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Integrating qualitative comparative analysis (QCA) and fuzzy cognitive maps (FCM) to enhance the selection of independent variables☆

Fernando A.F. Ferreira [a,b,*], Marjan S. Jalali [b], João J.M. Ferreira [c,1]

[a] Fogelman College of Business and Economics, University of Memphis, Memphis, TN 38152-3120, USA
[b] ISCTE Business School, University Institute of Lisbon, Avenida das Forças Armadas, 1649-026 Lisbon, Portugal
[c] Department of Business and Economics, NECE Research Unit, University of Beira Interior, Estrada do Sineiro, 6200-209 Covilhã, Portugal

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ABSTRACT

This study proposes the use of fuzzy cognitive maps (FCMs) in qualitative comparative analysis (QCA) applications to enhance the selection of independent variables in the QCA framework. QCA techniques hold great potential to identify the causal models that exist among different but comparable cases. Due to the complexity of causality issues, however, such techniques may not be able to uncover the "true" causal foundation of a given phenomenon. FCMs typically offer a fuller view of the cause-and-effect relationships between variables, thus allowing for a better understanding of their behavior; for instance, the manner in which variables relate to each other, or the measure of their intensity. This study thus proposes that such maps can be a useful support in the selection of independent variables for a QCA model, and provides specific guidelines and an illustrative example of how to integrate FCMs in QCA applications.

1. Introduction

Standing between quantitative and qualitative research, qualitative comparative analysis (QCA) holds great potential for "the analysis of small data sets for which the goal is to study the configurations of independent variables associated with high and low outcomes on a dependent variable" (Hess & Mai, 2014, p. 36). Berg-Schlosser et al. (2009) and Hudson and Kühner (2013) support this idea, noting that QCA strives to meet the advantages of both "quantitative" (variable-oriented) and "qualitative" (case-oriented) techniques. As such, QCA allows for the identification of multiple causal pathways, as well as their interactions, in a manner which is not possible through traditional statistical models. Indeed, in seeking such benefits, the technique and its overarching framework reveal remarkable progress (for evolutionary details, see Hess & Mai, 2014; Mendel & Korjani, 2012, 2013), resulting in tools such as fuzzy-set QCA (fsQCA), among others.

A number of challenges remain, however, particularly in the decision-making domain. Decision situations often involve a vast number of intuition- and subjectivity-based factors (Ferreira et al., 2014). Furthermore, such decision situations are typically multidimensional, and contain highly complex cause-and-effect linkages between conditions and outcomes. These characteristics pose difficult challenges for policy makers and practitioners (Hudson & Kühner, 2013; Woodside, 2013, 2014), which QCA techniques alone may not be able to overcome. From an operational standpoint, these challenges become even greater when the issue at hand requires the selection of independent variables and understanding how they relate with a dependent variable. This study aims to address precisely this issue, by showing how the use of fuzzy cognitive maps (FCMs) in QCA applications can enhance the selection of independent variables and contribute to overcoming some of the challenges of multi-dimensional, multi-participant decision-making contexts.

The dynamics behind the construction of a FCM allow for a better understanding and assessment of changes in the variables considered to the overall decision situation (Carlucci et al., 2013; Stach et al., 2010). Cognitive mapping, in turn, allows for the consideration of a much greater number of variables in the framework, contributing to a significantly fuller view of the problem at hand (Ackermann et al., 2014; Eden & Ackermann, 2001; Ferreira et al., 2012). As such, considerable scope exists to explore the integration of FCMs in QCA applications.

Integrating these two approaches can contribute to the literature in two main ways. At the methodological level, this study demonstrates the applicability and utility of the use of FCMs in QCA applications, and discusses the advantages and disadvantages of this integration over conventional approaches. At the theoretical level, this research contributes to the stream of theories and methods that argue for the

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* Corresponding author at: ISCTE Business School, University Institute of Lisbon, Avenida das Forças Armadas, 1649-026 Lisbon, Portugal.
E-mail addresses: fernando.alberto.ferreira@iscte.pt, fernando.ferreira@memphis.edu (F.A.F. Ferreira), marjan.jalali@iscte.pt (M.S. Jalali), jjmf@ubi.pt (J.J.M. Ferreira).
[1] Tel.: +351 275 319 600.

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relevance of integrating approaches from neuroscience with approaches from the social sciences (cf. Ferreira et al., 2014; Jalali et al., 2015; Santos et al., 2002). Recent discussions within the wider methodological literature are once more emphasizing the importance of integrating approaches in order to uncover causal inferences (cf. Hudson & Kühner, 2013; Woodside, 2014; Woodside et al., 2012). As such, an interdisciplinary approach that combines FCMs and QCA constitutes a response to that call and enables a more comprehensive selection of independent variables.

The next section introduces the methodological background, presenting the basics of the QCA approach and discussing some of its limitations in terms of variable selection. This section also presents a brief background of fuzzy cognitive mapping, discussing how its use can help surpass some of the limitations of QCA. Section 3 illustrates an application of our framework to a sustainable banking analysis. The last section presents conclusions, discusses the managerial implications of our proposal and establishes some lines for future research.

2. Methodological background and framework

2.1. Basics of the QCA approach

The QCA approach (Drass & Ragin, 1992; Ragin, 1987) provides researchers with an alternative methodological response to traditional quantitative and qualitative approaches. The method uses Boolean algebra and, according to Crawford (2012) and Warren et al. (2013), attempts to maximize the number of comparisons and identify causal inferences, in a small sample of cases. In the choice of sample size, then, QCA is different from traditional statistical methods: "the realm of QCA techniques – that is, the 'comparative method' in the more narrow sense of the term – thus has to be distinguished, in particular, from the 'statistical method', which proceeds on the basis of a large number of cases, drawn on a random basis if possible, and a relatively small number of variables. Both methods have their respective strengths and weaknesses" (Berg-Schlosser et al., 2009, p. 4; for a deeper discussion on the advantages and disadvantages of QCA over more traditional techniques, see Hudson & Kühner, 2013; Kim, 2011; Kopaneli, 2014; Skarmeas et al., 2014; Stokke, 2007; Warren et al., 2013). QCA applications thus help balance the depth of case study knowledge that qualitative analysis can provide with the breadth of analysis arising from quantitative data (cf. Hudson & Kühner, 2013).

In practical terms, with QCA, theoretical concepts are operationalized as variables. The most primitive form of QCA (i.e., crisp-set) codes variables as either 0 or 1 (with no intermediaries); while in an evolution of the technique (i.e., fsQCA) continuous variables are formed after calibration (cf. Hess & Mai, 2014; Mendel & Korjani, 2012 and 2013; Rihoux & De Meur, 2008; Woodside et al., 2015). Essentially, QCA deconstructs the knowledge for each case study provided into a certain number of conditions/independent variables, and an outcome/dependent variable. However, this segmentation into variables does not interfere with the perception of each case as a whole. This is important because QCA techniques concern "conjunctural causation", that is, the existence of various causal paths across observed cases (Berg-Schlosser et al., 2009). In addition, each one of these multiple paths (which can lead to the same outcome) "consists of a combination of conditions" (Berg-Schlosser et al., 2009, p. 8). This complexity is termed "multiple conjunctural causation", a conception of causality according to which: (1) most often, it is a combination of causality relevant conditions that generates the outcome (i.e., AB → Y); (2) several different combinations of conditions may produce the same outcome (i.e., AB + CD → Y); and (3) depending on the context, a given outcome may result from a condition when it is present and when it is absent (i.e., AB → Y but also aC → Y; meaning that A combined with B produces the occurrence of the outcome, but its absence (*a*) combined with C also produces the same outcome) (cf. Berg-Schlosser et al., 2009, p. 8).

These premises imply that permanent causality, uniformity of causal effects, unit homogeneity, additivity and causal symmetry cannot be assumed within the QCA framework. Indeed, in using QCA the aim is not to specify a single causal model that best fits the data, as conventional statistical techniques seek to do. Rather, the aim is to identify causal models that exist among different, but comparable cases. As Hudson and Kühner (2013) note, "QCA is first-and-foremost 'qualitative' as it aims to achieve thick description of complex cases in order to learn more about them" (p. 280).

As a result, the conclusions of any QCA analysis are context-sensitive, and dependent on the selection of cases and independent variables considered in the analysis. As such, and because "QCA techniques do not guarantee the final grasp of the 'true' causal grounds of a given phenomenon because the issue of causality is a much more complex matter" (Berg-Schlosser et al., 2009, p. 10), they can (and should) be integrated with other methodologies, for joint application at different levels of analysis.

In this context, FCMs can prove a useful tool for selecting and operationalizing independent variables. These maps can help understand, for instance, how such variables relate to each other and how to measure their intensity. In doing so, FCMs add to the QCA approach in a manner that reinforces the holistic perspective offered by such frameworks.

2.2. Background on fuzzy cognitive mapping

Cognitive mapping is an extremely versatile decision support "for modelling the complex relationships among variables of a problem/phenomenon" (Carlucci et al., 2013, p. 212). FCMs (Kosko, 1986; 1992) enhance the power of cognitive maps by considering fuzzy values for the concepts/variables, and fuzzy degrees for their cause-and-effect linkages (cf. Carlucci et al., 2013; Kok, 2009; Salmeron, 2009; Stach et al., 2005; Tsadiras et al., 2003). Fuzzy cognitive mapping is used in a wide range of decision situations (for further details, see Ferreira et al., 2015; Papageorgiou et al., 2012; Salmeron, 2012; Yaman & Polat, 2009), and FCMs have two specific features: (1) causality arrows and intensity values that range from −1 to 1 represent the linkages between variables; and (2) the system builds on a fuzzy logic, which includes feedback links between variables and allows for the dynamic analysis of temporal aspects in the decision process (Carvalho, 2013). Fig. 1 shows the typical structure of a FCM, where C_i is a concept/variable and *Wij* represents the intensity value of the link between concepts *i* and *j*.

As the literature indicates (cf. Ferreira et al., 2015; Kim & Lee, 1998; Kok, 2009; Mazlack, 2009; Salmeron, 2009; Yaman & Polat, 2009), all the values in a FCM can be fuzzy, such that a state value A_i for each variable considered can take on a fuzzy value in the range between [0, 1] (or at least follow a bivalent logic in {0, 1}). The linkages, in turn, can take on three different types of causality: (1) *negative* ($W_{ij} < 0$), when an increase (decrease) in the value of C_i leads to a decrease (increase) in the value of C_j; (2) *null* ($W_{ij} = 0$), when no relationship between the variables exists; and (3) *positive* ($W_{ij} > 0$), when an increase (decrease) in the value of C_i leads to an increase (decrease) in the value of C_j. Due to the fuzzy nature of FCMs, the intensity values can also be fuzzy within [−1, 1] (or at least follow a trivalent logic within {−1, 0, 1}).

Mathematically, this results in both a $1 \times n$ state vector A that gathers the values of the n variables, and a $n \times n$ weight matrix W (i.e., adjacency matrix) that gathers the weights W_{ij} of the links. Because a variable only seldom causes itself, the adjacency matrix usually presents all the entries on the main diagonal as equal to zero (cf. Kok, 2009). Furthermore, the previous value of each variable and the values of its interconnected variables (duly weighted) both influence its current value. Formulation (1) summarizes these relationships, where $A_i^{(t+1)}$ stands for the activation level of C_i at time $t+1$; f is a threshold activation function; $A_i^{(t)}$ is the activation level of C_i at time t; $A_j^{(t)}$