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Journal of Business Research



Qualitative analysis with structural associations☆

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ARTICLE INFO

Article history:

Received 1 February 2016

Received in revised form 1 March 2016

Accepted 1 April 2016

Available online xxx

Keywords:

Consistency

Fuzzy set Qualitative Comparative Analysis (fsQCA)

New consistency

ABSTRACT

This study proposes an approach to analyze the structural associations in multi-layer problems using the new consistency. Research methods are important in identifying correct associations between antecedents and outcomes. Studies suggest using fuzzy set Qualitative Comparative Analysis (fsQCA) to explore the associations. However, fsQCA presents two problems: the definition of consistency function and the propagation of consistency values in multi-layer problems. To facilitate the explanation, this study uses the proposed approach to analyze the structural research framework and data by Lin et al. (2009) to demonstrate the process of how to obtain the structural association of a multi-layer problem.

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1. Introduction

Woodside, Camacho and Lai (2013) stress that evaluating the outcomes of a problem requires the development of the configuration of causes that lead to the outcomes. Research methods themselves are critical in identifying correct associations between causes and outcomes. The conventional statistical methods tend to report the “net effects” (Woodside, Schpektor and Xia, 2013). Ragin (2008a) raises two concerns for the conventional statistical methods: the combination of three or more independent variables present a level of complexity that multiple regression analysis (MRA) can hardly implement. Second, MRA models systematic relationships, but the relationships between independent variables and dependent variables are often asymmetric. Hence, studies suggest using Qualitative Comparative Analysis (Ordanini, Parasuraman, & Rubera, 2014) or fuzzy-set Qualitative Comparative Analysis (fsQCA) to create new theory in social science (Woodside, 2013; Woodside & Zhang, 2013).

FsQCA differs from the statistical methods in four aspects (Ragin, 2008a): First, fsQCA focuses on set-theoretic associations, whereas statistical methods focus on correlational connections. Second, fsQCA calibrates the data into values ranging between 0.0 and 1.0 and processes the calibrated values, whereas statistical methods process the measured data directly. Third, fsQCA focuses on configurational of conditions, whereas statistical methods focus on independent variables.

Lastly, fsQCA provides the analysis of causal complexity, whereas statistical methods offer the analysis of net effects.

Studies use fsQCA to explore associations in problems but most are problems of one layer of antecedents. For example, one layer of four antecedents (PPP, Fixed phone lines, Population density, Corruption index) leads to an outcome (ICT development) in Fig. 1 (Huarng, 2015a). However, problems may consist of multiple layers of antecedents whose associations among antecedents and outcome are structural associations. Using fsQCA to solve the problems with structural associations may not be feasible because of the consistency function. FsQCA does not clearly address how to propagate the consistencies from one layer to the next. Fig. 2 depicts a problem with structural associations. Multiple layers of antecedents lead to the outcome. The first layer of antecedent consists of Familiarity with PB (private brands), the second layer consists of Perceived quality, Perceived risk, and Price consciousness, the third layer consists of PB attitude, and the outcome is PB purchase intention.

FsQCA uses set theory to analyze the associations between antecedents and an outcome. FsQCA uses two criteria to measure the associations: consistency and coverage. Theoretically, fsQCA considers the antecedent or the combination of antecedents as a subset of the outcome in the measurement of consistency. Hence, the calculation of consistency involves minimum function. Huarng (2015b) proposes a new consistency by logic theory. In comparison to the consistency function, that of the new consistency is more suitable to analyze the structural associations in a multi-layer problem.

This study proposes an approach to analyzing structural associations using the new consistency to extend the application of fsQCA. To that end, Section 2 addresses this problem of fsQCA. Section 3 introduces the variables and data, and proposes an approach. Section 4 contrasts the empirical analyses by using both the new consistency and

☆ The author acknowledges and is grateful for the financial support provided by the Ministry of Science and Technology, Taiwan, ROC under grant MOST 104-2410-H-035-027. Special thanks to C.-Y. Lin, Feng Chia University, for generously providing his research data for analysis.

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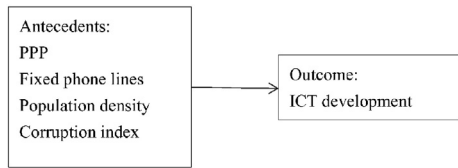


Fig. 1. ICT development: one layer association between the antecedents and the outcome. (Huarng, 2015a).

consistency functions. Section 5 discusses the relevant issues and concludes this article.

2. The problems with fsQCA

The fsQCA presents two problems: the calculation of consistency and the propagation of consistency values for structural associations.

2.1. Consistency

FsQCA requires the calibration of the data into values between 0.0 and 1.0 (Ragin, 2008b). After processing the calibrated data, fsQCA provides results such as

$$X \rightarrow Y \tag{1}$$

where X can be a single antecedent or a combination of antecedents; Y is the outcome. Eq. (1) means that X is a sufficient condition for Y. However, multiple sufficient conditions may exist for an outcome.

Suppose X is a combination of antecedents, let $X = X1 * X2 * X3 \dots$, where X1, X2, X3, ... are antecedents and * represents the logic AND.

The calculation of the calibrated value of a combination of antecedents, such as X is equal to

$$CV_{X,i} = \min(CV_{X1,i}, CV_{X2,i}, CV_{X3,i}, \dots) \tag{2}$$

where $CV_{X,i}$ represents the calibrated value of the i-th entry of data for the antecedent X.

In Eq. (1), suppose X and Y contain calibrated values $CV_{X,i}$ and $CV_{Y,i}$ ($i = 1, \dots, n$), respectively. Ragin (2008a) defines coverage and consistency as follows:

$$\text{coverage} = \frac{\sum_{i=1}^n \min(CV_{X,i}, CV_{Y,i})}{\sum_{i=1}^n CV_{Y,i}} \tag{3}$$

$$\text{consistency} = \frac{\sum_{i=1}^n \min(CV_{X,i}, CV_{Y,i})}{\sum_{i=1}^n CV_{X,i}} \tag{4}$$

However, following logical theory, $X \rightarrow Y$ is equivalent to NOT X OR Y, instead of X AND Y. In other words, the result of $X \rightarrow Y$ is equivalent to $\max(1-X, Y)$, instead of $\min(X, Y)$. Hence, on the basis of the logical

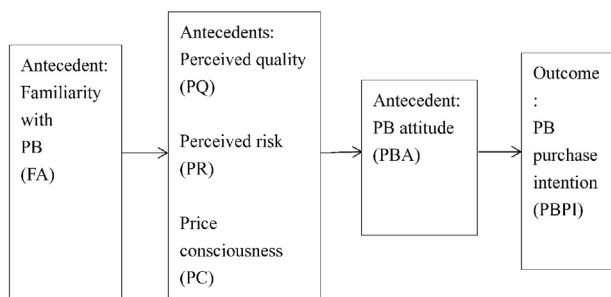


Fig. 2. Private brands: a problem with structural associations. (Lin et al., 2009).

Table 1 The data and the calibrated data.

	FA	PQ	PR	PC	PBA	PBPI	C_FA	C_PQ	C_PR	C_PC	C_PBA	C_PBPI
3	4.00	2.75	4.00	3	4.00	0.68	0.9	0.59	0.9	0.68	0.9	
2	3.67	3.25	3.00	3.5	3.67	0.32	0.85	0.75	0.68	0.82	0.85	
1.5	3.33	2	4.00	2	3.00	0.18	0.78	0.32	0.9	0.32	0.68	
3.5	5.67	2	5.33	4	3.67	0.82	0.99	0.32	0.99	0.9	0.85	
3.5	6.00	2.5	5.00	5	3.67	0.82	0.99	0.5	0.98	0.98	0.85	
6	4.67	2.5	4.67	5	4.33	0.99	0.96	0.5	0.96	0.98	0.94	
4	4.67	3	5.00	5	5.00	0.9	0.96	0.68	0.98	0.98	0.98	
5.5	5.67	2	3.33	5.5	5.00	0.99	0.99	0.32	0.78	0.99	0.98	
5.5	4.00	1.5	5.33	4.5	4.33	0.99	0.9	0.18	0.99	0.95	0.94	
4	5.33	2	3.33	4.5	4.00	0.9	0.99	0.32	0.78	0.95	0.9	
5	5.33	1	5.33	5	5.00	0.98	0.99	0.1	0.99	0.98	0.98	
2	3.67	4.5	3.33	2.5	2.67	0.32	0.85	0.95	0.78	0.5	0.56	
4	7.00	2.25	3.00	3.5	2.00	0.9	1	0.41	0.68	0.82	0.32	
4	4.33	3.25	6.33	3.5	4.33	0.9	0.94	0.75	1	0.82	0.94	
3	5.00	2.75	2.67	3.5	3.67	0.68	0.98	0.59	0.56	0.82	0.85	
3	5.67	1	5.33	5.5	4.67	0.68	0.99	0.1	0.99	0.99	0.96	
4	4.00	2.75	6.00	3.5	4.33	0.9	0.9	0.59	0.99	0.82	0.94	
4	4.00	3	4.67	4	4.00	0.9	0.9	0.68	0.96	0.9	0.9	
3	3.67	4.5	3.00	3.5	3.67	0.68	0.85	0.95	0.68	0.82	0.85	
5	3.67	3.5	6.00	3	2.33	0.98	0.85	0.82	0.99	0.68	0.44	

theory, Huarng (2015b) proposes a new consistency to replace the consistency in fsQCA:

$$\text{new consistency} = \frac{\sum_{i=1}^n \max[(1-CV_{X,i}), CV_{Y,i}]}{n} \tag{5}$$

2.2. Propagation of consistencies

FsQCA does not address clearly how to calculate the consistencies for the multi-layer problems. That is, the propagation of the values of consistency from one layer to the next theoretically. For example, in Fig. 2, fsQCA can calculate the consistencies for FA → PQ, FA → PR, and FA → PC, respectively. Similarly, fsQCA can calculate the consistency for PBA → PBPI. However, knowing how to propagate the consistencies of FA → PQ, FA → PR, and FA → PC to the outcome PBPI is much more interesting.

By using the new consistency, for a multi-layer problem $X \rightarrow Y \rightarrow Z$, scholars can propagate the values from (X → Y) to Z. This study proposes an approach to tackling this issue by using the new consistency.

3. Method

3.1. Variables and data

To illustrate the proposed approach, this study adopts the structural research framework from Lin, Marshall, Dawson (2009), appearing in Fig. 2, where multiple layers of antecedents lead to the outcome. The first layer of antecedent consists of Familiarity with PB (whose variable name and calibrated name are FA, C_FA, respectively), the second layer consists of Perceived quality (PQ, C_PQ), Perceived risk (PR, C_PR), and Price consciousness (PC, C_PC), the third layer consists of PB attitude (PBA, C_PBA) and the outcome is PB purchase intention (PBPI, C_PBPI).

Table 2 Combinations of antecedents.

X1	X2	X2	X3	X3	Combination	Eq. (2)
0.7	0.8	0.2	0.9	0.1	X1*X2*X3	0.7
0.6	0.6	0.4	0.8	0.2	X1*X2*X3	0.6
0.9	0.4	0.6	0.6	0.4	X1*X2*X3	0.6
0.8	0.2	0.8	0.7	0.3	X1*X2*X3	0.7
0.9	0.8	0.2	0.3	0.7	X1*X2*X3	0.7
0.7	0.9	0.1	0.4	0.6	X1*X2*X3	0.6

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