage, multi-phase, and multi-sample approaches	– Service quality scale developed based on a model with multiple stages, phases, and samples. – Use of a 20-item questionnaire as a measurement instrument to assess clients' perceptions of the level of service quality.	Acknowledgment of the need to carry out further studies to validate the measurement of service quality based on the four factors presented.
Wu et al. (2006)	DEA and neural networks approach	– Construction of a DEA model with neural networks in order to obtain a more robust analysis in which more efficient units are identified and more patterns of good performance are explored – Research addresses some DEA model limitations in terms of flexibility and assumptions.	Few theoretical studies on this approach, which requires more research. Sample confined to a single bank.
Oliveira and Hippel (2011)	Quantitative exploration of locus of innovation	– Exploratory quantitative model that addresses the need for innovation in services implemented by users themselves. – Focus on retail banking and commercial services.	Limitations of samples mentioned.
Paradi et al. (2011)	Two-stage DEA	– Model constructed to address managers' criticisms, avoid a single perspective, and reflect better the multifunctional nature of operating units. – Model's two phases simultaneously allow a comparative evaluation of operational units' performance and the aggregation of efficiency results from the first phase, thereby generating a composite index for each unit.	Use of only one financial institution. Limitations inherent to the DEA technique.
Eskelinen et al. (2014)	Extended value efficiency analysis	– Study focused on extending value engineering analysis through factual or non-factual comparative evaluations of profits and returns. – Approach with a greater capability for discrimination than an administrative evaluation dataset.	Limitations due to the model. Sample based on only one financial institution.

End of Table 1

Author	Method	Contributions	Limitations
Ferreira et al. (2016)	Fuzzy cognitive mapping	– Model focused on creating a holistic vision in order to identify service quality determinants in a bank branch and their cause-effect relationships. – Constructivist decision-support model using banking specialists to obtain results. – Identification of cause-and-effect relationships. – Study the only one to apply this methodology to bank-branch performance evaluations. – Approach allowing a gradual development of knowledge and learning process.	Study failed to conduct dynamic analyses of identified variables in the holistic structure.
Quaranta et al. (2018)	Multidimensional approach based on indexes	– Study focused on providing a combination of prior studies' strengths through a three-step procedure. – First step includes a large number of efficiency indices generated by all existing theories and methodological approaches.	Sample includes a single bank in a single region. Insufficient research on the model's contributions and limitations in the literature. Overly technical approach that fails to take into account organizational or management implications.

The present study sought to address the existing models' limitations. The objective was to create a broader, clearer, more transparent, and more informed conceptual model in this research context, which needs to facilitate the identification and comprehension of evaluation criteria and their cause-and-effect relationships. To this end, a constructivist perspective was adopted, and fuzzy cognitive mapping was integrated with the SD approach. FCMs can be the starting point for decision makers who need to identify the criteria to be included in assessment models and the degree of intensity of the cause-and-effect relationships among these criteria. The SD approach, in turn, enables analyses of the decision-support system, creating and testing scenarios and predicting the behavior of specific variables and/or the entire system.

In the present study, the combined use of these methods generated a holistic understanding of the dynamics of bank branch front-office employee performance. This approach helped increase transparency in the decision-making process whenever conflicts arose between multiple variables, actors, points of view, uncertainties, and interests (Liao, 2008; Ackermann, 2012). The next section presents the methodologies applied.

2. Methodology

The current research had a constructivist orientation based on the argument that knowledge is built through personal experiences and learning processes (Barger et al., 2018). According to this constructivist epistemological stance, societies, cultures, standards, and social contexts play an important role in building each individual's perceptions (Hursen & Soykara, 2012). Within this logic, high complexity decision problems emerge that require the use of PSMs because of the problems' unmanageable structure. PSMs are often called "soft operations research" or "soft systems", and these methods are effective tools with which trained facilitators can help groups facing challenges on a decision-making level (Marttunen et al., 2017; Smith & Shaw, 2019). Fuzzy cognitive mapping is one of the most well-known PSMs.

2.1. Fuzzy cognitive mapping

Cognitive maps are an aggregation of organized ideas structured into hierarchies, with cause-and-effect relationships represented by arrows. In other words, cognitive mapping functions as an epistemological structure with which individuals can organize their thoughts, experiences, and values (Faria et al., 2018). The relationships between variables and/or decision criteria in the defined, hierarchical network of ideas can be positive or negative depending on the nature of the cause-and-effect relationships (Ribeiro et al., 2017). That is, cognitive maps are mental models that individuals create during analyses of problems, and each cognitive structure depends on each person's rationalization, cognition, and perspective (Peña et al., 2008; Carayannis et al., 2018).

Cognitive mapping is widely acknowledged as an important instrument for structuring and clarifying highly complex situations during decision-making processes, thereby generating more transparent, coherent solutions that incorporate objective and subjective aspects (Ferreira et al., 2017; Carayannis et al., 2018). This means that, regardless of its subjective nature, cognitive mapping has a strong potential for structuring problems mainly because this technique, first, promotes exchanges of ideas and dialogues between decision makers. Second, it reduces the omission of important criteria and, third, successfully handles qualitative variables. Fourth, cognitive mapping allows the decision-making process to stimulate continuous learning, as well as a deeper understanding of the defined criteria and causalities. Fifth, this tool facilitates the organization of difficult decision problems and, last, helps decision makers to develop and implement strategic guidelines (Ferreira et al., 2012; Canas et al., 2015; Faria et al., 2018).

The present study used an FCM as an upgraded form of cognitive mapping in order to determine the causal structure of the decision problem in question and the social systems involved (Ziv et al., 2018). The map generated for the current research introduced facilitators to the involved individuals' different perspectives and perceptions, which is what makes cognitive mapping a knowledge-based methodology (Ladeira et al., 2019). Fuzzy cognitive mapping first appeared in Kosko's (1986) work, as the cited author added the fuzzy logic approach developed in the 1960s to traditional cognitive mapping (Ribeiro et al., 2017). Fuzzy logic is an extension of traditional dual logic, which helps decision makers to deal with problems characterized by ambiguity due to the absence of well-defined decision criteria or more reliable forms of variables. Thus, fuzzy cognitive mapping is the ideal approach to the description of real, behavioral problems in which imprecise quantitative data can be observed (Pluchinotta et al., 2019).

This method strengthens cognitive mapping by introducing fuzzy values between $[-1, 1]$ (*i.e.*, real values), which are attributed to the criteria and their cause-and-effect relationships (Ferreira et al., 2017). Fuzzy cognitive mapping was developed in order to address the criticism that cognitive maps lack the option of including dynamic analyses of interactions between criteria within the decision-support systems depicted in these maps. Dynamic analysis is necessary to predict accurately changes in the systems' components (Ziv et al., 2018). The combination of fuzzy logic with cognitive maps facilitates representations of vague knowledge and approximations involving rationalization when uncertainty is present in variables

(Pluchinotta et al., 2019). FCMs are a simple approach to extracting individuals' mental models that contain various forms of knowledge about specific domains or systems, thereby allowing human knowledge to be incorporated into decision making within the specific contexts under study (Ladeira et al., 2019). FCMs are thus dynamic models with intelligible content that is fully executed and represented (Ladeira et al., 2019).

FCMs' concepts work as the decision-support system's key drivers, with connections representing cause-and-effect relationships between any two concepts *Ci* and *Cj*. Feedback can be obtained by measuring interactions between any two concepts (Kok, 2009; Ziv et al., 2018). In terms of decision criteria or concepts, a bivalent logic is followed, in which fuzzy values between [0, 1] (*i.e.*, real values) can be assigned. The relationship (*i.e.*, arches) weights between criteria can be measured using a trivalent logic in which fuzzy values between {–1, 0, 1} can be assigned. This means that causality can be negative, neutral, or positive (Ferreira et al., 2017).

Positive causality indicates a stimulating relationship, whereas negative causality implies an adverse relationship between concepts (Kok, 2009). Thus, the information derived from FCMs retains cognitive mapping's qualitative component but adds a more quantitative approach through which the represented system's dynamics can be analyzed. This provides opportunities to analyze future scenarios (Ziv et al., 2018). Figure 1 is an example of an FCM showing the causality between concept nodes and their weights.

FCMs are, therefore, an approach used to represent the behavior of complex systems through the representation of cause-and-effect relationships. According to Olazabal and Pascual (2016, p. 21), FCMs are *"considered a useful tool for setting* […] *management objectives*, [as well as] *communicating and learning* […, e]*specially in the context of scenario planning applications driven by uncertainty and complexity"*. Even though this approach has some limitations (see Özesmi & Özesmi 2004; Olazabal & Pascual 2016), FCMs are frequently recommended as a way to deal with highly complex issues. These maps' simplicity and flexibility allow this technique to be applied in many areas, and FCMs' benefits can be maximized when combined with SD (Kok, 2009).

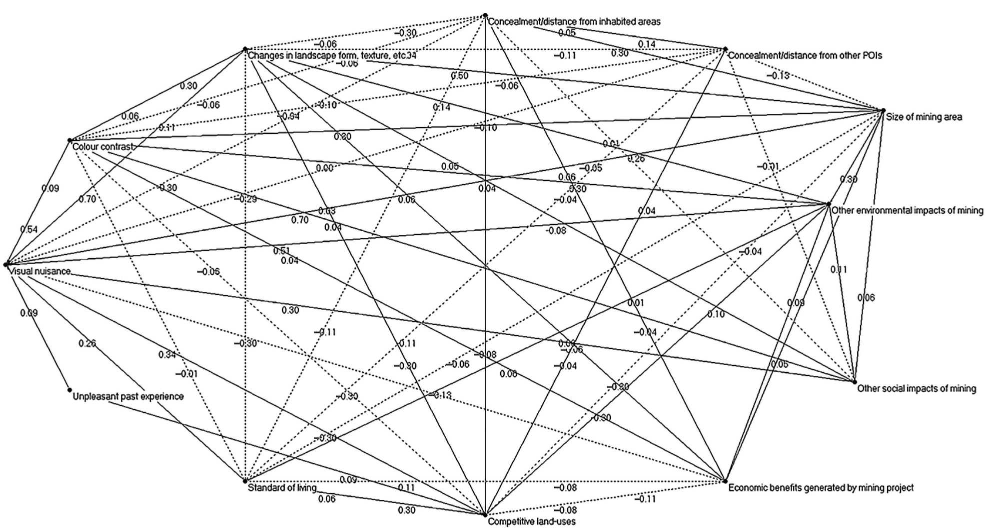

Figure 1. Example of an FCM (source: Misthos et al. 2017, p. 6)

2.2. System dynamics

All complex dynamic systems are characterized by counterintuitive behavior caused by agents' interactions through time, which is a consequence of constant changes in systems and their intrinsic features (Franco et al., 2018). The decision problems addressed by SD are aggravated by two conditions. First, SD involves variables whose amounts change over time, and, second, the variables include complex feedback structures (Sederati et al., 2019). Learning is thus nonlinear in complex, dynamic systems, becoming as a result a time-consuming process.

SD-related problems are mainly due to individuals' use of heuristics when evaluating the patterns of event causalities in these systems, making decision makers insensitive to even quite central components of complex systems (Sterman, 2002). Consequently, important elements such as the systems' internal feedback, nonlinear relationships, and inability to process new information or decisions within the time available are not considered. These omissions create temporal delays between the actions taken in the systems and the verification of the results and/or consequences (Papachristos, 2019). In other words, the causes and their effects are separated in time, which, when added to the multiple relationships among the variables involved, undermines the understanding needed to determine exactly what events triggered the systems' behavior (Sterman, 2002; Papachristos, 2019).

SD method was introduced by Forrester (1961) – in the form of modeling method – to map and explain industrial problems through control theory. Despite its origins in control theory and servomechanisms, which were developed within the "hard" sciences (*i.e.*, engineering and mathematics), SD is fundamentally interdisciplinary. It can be applied to human behavior within psychology, economics, and other social sciences because learning about complex behavioral systems requires more than simple mathematical models (Sterman, 2002). This approach is, however, in part a methodology used to develop and test formal mathematical models and computational simulations of complex systems' linear and nonlinear dynamics, in order to analyze their behavior over time (Sterman, 2002; Song et al., 2017).

The SD approach facilitates the identification of structural elements and policies that lead to decisions, successfully overcoming nonlinear relationships' "noisy" environment generated partly by decision makers' perceptual and cognitive limitations (Papachristos, 2019). This approach seeks to split the decision-support system into smaller fragments, examining each element as a way to analyze change impacts and results in terms of the remaining elements under study (Sederati et al., 2019).

SD models are usually formulated following a logic based on higher order, nonlinear, and stochastic differential equations in order to represent the relevant decision makers' rules, natural processes, and physical structures (Sterman, 2002). When numerous nonlinear relationships are included, SD models cannot be estimated using numerical methods because these are higher-order models, as can be seen in Eq. (1) (Sterman, 2002):

$$Stock_{(t)} = \int_{t_0}^{t} Inflow(s) - Outflow(s)ds + Stock_{(t_0)}, \tag{1}$$

in which $Stock_{(t)}$ is the calculated final value and t_0 is the initial time. In addition, the rates $Inflow(s)$ and $Outflow(s)$ represent the stock's inflows and outflows, respectively. The $Inflow(s)$ portray the value of inputs at any time *s*, between the initial time t_0 and the current time *t*, and the $Outflow(s)$ relate to the value of the outputs at any time *s*, between the

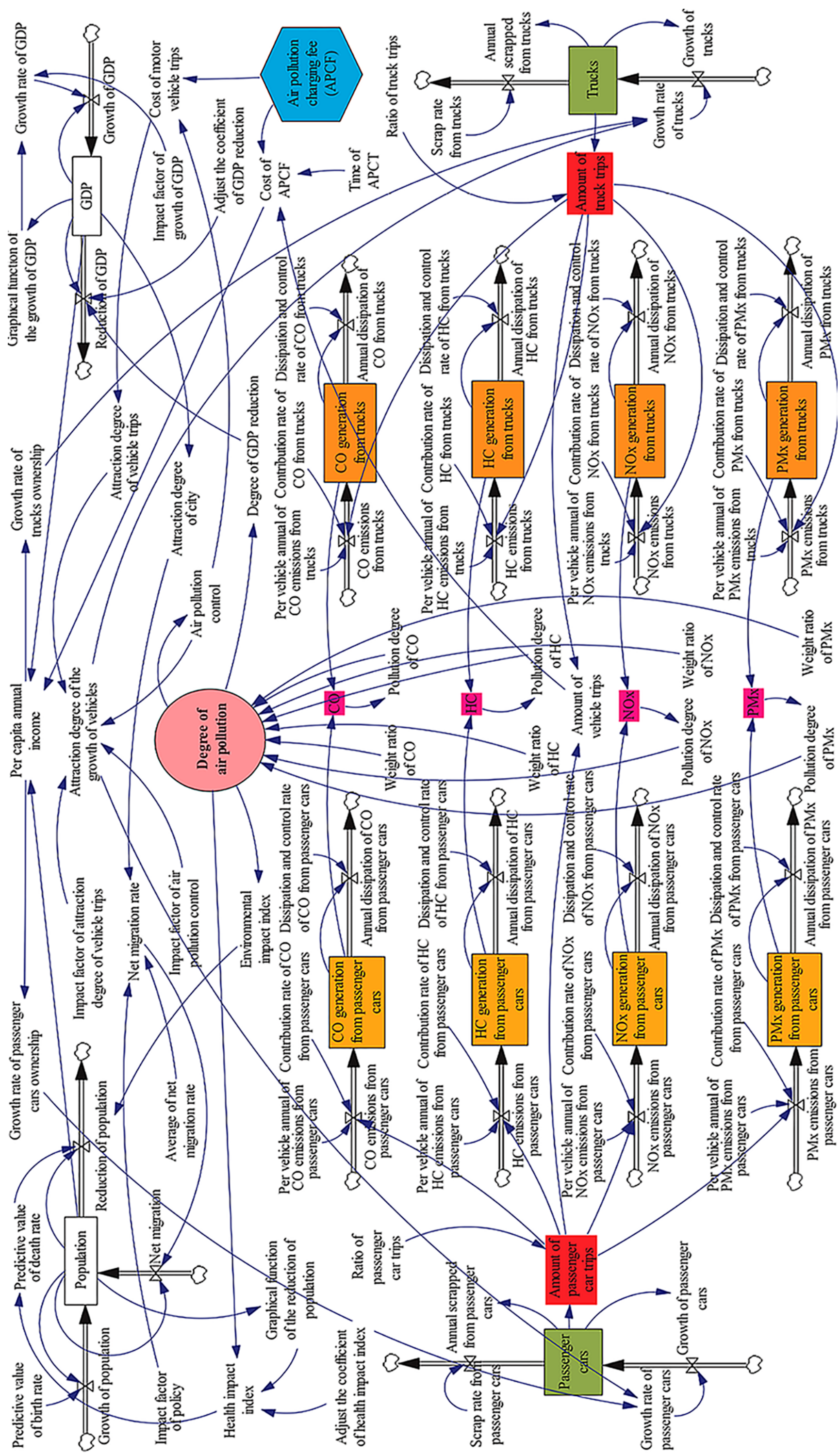

Figure 2. Example of a stock-and-flow diagram (source: Jia et al. 2019, p. 34)

initial time t_0 and the current time t. Finally, the stock exchange's net rate will be equal to the $Outflow(s)$ subtracted from the $Inflow(s)$ (Sterman, 2002; Sing et al., 2019). Figure 2 privides an example of a stock-and-flow diagram.

Given the above specifications, the SD approach allows decision makers to understand and analyze how each element or segment within systems interacts with other system elements, based on a diagram such as the one shown in Figure 2. This facilitates the formulation of predictions about decision-support systems' behavior (Sederati et al., 2019). Therefore, computational modeling software can be used to understand better the connections between systems' structure and behavior and to look for endogenous explanations of dynamic problems. These findings, in turn, help decision makers establish policies that lead to the desired changes (Sederati et al., 2019).

The present study had the objective of developing a holistic perspective on the decision problem under study. SD combined with fuzzy cognitive mapping provided tools not only to conceptualize and implement performance evaluation models but also to analyze and use the information obtained during performance assessment, thereby providing data to the top management making the decisions (Santos et al., 2002). This methodology included simulations that added a more dynamic component to the FCM, working alongside narrative structuring, gathering feedback from key drivers (Kok, 2009), and thus following a constructivist logic. Despite its limitations, SD proved to have remarkable features ideal for dealing with dynamic, complex decision-support systems. The present results demonstrated why SD is the preferred method used to model and simulate complicated system problems, with known applications in various fields of research.

3. Application and results

Decision problem structuring phase is of great importance as the structure produced serves as a basis for the remaining phases of the decision-making process (Bana e Costa et al., 1997; Rodrigues et al., 2017). Guarnieri et al. (2016, p. 1109) report that, *"by structuring the problems, actors feel more comfortable stating their values and preferences and as a result, create a more democratic environment for decision-making"*. In this phase, decision makers also clarify their goals and motivations with respect to the model.

Belton and Stewart (2002) argue that, to structure and understand a decision problem fully, a panel of decision makers (*i.e.*, experts) needs to be involved. According to Rosenhead (2006, p. 762), PSMs, such as the fuzzy cognitive mapping and SD approaches, *"are designed for deployment in a group format* [… They] *permit the simultaneous consideration of alternative perspectives* […, and they] *are participative in nature, with interaction*[s] *among participants, and between participant*[s] *and facilitator*(*s*)*"*. In the current study, a panel of seven decision makers was created based on the following guidelines. First, the facilitators needed to ensure the panel could function well as *"a group of people working together to explore an issue of common concern* (*say, five to ten persons*)*"* (Belton & Stewart, 2002, p. 40). Second, the participants had to be able to identify the issue's components, and all the experts involved in the process had to share a broad understanding of the topic. Third, the participants needed to have knowledge and experience in the banking industry and, in particular, bank branch front-office employee evaluations. Last, the panel had to be heterogeneous in terms of gender, age, and professional experience. Notably, the objective of the expert panel meetings was not to achieve representativeness – or the ability to form generalizations – but rather to maintain a strong focus on process. The latter would ensure an enriched discussion of bank branch front-office employee evaluation. Bell and Morse (2013, p. 962) argue that, in this type of research, *"there is less emphasis on outputs per se and more focus on process"*. A facilitator (*i.e.*, researcher) took part in the group sessions, assuming responsibility for mediating the decision-makers' interactions, as well as registering the results.

3.1. Collective cognitive map and causal intensity assessment

The first session started with initial introductions of each participant, as well as an explanation of the methodologies to avoid any eventual misunderstandings among the group members. The following trigger question was then asked: *"Based on your values and professional experience, which factors and characteristics influence bank branch front-office employee performance?"*. The subsequent debate was facilitated by the "post-its technique" (Eden & Ackermann, 2001), which enabled for the construction of a group cognitive map.

During this process, the decision makers were invited to share values and experiences and write each idea on a separate post-it note. The post-it notes were marked with either a minus (–) or plus (+) sign whenever a negative or positive cause-and-effect relationship was found between the criteria and the employees' evaluation (*i.e.*, a given criterion negatively or positively influences bank branch front-desk employee performance) (Ribeiro et al., 2017). The debate continued among the experts until the group expressed generalized satisfaction with the number and depth of the identified criteria.

According to Ferreira (2016, p. 135), *"the construction of a collective cognitive map assumes a subjective nature strongly dependent on the facilitator's skills and deeply influenced by the perceptions of the group"*. This process produced about 180 different criteria that represented the collective perception of this particular group of decision makers. The second stage could then begin, during which the decision makers were invited to create clusters within the wide range of criteria generated by their discussion. The criteria were grouped by areas of concern, with the result that six different areas were identified. These were: (1) *Organizational Environment*; (2) *Circumstantial Factors*; (3) *Physical Conditions at Work*; (4) *External Factors*; (5) *Psycho-Social Factors*; and (6) *Relationships and Teamwork*. In addition, *trust* and *credibility* were considered strategic criteria with connections to all clusters. The first session continued with the facilitator asking the participants to organize the criteria by order of importance inside each cluster. This facilitated the construction of a simple collective cognitive map using the *Decision Explorer* software (https://banxia.com/), which was subsequently collectively analyzed and validated by the group (see Figure 3).

The second group session was convened to continue the structuring process and was attended by 6 out of the 7 initial decision makers. According to the literature (*e.g.*, Azevedo & Ferreira, 2019), this situation is common, and the absence of one expert does not jeopardize decision-making processes. In addition, the number of participants was still in the range suggested by the relevant literature.

In this second session, fuzzy logic was applied to the cause-and-effect relationships identified in the collective cognitive map. Intensity values between –1 and 1 were assigned to each cause-and-effect relationship. This procedure was accompanied by intense debate and negotiation due to the different perspectives discussed. However, the results permitted the construction of an FCM, which was latter transformed into a stock-and-flow diagram using the *Vensim PLE Plus* software (https://vensim.com).

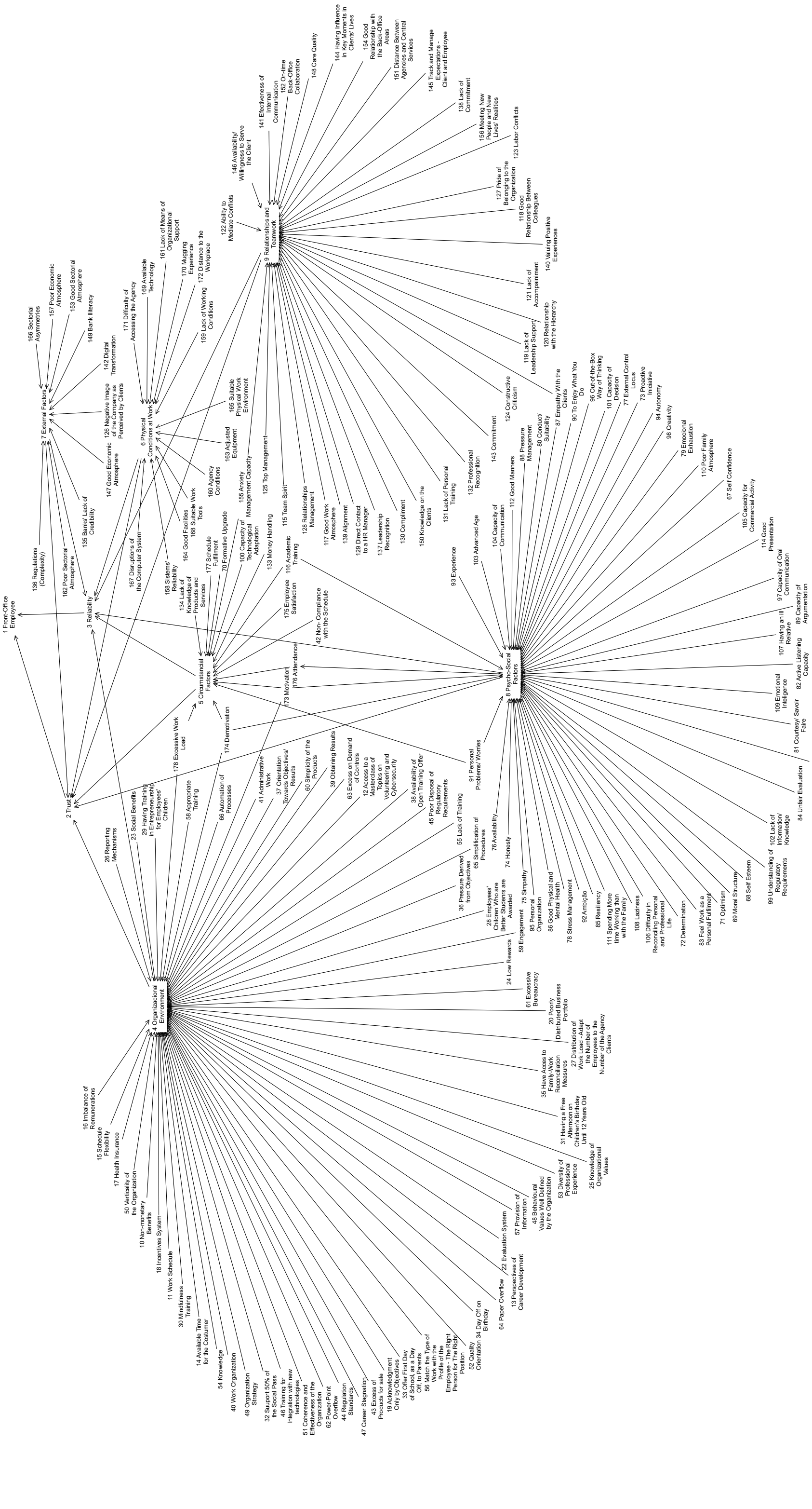

Figure 3. Collective cognitive map

Using the SD approach, a dynamic decision-problem model was then developed in order to verify the system's behavior over time. The basis for this procedure was the cognitive map previously generated and approved by the panel of experts, as well as the fuzzy values assigned by the decision makers to each cause-and-effect relationship highlighted in this complex system. Figure 4 presents the stock-and-flow diagram obtained, which was next used to create and test scenario simulations and to conduct dynamic analyses of the variables.

A set of simulations were run to test the model's robustness, identify the criteria with the most impact on front-office employee evaluations, as well as the criteria's most important relationship dynamics, and observe the model's behavior in the face of changes. This simulation procedure, in turn, facilitated a battery of dynamic analyses.

3.2. Dynamic analysis of bank branch front-office employee performance

In this study, the proposed model was tested by running 15 simulations, which allowed for the comparison of different scenarios. Before the testing phase, different aggregation equations were created based on the fundamental features of FCMs and SD, as shown in Eq. (2). For the strategic criteria of *trust* and *reliability*, these equations were used to gather the previously calculated values and add to them the decision-maker panel's contributions regarding the relationships between each cluster and the strategic criteria, as expressed in Eqs (3) and (4) (although similar in terms of mathematical formulation, these equations are based on different degrees of intensity).

$$Cluster\,i = \int \frac{\Sigma\, Determinants\, i}{100}; \tag{2}$$

$$Trust = \int \ln\left(\sum_{i=1}^{n}\left(Cluster\,i + Initial\,Value\,of\,Cluster\,i\right)\right); \tag{3}$$

$$Reliability = \int \ln\left(\sum_{i=1}^{n}\left(Cluster\,i + Initial\,Value\,of\,Cluster\,i\right)\right). \tag{4}$$

However, the flow variable was calculated differently from the remaining criteria. To achieve scale normalization, logarithms were used to obtain similar results to the remaining stocks, as shown in Eq. (5). Finally, the product of the variable *front-office* employees' evaluation was calculated by following a normalization logic similar to that applied to the clusters, although only one variable was considered, as expressed in Eq (6). In all cases, the scales were normalized to help the panel members make cognitive comparisons:

$$\begin{aligned}&Front\text{-}Office\,Employee = \\ &\ln\left(Trust + Trust\text{'}s\,Initial\,Value + Reliability + Reliability\text{'}s\,Initial\,Value\right);\end{aligned} \tag{5}$$

$$Front\text{-}Office\,Employees\text{'}\,Evaluation = \int \frac{Front\text{-}Office\,Employee}{100}. \tag{6}$$

Several simulations were run to test the decision-support system's robustness and observe the criteria with the most impact on employee evaluations, as well as to analyze the model's behavior before changes. These simulations allowed the system's performance to be monitored under business anomalous conditions (Torres et al., 2017). The runs performed

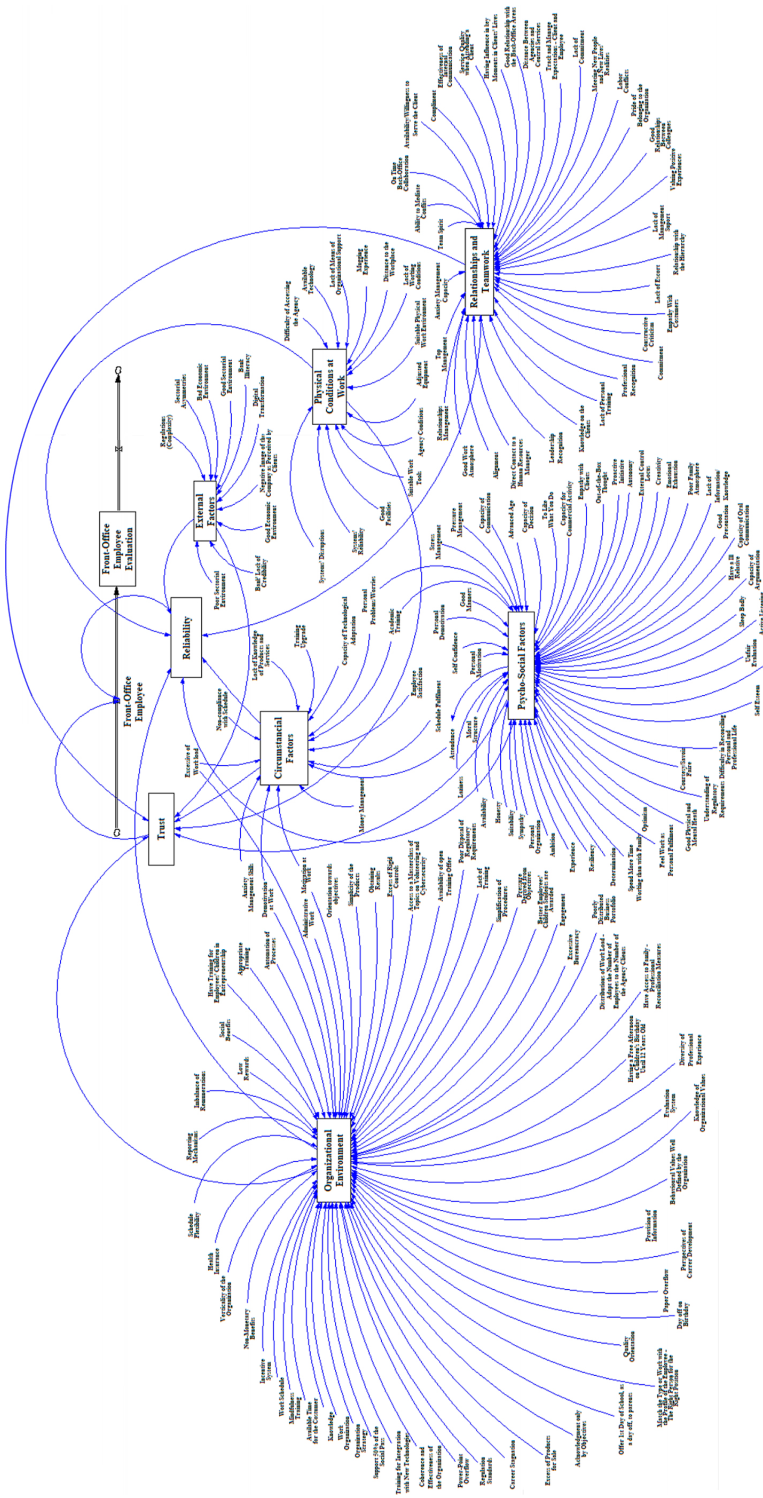

Figure 4. Stock-and-flow diagram

facilitated a direct comparison of the curves obtained from the graphics so that, in addition to comparing the curves with the base scenario, different behaviors of variables over time could be verified.

All 15 simulations provided high-value information about the decision-support system's behavior in scenarios such as economic and financial crises, improvements in bank tools and processes, changes in employees' psychological conditions, or aggravations and/or improvements within specific clusters. Multi-cluster analyses were also performed that sought to measure criteria intensities when these variables were connected to more than one cluster. The *attendance* criterion, for instance, has two cause-and-effect relationships, and its role is unique in the system because the decision-maker panel considered that this criterion is dependent on *psycho-social* factors, as shown in Eq. (7):

$$Attendance = -0.5 + Psycho\text{-}Social\ Factors. \tag{7}$$

Thus, one of the first observations made was the impact of the attendance criterion on the circumstantial factors cluster, which produced quite different curves and revealed varied behaviors from other clusters (see Figure 5).

Basically, criteria that belong to more than one cluster are quite important to the system given that a change in them would have a stronger impact because this alteration would affect more than one cluster at the same time. Scenarios in which the change focus is on strategic criteria and their connections also produce deeper and more visible alterations as the criteria effects are more comprehensive. Figures 6 to 9 show the impacts of all scenarios for *trust*, *reliability*, *front-office employees*, and *front-office employee evaluations*.

Tables 2 and 3 reveal further details about the behavior of front-office employees and front-office employee evaluation determinants over time. All the determinants included in the stock-and-flow diagram can affect how front-office employee evaluations evolve overtime, so decision makers must constantly analyze and control the model's possible variations and take corrective actions as needed.

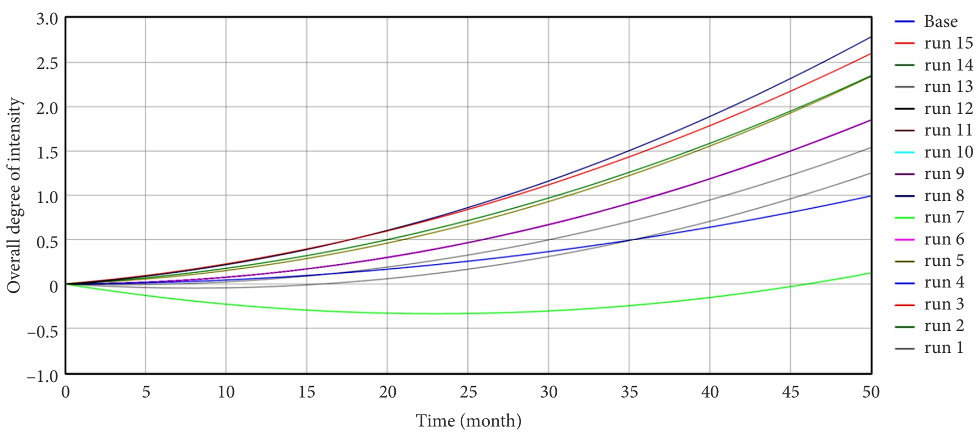

Figure 5. All Runs for circumstantial factors

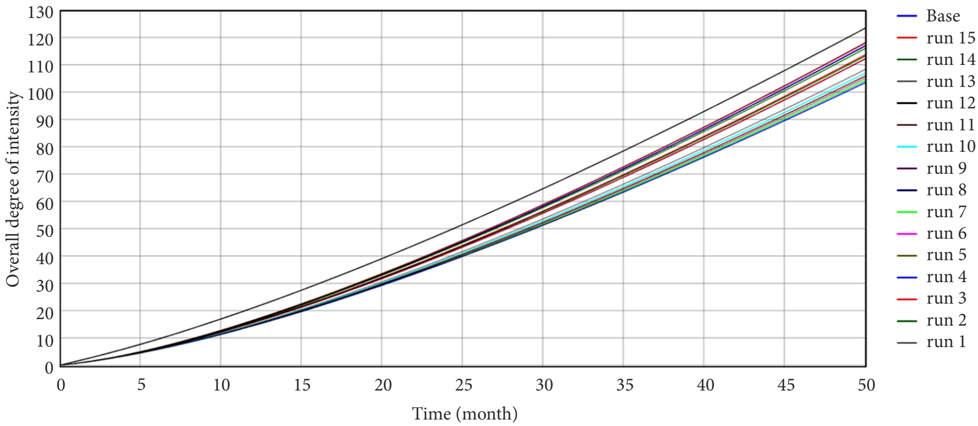

Figure 6. All runs for trust

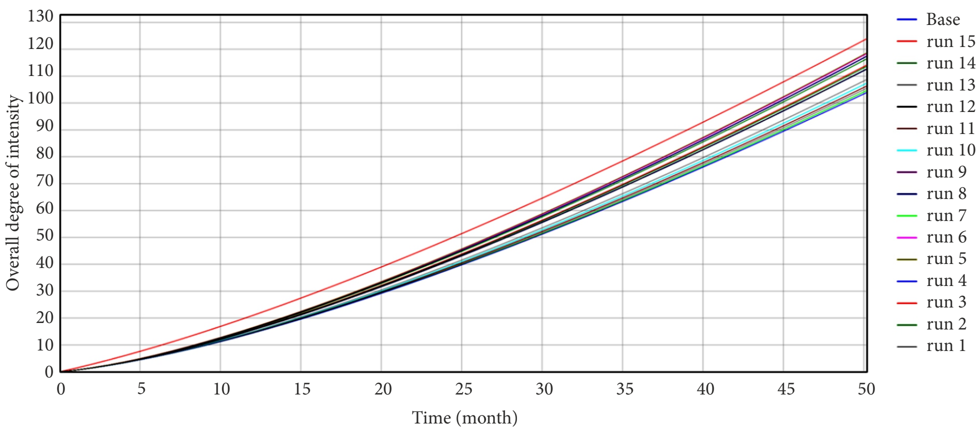

Figure 7. All runs for reliability

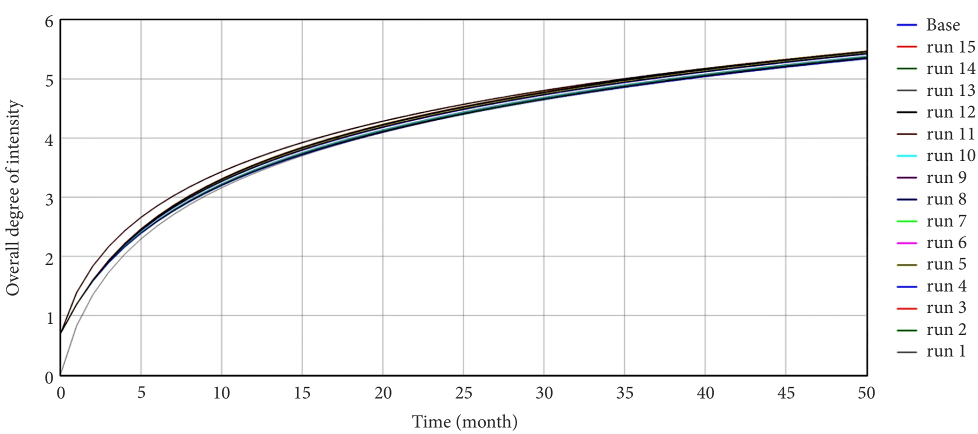

Figure 8. All runs for front-office employees

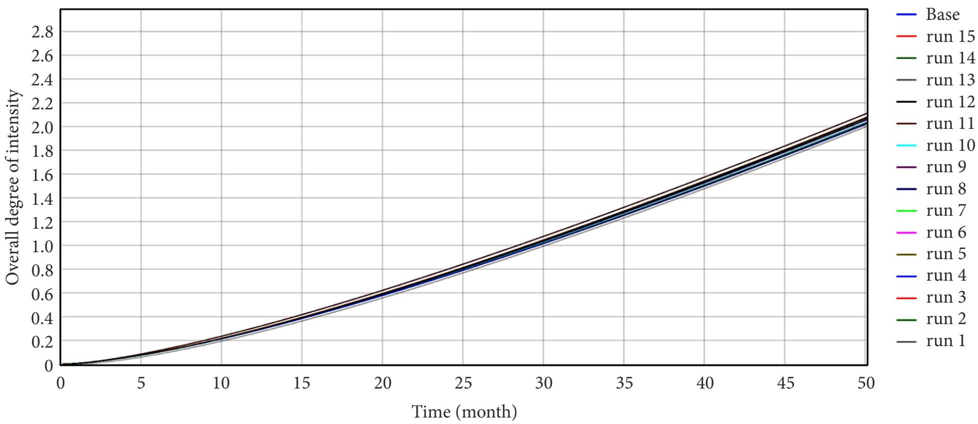

Figure 9. All runs for front-office employee evaluations

As can be seen from the results presented in Tables 2 and 3, the dynamic analyses carried out provided a deeper understanding of the cause-and-effect relationships between determinants of bank branch front-office employee evaluation. Although statistical models are by far more popular in this research context, these models impose rigorous distribution assumptions, require particular scaling properties of the data, and remain limited in flexibility (*cf.* Castela et al., 2018). In addition, correlations do not necessarily imply causation, which means that, to model and analyze complex systems' behavior, cause-and-effect relationships need to be examined carefully, thus strengthening the attractiveness of using the proposed FCM-SD-based approach.

3.3. Consolidation and recommendations

To test the validity of the model constructed, a meeting was held with the director of Millennium BCP's Business Process Management Competence Center, as this director is responsible for the introduction of new systems, processes, and business tools. At the meeting, the director was informed of the proposed decision-support system and its results. The meeting was intended to be a consolidation session since the goal was to elicit the opinion of a banking specialist who was considered neutral because he did not participate in the panel meetings. To this end, the session was divided into two parts, of which the first presented the methodologies adopted (*i.e.*, fuzzy cognitive mapping and SD). In the second part, the results obtained and the model's possible practical applications were discussed.

Overall, the interviewee provided quite positive feedback regarding the methods and results, thereby supporting the integrated use of FCM and SD in analyses of bank branch front-office employee performance. This dual-methodology use in the present study *"allowed the opinions of different experts to be aggregated*, *creating a holistic framework that was shared by all*, […] *within which cause-and-effect relationships between variables could be detected and understood*" (in the director's words).

Despite the proposed model's contextualized contents and the impossibility of extrapolating the obtained results directly to other contexts, the interviewee felt this research was an example of how technology and processes can be successfully matched. The dual methodology fosters a useful *"indirect approach to technology"* (also in his words) because a strategic

Table 2. Runs for front-office employee evaluations

Time (month)	0	1	2	3	4	5	6	7	8	9	10
Front-Office Employee Evaluation: Base	0	0.00693147	0.0188212	0.0347316	0.05394	0.0759131	0.100252	0.12665	0.154867	0.184709	0.216019
Front-Office Employee Evaluation: run 15	0	0.00693147	0.0208015	0.0391484	0.060839	0.0852099	0.111821	0.14036	0.170589	0.202324	0.235417
Front-Office Employee Evaluation: run 14	0	0.00693147	0.0188212	0.0348021	0.0541479	0.0763112	0.10088	0.127539	0.15604	0.186184	0.217809
Front-Office Employee Evaluation: run 13	0	0.00693147	0.0188212	0.0346649	0.0537414	0.0755297	0.0996423	0.125782	0.153716	0.183257	0.214249
Front-Office Employee Evaluation: run 12	0	0.00693147	0.0208015	0.0391484	0.060839	0.0852099	0.111821	0.14036	0.170589	0.202324	0.235417
Front-Office Employee Evaluation: run 11	0	0.00693147	0.0188212	0.0346229	0.0536157	0.0752857	0.0992528	0.125226	0.152976	0.182319	0.213104
Front-Office Employee Evaluation: run 10	0	0.00693147	0.0188212	0.0346407	0.0536691	0.0753896	0.0994189	0.125464	0.153293	0.18272	0.213595
Front-Office Employee Evaluation: run 9	0	0.00693147	0.0188212	0.0348206	0.054202	0.0764142	0.101042	0.127767	0.15634	0.186561	0.218266
Front-Office Employee Evaluation: run 8	0	0.00693147	0.0188212	0.0348153	0.0541868	0.0763858	0.100998	0.127706	0.156261	0.186463	0.218149
Front-Office Employee Evaluation: run 7	0	0.00693147	0.0188212	0.0346013	0.0535502	0.0751575	0.0990465	0.124929	0.152579	0.181813	0.212482
Front-Office Employee Evaluation: run 6	0	0.00693147	0.0188212	0.034839	0.0542556	0.0765162	0.101202	0.127993	0.156636	0.186932	0.218715
Front-Office Employee Evaluation: run 5	0	0.00693147	0.0188212	0.0348421	0.0542649	0.076534	0.10123	0.128033	0.15669	0.186999	0.218797
Front-Office Employee Evaluation: run 4	0	0.00693147	0.0188212	0.0346022	0.0535525	0.0751608	0.09905	0.124932	0.152579	0.18181	0.212473
Front-Office Employee Evaluation: run 3	0	0.00693147	0.0188212	0.0347586	0.0540198	0.0760662	0.100494	0.126993	0.15532	0.18528	0.216713
Front-Office Employee Evaluation: run 2	0	0.00693147	0.0188212	0.0347496	0.0539933	0.0760155	0.100414	0.126879	0.15517	0.185091	0.216483
Front-Office Employee Evaluation: run l	0	0	0.008258	0.0217372	0.0390774	0.0594887	0.0824503	0.107591	0.134635	0.163364	0.193607

Table 3. Runs for front-office employee

Time (month)	0	1	2	3	4	5	6	7	8	9	10
Front-Office Employee: Base	0.693147	1.18897	1.59104	1.92084	2.19731	2.43387	2.6398	2.82168	2.98423	3.13098	3.26457
Front-Office Employee: run 15	0.693147	1.387	1.83469	2.16906	2.43709	2.66116	2.85383	3.02289	3.1735	3.30931	3.43294
Front-Office Employee: run 14	0.693147	1.18897	1.59809	1.93458	2.21633	2.4569	2.66588	2.85008	3.01441	3.16253	3.2972
Front-Office Employee: run 13	0.693147	1.18897	1.58437	1.90765	2.17883	2.41126	2.61401	2.7934	2.95402	3.09923	3.23162
Front-Office Employee: run 12	0.693147	1.387	1.83469	2.16906	2.43709	2.66116	2.85383	3.02289	3.1735	3.30931	3.43294
Front-Office Employee : run 11	0.693147	1.18897	1.58017	1.89928	2.167	2.3967	2.5973	2.77501	2.9343	3.07846	3.21001
Front-Office Employee: run 10	0.693147	1.18897	1.58195	1.90284	2.17205	2.40293	2.60446	2.78291	2.94278	3.08741	3.21933
Front-Office Employee: run 9	0.693147	1.18897	1.59994	1.93814	2.22122	2.46279	2.67252	2.85728	3.02205	3.1705	3.30542
Front-Office Employee: run 8	0.693147	1.18897	1.59941	1.93715	2.2199	2.46124	2.67082	2.85548	3.02019	3.16861	3.30353
Front-Office Employee: run 7	0.693147	1.18897	1.57801	1.89489	2.16073	2.3889	2.58826	2.76497	2.92344	3.06692	3.19791
Front-Office Employee: run 6	0.693147	1.18897	1.60178	1.94166	2.22605	2.4686	2.67906	2.86436	3.02954	3.1783	3.31346
Front-Office Employee: run 5	0.693147	1.18897	1.60209	1.94228	2.22691	2.46965	2.68025	2.86568	3.03095	3.1798	3.31503
Front-Office Employee: run 4	0.693147	1.18897	1.5781	1.89502	2.16084	2.38892	2.58817	2.76474	2.92305	3.06637	3.19718
Front-Office Employee: run 3	0.693147	1.18897	1.59374	1.92612	2.20465	2.44278	2.64991	2.83271	2.99597	3.14327	3.2773
Front-Office Employee: run 2	0.693147	1.18897	1.59284	1.92437	2.20222	2.43983	2.64657	2.82907	2.9921	3.13921	3.2731
Front-Office Employee: run l	0	0.8258	1.34792	1.73402	2.04113	2.29615	2.51412	2.70432	2.87294	3.02429	3.16151

vision of banking needs to be well-aligned with all operational processes. Although the proposed approach is not a substitute for statistical approaches, its application by managers and decision makers can provide insights into key feedback loops in the decision-support system, which might otherwise go undetected by statistical approaches alone.

The results' subjective nature and dependence on a specific banking context naturally produce idiosyncratic results, which means that they cannot be extrapolated to other contexts without procedural adjustments (*e.g.*, other countries). This limitation is arguably compensated for, however, by the amount of information the panel members analyzed and discussed. The level of detail facilitated a better understanding of the determinants of bank branch front-office employee evaluations, as well as their respective cause-and-effect relationships. A review of the relevant literature confirmed that this methodological combination is a novel approach in this research context.

Conclusions

Bank branch front-office employee evaluation has always been quite important to banking institutions. This decision-making process is an extremely complex and dynamic system in which, besides objective goals, subjective components should also be included to ensure these employees' performance assessments are complete. Inherent features of the decision-support system, such as causal dynamics, require top managers and banks to develop a different, more detailed understanding of criteria. Thus, the combined used of FCM and SD techniques facilitated the construction of an analytical model of bank branch front-office employee evaluation that considers the established cause-and-effect dynamics of performance criteria. This decision-support system is a simple tool that is easy to read and interpret. Through a holistic vision of the problem in question, this instrument seeks to give managers essential information needed to evaluate bank branch front-office employee performance, as well as providing guidelines for making necessary strategic decisions.

On a methodological level, combining these techniques overcomes the identified limitations of previous models by, first, identifying a larger number of criteria, thereby permitting a more integrated, holistic approach to the decision problem. Second, the dual methodology incorporates subjective determinants through specialists' opinions, values, and experience. Third, the techniques highlight the identified criteria's relationships and quantify those relationships' weight, which offers a broader understanding of the decision-support system's dynamics. Last, this approach includes a stable, strong decision-making tool able to simulate different scenarios.

Specifically regarding implications for management, the applied techniques and the resulting model offer various benefits. First, the model provides a clear visual representation of the decision problem, thereby assuring a deeper understanding of front-office employee evaluation components. Second, this approach has the capability to identify the decision-support system's negative aspects and opportunities for improvement in order to enhance the decision-making process. Third, the model can be used to identify the criteria with the strongest impact on employee performance evaluations. Last, the methodology facilitates the creation of scenarios so that managers can observe and preview the system's behavior in the face of changes that might occur. Therefore, methods based on constructivist thinking, such as (fuzzy) cognitive mapping and SD, produce more realistic evaluation models because subjective components are incorporated through decision makers' knowledge about decision-making processes.

Despite the useful results discussed above, the present study was grounded in a learning logic based on constructive debate and the continuous sharing of ideas and experiences among decision makers, which does not seek to achieve optimum solutions. In light of the current findings and prior models' results, the proposed decision-support system is not without its limitations. Two main limitations were identified of which the first was that the model's development required a great deal of time and dedication from each member of the decision-maker panel. The second limitation was that the entire modeling and construction process was extremely dependent on the specific context, experts' personal and professional experience, and their receptivity and contributions, which implied idiosyncratic behaviors. As a result, although the combined use of cognitive mapping techniques and SD allows for changes in the model at any time and ensures much flexibility, any extrapolation of the present results without appropriate adaptations could be misleading.

Future research must keep in mind that the proposed model focuses on Portuguese banks' realities and, thus, its usefulness in other contexts will depend on the changes introduced by decision-maker panels. Nonetheless, the methods applied should remain valid because of the present study's processual approach, even though the current results' limited potential for extrapolation is the methodologies' greatest shortcoming. Keeping this in mind, bank branches in different contexts (*e.g.*, other specialists and geographical contexts) should be able to structure their front-office employee performance evaluation criteria using similar techniques. One possible future line of research could involve developing different scenarios based on new challenges that might arise in the market. These scenarios would allow experts to understand the decision-support system's behavior and find ways to improve the proposed model's focus. A larger number of simulations are needed to ensure a stronger model and more informed and prepared management to maintain control over decision-making processes. Overall, the methodologies applied in the present study need to be used primarily as a complement to other analytical tools, namely, multicriteria evaluation models or other constructivist models (for examples, see Belton and Stewart (2002) and Zavadskas et al. (2014)). The proposed dual methodology could also be combined with artificial intelligence methods to provide further insights into bank branch front-office employee evaluation, thereby generating further developments in this field.

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