Examining the key determinants towards online pro-brand and anti-brand community citizenship behaviours: a two-stage approach

Abstract

Purpose – A research model is proposed to identify the key determinants and examine their impact towards online pro-brand and anti-brand community citizenship behaviours (CCBs).

Design/methodology/approach – A survey based on the research model is used to collect empirical data from 260 and 200 members of online pro-brand communities (OBCs) and online anti-brand communities (OABCs) respectively. A two-stage approach employing fuzzy-set qualitative comparative analysis (fsQCA) and artificial neural network (ANN) is firstly applied to uncover new observations.

Findings – Moral identity and positive brand emotion are the two most influential factors driving both online pro-brand and anti-brand CCBs. A higher level of internalisation might be required to exhibit online anti-brand CCB as opposed to online pro-brand CCB. This contradicts the current understanding that anti-brand behaviours are less morally restricted given the virtuality and anonymity of online communities. OABC members may need to better justify themselves internally to overcome positive brand emotion when exercising anti-brand action. Also, brand identification, brand dis-identification and brand emotion would be used to identify two types of OABC members.

Research limitations/implications – The effect of motives other than pro-social remains unclear on online pro-brand and anti-brand CCBs.

Originality/value – This is the first paper to develop two new dimensions which provide a more complete definition of CCB. Also, some new observations are uncovered by comparing the effect of different key determinants on online pro-brand CCB against that of online anti-brand CCB. Our research model can be used to define and improve member (or brand) engagement which would enhance the management of OBCs and OABCs.

Keywords: online community participation, social support, social identity theory, community citizenship behaviour, fuzzy-set qualitative comparative analysis, artificial neural network.

Article Type: Research paper

1. Introduction

Online communities are widely known as web-based online services supporting and facilitating information exchanges among community members (Malinen, 2015). One major feature of online communities is the member engagement which can be seen as dependency on members for generating or sharing online content, hence also known as member participation. If the core focus of an online community is the brand itself, this community is then known as online pro-brand community (OBC) where the online content is developed around brand-related consumption experiences (Wirtz et al., 2013). By proper management of OBCs, firms can effectively respond to consumer feedback which would help drive business improvement. For example, consumers can actively contribute to value co-creation by offering new ideas or suggestions which would help uncover new business opportunities (Liao et al., 2017). Opposing to OBC, online anti-brand community (OABC) aims to generate or share anti-brand-related information to promote brand rejection behaviours such as negative brand relationship and oppositional attitudinal loyalty (Dessart et al., 2016). In this connection, it is vital to examine what factors affect the level of member engagement and how such engagement can be realised in both communities. This can be termed as the study of online community participation which has been seen as key to successful OBCs and OABCs.

This paper is structured as follows. Section 2 shows the past work done and specifies the research gaps. Section 3 describes the research model derived from the current literature. Section 4 details the mechanism of the proposed two-stage approach with analysis results reported in Section 5. Key findings are discussed in Section 6. Section 7 concludes the whole paper.

2. Literature Review

Online community participation can be studied from two main perspectives: personal and social. From the personal perspective, most of the current studies have adopted various theories or models to justify the individual behaviour towards online community participation. For example, technology acceptance model (TAM) has been used to examine how one's attitude might determine one's adoption towards a new technology (i.e. participation in OBCs) (Casalo et al., 2011; Agag and El-Masry, 2016). (Elliot et al., 2013) have examined the impact of OBC quality on member's intention to transact via member's satisfaction and trust towards OBC. Analysis suggested that quality was a key to affect both satisfaction and trust which did have indirect effect on intention to transact via brand attitude and stickiness. Some new insights were generated regarding the growing influence of new measure (such as stickiness) as compared to traditional measure (such as trust). Other theories such as theory of reasoned action (TRA) and trust theory have been applied to explain the correlation between intention and action in the context of community participation(Hsu and Lu, 2007; Kozinets et al., 2010).

From the social perspective, one's attitudes, intentions and actions towards online community participation have been explained in consideration of various social theories or models. For example, social exchange theory has been used to examine how members exchange information via OBCs and what factors drive that participation (Benoit et al., 2016). In their paper, factors specific to three parties (member, co-member and provider) were examined. Analysis results suggested that co-member's cooperation was deemed negatively correlated with community participation which contracted the theory. Member's role clarity and enjoyment together with provider's responsiveness were deemed significant to drive community participation. Another commonly used theory, social identity theory, specifies how one's action would be influenced by one own perceived status (membership) within a community. Based on this theory, (Chiu et al., 2015) have reported that social identity (driven by perceived external prestige and perceived community distinctiveness) has positive effect on community participation. In addition to social identity, social influence theory depicts how one's attitudes actions would be changed by social influence which can be realised by compliance, internalisation and identification. Analysis results suggested that internalisation was found significant while both compliance and identification were deemed as insignificant, which again contracted the theory (Cheung et al., 2011). Moreover, social capital theory has been applied to address how social structures and relationships among members would impact the voluntary community participation (Son et al., 2016). Conventionally, social capital has three dimensions, i.e. structural, relationship and cognitive. (Yang and Li, 2016) have explored the inter-connection among these dimensions in driving the community participation which was measured by the popularity of consumer-generated content (i.e. the total number of comments). Analysis results suggested that strong correlations were found between these dimensions and structural dimension had no direct but indirect impact via the other two dimensions for driving the popularity. This reinforced the fact that community participation is mainly driven by member's attitude and action rather than the provider. Other theories such as social presence theory, social loafing, and social network theory have been also used to examine the impact of different social factors on community participation (Shiue et al., 2010; Cheung et al., 2011; Lee et al., 2011).

Based on the theories or models adopted, researchers have developed different factors (or determinants) that drive the community participation (Muniz and O'Guinn, 2001; McAlexander et al., 2002; Jeppesen and Frederiksen, 2006; Schau et al., 2009) and addressed different outcomes (or consequences) of community participation (Casaló et al., 2008; Jang et al., 2008). For example, determinants can be divided into different attributes such as social (e.g. trust, internalisation, communication, etc) and psychological (e.g. affiliation, identification, satisfaction, etc) while consequences can be observed in different context such as brand (e.g. brand loyalty, brand commitment, brand image, etc), consumer (e.g. consumer trust, consumer satisfaction, consumer equity, etc), and community (e.g. shared consciousness, obligation to society, moral responsibility, etc). Apart from determinants and consequences, some studies have also investigated the impact of moderators (e.g. community type, membership length, community size, etc) and mediators (e.g. mutual agreement, perceived social value, perceived goal instrumentality) on the causal relationship between determinants and consequences. Readers can refer to the study of (Kamboj and Rahman, 2017) for a more comprehensive review on community participation.

While most of the current studies have investigated determinants and consequences of community participation, there is very limited attention being paid to the formation of community participation, i.e. what defines community participation (Wang et al., 2015; Kamboj and Rahman, 2017). Also, there is a need of examining more brand related determinants towards community participation (Munnukka et al., 2015; Shim et al., 2015; Kamboj and Rahman, 2017). Hence, there is a very small number of studies that empirically verify models considering the direct connection between determinants and formations of OBC participation (Algesheimer et al., 2005; Bagozzi and Dholakia, 2006a; Bagozzi and Dholakia, 2006b; Woisetschläger et al., 2008; Madupu and Cooley, 2010), not mention about the same investigation for OABC participation, which is a relatively new area.

To address the above three research gaps, i.e. (i) explicit definition of community participation, (ii) examination of brand-related determinants and (iii) development of empirical model linking determinants and formations of OBC as well as OABC participation, a research model is developed to define determinants and formations of community participation and formulate their relationships using empirical data collected from well-structured questionnaire. A two-stage approach is then applied to examine the empirical data with an aim to uncover new observations about both online pro-brand and anti-brand community participation.

3. Research model development

OBC members may have different intentions and expectations to determine the degree of community participation. The same could be observed for OABC members (Kucuk, 2016). Although various determinants and formations of community participation have been examined for both OBCs and OABCs, there is a lack of empirical model to validate this concept. In this connection, a research model is developed to empirically understand the relationship between determinants and formations of both online pro-brand and anti-brand community participation. Analysis is done to confirm such relationship and make comparisons across online pro-brand and anti-brand community participation.

The research model is built upon an integration of various fundamental theories. This includes brand emotion, social identity theory (moral identity, brand identification and brand dis-identification), and organisational citizenship behaviour. These theories are usually used to explain a person's roles and responsibilities in an organisation. However, in an online community setting, most of the pro-brand/anti-brand community members are exercising voluntary and discretionary effort as they are not working for the brands and brand owners. Out of an organisational context, it is interesting to know why an individual inclines to support or oppose an online community. By developing a model based on these theories, we attempt to explain how one's attitude and emotion would determine his/her voluntary behaviour towards an online community.

Based on an extensive literature review of community participation studies, four categories of variables namely (i) moral identity (MI), (ii) brand identification (BI), (iii) brand dis-identification (BD), and (iv) brand emotion (BE), are considered towards online pro-brand and anti-brand community participation. The concept of organisational citizenship behaviour is used to define the formations of community participation, i.e. community citizenship behaviour (CCB). The research model defining the relationship between the four variables and CCB is shown in Figure 1.

"Figure 1"

It is vital to point out that this research serves a dual purpose to understand one's attitude, emotion and behaviour in an online community setting. First, we attempt to confirm the reliability of the model that defines the relationship between the four variables and CCB in the context of online community participation. Second, we aim to examine the differentiation between a supporter and an opposing member and more importantly, what determines such discrepancy.

3.1. Moral identity

Identity refers to the level of perception to which brand community members share the same defining attributes with the community (Ahearne et al., 2005). The identity and attachment of members to the community are positively correlated with the level of their participation and interaction within the community (Bhattacharya and Sen, 2003; Algesheimer et al., 2005).

Moral identity (MI) is defined as a “mental representation that a consumer may hold about his or her moral character” (Reed et al., 2007). The contemporary consumer research about altruistic consumer behaviour has found evidence for the links between moral identity and voluntary behaviour such as donation and pro-social motives for social topic in the context of online community participation (Shao et al., 2008).

A person’s moral identity can be examined in two dimensions, private and public moral self-schema. The private dimension is defined by internalisation (IN), which focuses on an individual’s “degree to which the moral traits are central to the self-concept” (Aquino and Reed Ii, 2002). This dimension is often implicit but influential. Another dimension, the public, is also known as symbolisation (SB), which explains the level of moral self-schema projected outwardly through his or her explicit actions (Shao et al., 2008). In other words, as a good citizen, he/she must have possessed “a strong sense of duty or obligation to the community as a whole, and to its individual members” (Muniz and O'Guinn, 2001). It is believed that members with high moral identity in terms of IN and SB to the OBC are more likely to have higher level of voluntary CCB. Hence, it is hypothesised that:

H1-1a: Internalisation (IN) is positively associated with online pro-brand CCB.

H1-2a: Symbolisation (SB) is positively associated with online pro-brand CCB.

Likewise, members of an OABC are also assuming a moral and voluntary role to sustain the community and make the voice of the like-minded people be heard.

H1-1b: Internalisation (IN) is positively associated with online anti-brand CCB.

H1-2b: Symbolisation (SB) is positively associated with online anti-brand CCB.

3.2. Brand identification

An OBC is usually set up for supporters of the brand to cultivate the feeling of “we-ness” and “consciousness of kind” with the like-minded people (Szmigin and Reppel, 2004). Through the brand community, members can share useful information about the brand in order to enhance the sense of belonging. As a result, a close bond can be usually formed among community members (McWilliam, 2000).

In this regard, brand identification (BI) can be defined as the level of perception to which brand community members attach themselves to the brand’s success. This perception can be also related with one's satisfaction to the brand and the reputation of brand (Kuenzel and Vaux Halliday, 2008). BI has deemed to have a positive effect on both customers' in-role behaviours, such as willingness to pay and loyalty (Ahearne et al., 2005; Homburg et al., 2009) as well as extra-role behaviours, such as helping the in-group members and sharing knowledge (Wiertz and de Ruyter, 2007). Hence, it can be hypothesised that:

H2a: Brand identification (BI) is positively related to online pro-brand CCB.

On the contrary, as a result of consumerism and collective action, many OABCs are developed mainly to discourage adoption of a brand by revealing the unpleasant practice of the brand and brand owner (Krishnamurthy and Kucuk, 2009). People with strong BI are less likely to join an OABC targeting the same brand. Therefore, it is believed that:

H2b: Brand identification (BI) is negatively associated with online anti-brand CCB.

3.3. Brand dis-identification

Brand dis-identification (BD) is defined as "a self-perception based on (i) a cognitive separation between a person's identity and his/her perception of the identity of an organisation and (ii) a negative relational categorisation of the self and the organisation" (Bhattacharya and Elsbach, 2002). Therefore, people with strong BD will try to detach themselves from the brand in order to demonstrate his/her independence from it. As such, people with high BD would not contribute to the brand's success and even may behave in a way to cause detriments to the brand. So, it is believed that:

H3a: Brand dis-identification (BD) is negatively associated with online pro-brand CCB.

Past research in the management field has illustrated the fact that people with high organisational dis-identification would make criticism and contest against the organisation both publicly and individually (Elsbach and Bhattacharya, 2001; Kreiner and Ashforth, 2004). With the same logic, members with high BD would contribute positively to the co-creation of negative feedback and word-of-mouth against the brand in the OABC, which can be understood as:

H3b: Brand dis-identification (BD) is positively associated with online anti-brand CCB.

3.4. Brand emotion

Brand emotion (BE) can be defined as a complex state of feeling to a brand and its related activities resulting from psychological and physical changes that affect thought and behaviour (James, 1884). The psychologist, (Ekman, 1999) has identified two consistent dimensions of emotion across different cultures, namely positive brand emotions (BE+) (e.g. happiness, amusement, contentment and satisfaction) and negative brand emotions (BE-) (e.g. anger, disgust, sadness and shame). In addition, it has been proved that, given the strong link between emotions and behaviours (Thomson et al., 2005), there is a positive correlation between one's emotional attachment to a brand and one's community participation (Yong et al., 2011). Using the same logic, it is not difficult to observe a negative relationship between one's emotional detachment to a brand and one's community participation. So, it can be hypothesised that:

H4-1a: Positive brand emotion (BE+) is positively associated with online pro-brand CCB.

H4-2a: Negative brand emotion (BE-) is negatively associated with online pro-brand CCB.

In general, some supporters of a brand may join the OABC just because they want to show agreement with their peers from the social perspective or simply look for fun. Another more "decent" reason is that they are eager to express their dissatisfaction to the like-minded people but still hope that their voices would be heard by the brand owner resulting in improvement (Romani et al., 2013). In other words, these supporters use the OABC as a channel to make constructive feedback and they still have positive expectation on the brand (Woisetschläger et al., 2008). So, most of them would act as "lurker" in the OABC as they are not really committed to that community. So, it is logical to assume that:

H4-1b: Positive brand emotion (BE+) is negatively associated with online anti-brand CCB.

Due to disapproval of and disagreement with the brand's business practices, activities and policies, people may develop negative emotions towards the brand and hence participate in OABC as a result of consumer activism and complaining behaviour (Bailey, 2004; Hollenbeck and Zinkhan, 2010; Zarantonello et al., 2016). Members with BE- would be more committed to contribute their time and effort voluntarily in the OABC such as providing feedback and sharing knowledge with an aim to mobilise and convince more people to join the anti-brand movement. Hence, it is well-understood that:

H4-2b: Negative brand emotion (BE-) is positively associated with online anti-brand CCB.

3.5. Community citizenship behaviour

Community citizenship behaviour (CCB) can be considered as a direct extra-role behaviour of community members. Based on the study of (Yi et al., 2011), CCB is defined as the voluntary and discretionary behaviour that directly promotes the effective functioning of an online community. Hence, community participation can be best described by CCB with root in organisational citizenship behaviour. According to (Groth, 2005), CCB can be realised by three dimensions which define the willingness of members in (i) making recommendations, (ii) helping others, and (iii) providing feedback, respectively. Since CCB is an extra-role conduct in the online context, we argue that it is essential to examine two new dimensions which define the willingness of members in (iv) sharing knowledge and (v) making moderation. Considering all the five dimensions will enhance the comprehensiveness and validity of the measurement of CCB in the context of online community.

4. Research methodology

We first conduct online survey targeting web users from online pro-brand and anti-brand communities based on the research model. A conventional approach, multivariate analysis, is used to verify the research model. To overcome its inherent drawbacks, a two-stage approach is proposed and applied to evaluate the same research model: (i) fuzzy-set qualitative comparative analysis (fsQCA) is applied to uncover the interplay among the six determinants toward CCB, and (ii) artificial neural network (ANN) analysis is used to determine the relative importance of each determinant (given the interplay) toward online pro-brand and anti-brand CCBs. Comparisons are made to explain the differentiations in cause-and-effect relationship between key determinants and online pro-brand/anti-brand CCB with an aim to generate new observations.

4.1. Survey design

An online survey is developed based on the research model. There are six constructs (determinants) corresponding to IN, SB, BI, BD, BE+ and BE-, that would lead to CCB. The 7-point Likert scale is used in the survey. For each construct, an appropriate measurement scale is adopted (see Table 1). Details of survey design can be referred to Appendix A1.

"Table 1"

4.2. Data collection

Using the online survey, data was collected from web users who were members of OBCs and OABCs. Companies (brands) were selected from the combined list of 147 global companies ranked in Business Week's 100 Best Global Brands and Millward Brown's BrandZ Top 100 Most Valuable Global Brands. A well-known search engine, Google, was used to identify online pro-brand and anti-brand communities for the selected brands (Kucuk, 2008). Due to huge research results, online pro-brand/anti-brand communities were selected if member number was over 100 and the last discussion was recorded within the past 12 months.

Members of six well-known OBCs and OABCs were invited to join the pilot test. All respondents hold a master degree or above. They were asked to complete the online survey and make critical comments over the survey design so as to test the face validity of the survey instrument. Total 52 completed surveys were collected. Exploratory factor analysis was done followed by a reliability test. Analysis results revealed that all constructs were reliable and the minimum acceptable cut-off value of 0.7 in Cronbach's Alpha was achieved.

The validated online survey was then posted to a total of 1,099 online community websites of those selected brands, in which 409 of them are OBCs and 690 are OABCs within a 5-month window. Incentives were used to enhance the response quality and response rate. US$20 Amazon vouchers were randomly given out to 20 respondents who completed the survey. IP address and completion time were checked to confirm the genuineness of all respondents. After removing all the invalid responses, a total of 460 datasets was found valid, in which 260 and 200 were collected from OBC and OABC respectively.

4.3. Multivariate analysis

For benchmarking purpose, multivariate analysis is first conducted using structural equation modeling (SEM). Since we aim to predict the determinants of CCB variances, partial least squares structural equation modeling (PLS-SEM) is deemed more relevant (Hair Jr et al., 2016). In PLS-SEM, researchers have to assess both measurement models (the outer models) and structural models (the inner models). The outer model refers to the relationship between the latent constructs and their indicators (Henseler et al., 2009) while the inner model includes the relationships among the latent variables (Jarvis et al., 2003).

The outer models are assessed by the first order individual reliability, internal reliability, convergent validity and discriminant validity. Reliability reflects the degree to which a given measure generates consistent outcomes under identical conditions while validity refers to the extent to which a group of indicators jointly measure what they are intended (Hair Jr et al., 2016). In this study, outer loadings are used to assess items' individual reliability, whereas composite reliability (CR) and Cronbach's Alpha (α) indicate constructs' internal reliability. The Average Variance Extracted (AVE) and square roots of AVE are used to examine both convergent validity and discriminant validity. The path coefficients (β), the significance levels and the coefficient of determinations (R^2) are used to assess the inner models.

4.4. FsQCA analysis

The *first* stage of the proposed approach involves the use of the fuzzy-set qualitative comparative analysis (fsQCA). Introduced by (Ragin, 2000), fsQCA is a set-theoretic approach to causality analysis that is mainly based on the premise that outcomes are most often caused by the interplay of a number of factors, rather than any single cause (Ordanini et al., 2013). The principle that each determinant has its own isolated net effect on the proposed outcome (an assumption often made by the classical multiple regression analysis) is being increasingly challenged (Ragin and Rihoux, 2009). Instead, the fsQCA approach analyses how various combinations of causal conditions (if any) generate a given outcome (Fiss et al., 2013; Woodside, 2013).

FsQCA is a case-based technique considering the contrarian cases that do not necessarily fit within the general trend of the data (Woodside, 2014). It is often able to identify multiple solutions that can successfully lead to the same outcome. It therefore helps address the issue of "equifinality" which often exist in management-related phenomena. The concept of equifinality refers to situations when different yet equally effective combinations of factors generate the same outcome (Fiss, 2007). FsQCA analysis may uncover patterns within the dataset that would have been difficult to highlight when using a traditional multiple regression analysis (Vis, 2012). In summary, fsQCA is a more comprehensive approach, unlike multiple regression analysis, can account for heterogeneity and complex causality issues (Schlittgen et al., 2016). Hence, fsQCA was applied to the present study in order to examine the various combinations of factors influencing the degree of people's involvement in supporting an online community (online pro-brand CCB) and opposing an online community (online anti-brand CCB) as shown in Figure 2.

"Figure 2"

4.4.1. Calibration

The raw data must be first transformed into fuzzy set scores in order to apply fsQCA analysis (Ragin and Rihoux, 2009). This is known as "data calibration". Fuzzy sets are different from the traditional variables. A set is a group of continuous values, ranging from 0 to 1, that illustrates the degree of membership in a given condition (Skarmeas et al., 2014), e.g. the degree to which a person is a member of the set "high positive brand emotion". In this study, Likert scales were used to assess each variable. To calibrate these variables, three cutoff values are identified from the Likert scales that would correspond to the three fsQCA qualitative anchors determining the level of membership, which are 1 for full membership, 0 for non-membership and 0.5 for the crossover point (Ragin and Rihoux, 2009). The choice of the Likert scale cutoff values should be based on theoretical knowledge (Ragin, 2008). In this study, the researchers defined the scores 1 (strongly disagree), 4 (neutral) and 7 (strongly agree) as representing non-membership, crossover point and full membership.

4.4.2. Necessity analysis

The necessity analysis examines whether any of the present factors has a high probability to be a "necessary" condition (yet not sufficient) for the targeted outcome (Kent, 2015). A condition can be considered as necessary when its consistency score exceeds 0.90 (Kent, 2015; Tóth et al., 2015). Similar to significance level in multivariate techniques (Woodside and Zhang, 2012), consistency illustrates the proportion of the cases with a given condition exhibiting the outcome. The higher the cases with this condition NOT displaying the outcome, the lower the consistency score (Tóth et al., 2015). Next, a sufficiency analysis is conducted to tell whether a necessary condition is "sufficient" for causing the targeted outcome.

4.4.3. Sufficiency analysis

Three steps are involved during the sufficiency analysis (Tóth et al., 2015). First, a "truth table" is produced where all possible combinations of the factors are listed (Ragin, 2008). The number of possible combinations is 2^k where *k* refers to the number of conditions. In this study, $2^6 = 64$ possible configurations are displayed. However, not necessarily all combinations are empirically valid. A valid combination should include a minimum number of cases with greater than a 0.5 membership (known as the frequency threshold) and consistency threshold (Woodside and Zhang, 2012).

The second step is to define these thresholds. When dealing with small samples, the frequency threshold is often set as one single case, i.e. a valid combination should include at least 1 case with a membership greater than 0.5. However, when large samples are involved, the frequency cutoff should be set higher, such as 5 or 10 (Ragin et al., 2008). As for setting the consistency threshold, it will depend on the nature of the targeted outcome. In this vein, a drop in the consistency threshold could delineate the cutoff point (Ragin, 2008). This being said, a consistency value of 0.75 or more generally posits an acceptable combination (Woodside, 2013; Skarmeas et al., 2014).

The third step involves reducing the number of combinations causing the outcome. This is known as "boolean minimisation" which aims at eliminating logically redundant conditions, i.e. if two acceptable combinations (leading to the same outcome) only differ in one condition

(Kent, 2015), such condition will be removed. For each combination, values for consistency and coverage are provided. Coverage reflects the proportion of cases explained by the combination (raw coverage) (Ragin, 2008; Kent, 2015). In regression analysis, coverage is akin to the effect size (Woodside and Zhang, 2012). Additionally, the overall solution coverage is generated. This is similar to the R-square value reported in variable-based techniques and illustrates the explanatory power of the proposed conditions (Woodside, 2013).

4.5. ANN analysis

The *second* stage of the proposed approach is to tell which condition in a combination (obtained from fsQCA analysis) is more influential using a typical three-layer feed-forward backpropagation artificial neural networks (ANNs) with Levenberg-Marquardt training function. This analysis can overcome a major limitation of fsQCA in which it does not indicate the importance of each condition (determinant) but only emphasise the *presence* or *absence* of a condition in a combination. It is well-known that there is no universal method of identifying the relative importance of the presence of conditions (Wong and Chan, 2012). In this study, we apply a change of mean square error (COM) method which is proved reliable in capturing relative importance of conditions leading to the same outcome (Wong and Chan, 2015).

Based on the valid combinations of conditions derived from fsQCA analysis, an ANN is developed to model each combination depicting the relationship between various conditions and online pro-brand/anti-brand CCB. Each of these ANNs is then trained and evaluated via a 10-fold cross validation and 90% of the data are used for training whereas the remaining 10% are for validation. A trial-and-error approach is used to determine the number of neurons in the hidden layer (P) of an ANN (Wang and Elhag, 2007). It is well-known that a large P would improve the ability of ANN to learn and memorise the dataset, but its ability to generalise may be reduced. But, a small P may restrict ANN from learning (Wong and Chan, 2012).

After training and evaluation, an ANN that can best model the relationship between various conditions and online pro-brand/anti-brand CCB in each combination is identified. The COM method is then applied to each of these ANNs in order to determine the relative importance of a condition in each combination as follows: (i) compute mean square error (MSE) with all conditions in a valid combination (MSE_{all}) as defined by Equation (1) where A_i and P_i are the actual values and predicted values of i-th testing dataset respectively, and D is the total number of tested dataset, (ii) compute MSE after removing only condition n from the combination (MSE_n), (iii) calculate the change in MSE before and after removing condition n (CH_n) as shown in Equation (2), and (iv) calculate the relative importance of condition n (RI_n) by the ratio of CH_n over the total changes associated with all conditions (ΣCH_i for i=1…N) as defined by Equation (3) where N defines the total number of conditions in the combination.

$$MSE = \frac{1}{D}\sum_{i=1}^{D}\left(A_i - P_i\right)^2 \qquad (1)$$

$$CH_n = \left| MSE_n - MSE_{all} \right| \tag{2}$$

$$RI_n = \frac{CH_n}{\sum_{i=1}^{N} CH_i} \tag{3}$$

5. Findings

5.1. Results of multivariate analysis

Since the second-order construct, CCB, is defined by five first-order dimensions (variables) in the outer model, a two-step approach is used to evaluate the reliability and validity of these first-order variables (Chiu et al., 2015). Table 2 reports that Cronbach's α and CR were above the cut-off value of 0.7, hence indicating acceptable individual and internal reliabilities(Schmiedel et al., 2014). Table 2 also reports that AVE scores exceeded the 0.5 threshold, whereas the square root of AVE of each construct was greater than the correlations involved in the remaining constructs. Therefore, acceptable values for both convergent and discriminant validities are established. Furthermore, multicollinearity issues and common method bias were also examined for all independent constructs through the variance inflation factor (VIF) and the Harman's single factor test (Podsakoff et al., 2003) respectively. In this regard, no major issues of collinearity emerged as all VIF values varied around 1.20 – 2.02 for the pro-brand group and 1.63 – 2.36 for the anti-brand group (all below the critical value of 5). Regarding the common method bias, Harman's test also showed no major sign of common method bias (single factor accounting for less than 50%) (Lings et al., 2014).

"Table 2"

In the inner model (Figure 3), brand and anti-brand groups are examined together. For the pro-brand group, it shows that SB, BI and BE+ were the strongest determinants of online pro-brand CCB. Hence, only H1-2a, H2a and H4-1a are accepted. For the anti-brand group, IN, SB and BE+ were the strongest determinants of online anti-brand CCB. Therefore, only H1-1b and H1-2b are accepted. It is noted that the determinants of CCB explained 52% of the variances for the pro-brand group while 54% of CCB was explained by its determinants in the anti-brand group.

"Figure 3"

5.2. Results of fsQCA analysis

Following the process described in Section 4.4, Table 3 presents the results of necessity analysis for both online pro-brand CCB and online anti-brand CCB after data calibration. It shows that the presence of IN, SB, and BE+ are probably "necessary" to promote online pro-brand CCB. Alternatively, only IN appears to be a "necessary" condition to promote online anti-brand CCB. However, these conditions may not be sufficient. The next step is to conduct a sufficiency analysis in order to identify the various combinations that would contribute to online pro-brand and anti-brand CCBs.

"Table 3"

In this study, we set the frequency threshold as 4, which captured 80% of the cases for both online pro-brand and anti-brand CCBs, exceeding (Ragin et al., 2008)'s criterion (Cheng et al., 2013; Ren et al., 2016). Consistency threshold is used to define the proportion of the cases, under a given combination, exhibiting online pro-brand/anti-brand CCB. A drop in the consistency was noted at 0.90. Hence, a threshold of at least 0.90 was chosen such that combinations with a consistency score below 0.90 are not considered in the analysis and are called "remainders".

Tables 4 and 5 present the "truth tables" specifying different combinations of conditions leading to online pro-brand CCB and online anti-brand CCB respectively. The complex solution is used in this study as it makes no simplifying assumptions (Skarmeas et al., 2014). It is noted that, not one but multiple combinations of conditions can lead to both online pro-brand and anti-brand CCBs. Hence, this helps confirm the "equifinality" phenomenon that cannot be uncovered using traditional multivariate techniques.

"Tables 4-5"

In Table 4, the first two solutions indicate that IN, SB, and BE+ together would lead to online pro-brand CCB while BI and BD are mutually exclusive, i.e. a member supporting an online community would only show sign of either BI or BD. Solution 3 confirms the importance of IN, SB and BE+ and emphasises the absence of BE- while overlooking the effect of BI and BD. All solutions together explained 82% of the cases for OBC. In short, all hypotheses specific to online brand CCB are proved reliable except H2a and H3a.

In Table 5, similar to online pro-brand CCB, the first two solutions indicate that IN, SB and BE+ together would lead to online anti-brand CCB while BI and BE- are mutually exclusive. Solution 3 can be ignored due to low unique coverage (Tóth et al., 2015). Solution 4 confirms the importance of IN, SB, and BE+ and emphasises the presence of BD and BE-. All solutions (solution 3 excluded) explained 64% of the cases for OABC. Hence, all hypotheses specific to online anti-brand CCB are proved reliable except H2b, H4-1b and H4-2b.

5.3. **Results of ANN analysis**

In this study, the performance of ANNs is assessed by mean absolute percentage error (MAPE) and standard deviation (SD). MAPE is defined by Equation (4) where A_i and P_i are the actual values and predicted values of i-th testing dataset respectively, and D is the total number of tested dataset. Table 6 shows the performance of ANNs with varying P for each of the solutions (combinations) in both pro-brand and anti-brand groups. The best value of P is addressed if it gives an ANN the smallest MAPE. The COM method is then applied to the well-tuned ANN for each solution (combination). Table 7 reports the relative importance (RI) of each condition in each of the solutions (combinations) for both pro-brand and anti-brand groups. The average RI is obtained for conditions which are found in more than one combination. The normalised RI of each condition is then obtained for ease of comparison.

$$MAPE = \frac{1}{D}\sum_{i=1}^{D}\frac{|A_i - P_i|}{A_i} \times 100 \qquad (4)$$

"Tables 6-7"

6. Discussions

For benchmarking purpose, multivariate analysis is first done. Table 8 reports the results of multivariate analysis which suggest that only SB, BI and BE+ contribute significantly towards online pro-brand CCB while only IN and SB contribute towards online anti-brand CCB. Generally, the results reinforce what is known in the current literature. Due to the inherent limitation of multivariable analysis, interplay between factors is overlooked, hence, no new insight is generated.

To uncover new observations, fsQCA analysis, which is the first stage of our proposed approach, is performed. Table 8 reports the results of fsQCA analysis method which suggest that IN, SB, and BE+ contribute significantly towards online pro-brand CCB. Moreover, BI and BD are found mutually exclusive towards online pro-brand CCB. On one hand, people with BI (BD is absent) tend to show higher attachment to the brand's success when being a member of OBC and this greatly conforms to the current understanding. On another hand, people with BD (BI is absent) being a member of OBC tend to detach themselves from the brand and this contradicts the theory. One possible explanation is that people with BD joining OBC may want to fulfill his/her pro-social motive by conveying disappointment or frustration about the brand (Dessart et al., 2016). As a result, improvement can be possibly made, and thus the sustainability of the OBC as well as the brand itself can be enhanced (Fournier et al., 2015). This explanation conforms to the understanding that people with pro-social motive would perform any action that is beneficial to other people (Mantovani et al., 2017). In other words, members of OBC with BD (BI is absent) may have stronger pro-social motive than members of the same community with BI (BD is absent).

For anti-brand group, fsQCA analysis results suggest that IN, SB, and BD have positive effect on online anti-brand CCB which conform well to the theory. In addition, BI and BE- are found mutually exclusive. It means that people with BE- (BI is absent) tend to show negative emotion and lower attachment to the brand's success when being a member of OABC and this greatly reinforces the theory. On another hand, people with BI (BE- is absent) tend to show higher attachment to the brand's success without negative motion when being a member of OABC. This again contradicts the theory but can also be explained by the pro-social motive. In other words, members of OABC with pro-social motive intend to post deviant content that may lead to positive discussions and foster further improvement, also known as constructive co-creation (Gatzweiler et al., 2017). This can be confirmed by the presence of BE+ which indicates that some of them actually feel good about the brand. Also, this may be partially due to consumer movement which is an effort to promote more consumer protection by critically evaluating the current business practice (Kozinets and Handelman, 2004).

"Table 8"

The second stage of our proposed approach, ANN analysis, is to measure the RI of each condition in each of the interplays among determinants. For pro-brand group, Table 7 clearly shows that SB and BE+ are the two most influential determinants with overall influence over 70% towards online pro-brand CCB, followed by IN, BD or BI. While the effect of BE+ is reinforced, SB is found to be more influential than IN. This may suggest that moral action is a better indicator of online pro-brand CCB. The RI of BD is small (12%), so this implies that the overall effect of pro-social motive in the pro-brand group is weak. For anti-brand group, IN, SB, and BE+ are the three most influential determinants with overall influence over 80% towards online anti-brand CCB, followed by BD, BE- and BI. Unlike pro-brand group, the effect of IN is found slightly stronger than that of SB. This may suggest that moral thought is a better indicator of online anti-brand CCB, i.e. one may need more inner triggers (internalisation) to oppose the brand. This contradicts the current understanding that anti-brand (detrimental) behaviours are less morally restricted given the virtuality and anonymity of the online communities. Since the majority of OABC members show positive brand emotion, our results suggest that members may need to better justify themselves internally (IN) to overcome positive brand emotion (BE+) when exercising anti-brand action. Contrary to pro-brand group, pro-social motive may be more obvious among some OABC members given the overall influence of BI and BE+ is 43%. The overall influence of BD and BE- is 45% which also infers that some members are indeed opposing the brand. This may suggest that there are at least two types of members within the anti-brand group: (i) members with weak pro-social motive and intrinsically opposing the brand (brand adversary); and (ii) members with strong pro-social motive and intrinsically supporting the brand (brand supporter). However, there is no clear dominance of one member type over another.

In short, important observations obtained from our two-stage approach are summarised as follows. For online pro-brand community (OBC),

- Symbolisation (SB) and positive brand emotion (BE+) are the two most important determinants that drive online pro-brand CCB.
- Regarding moral identity (MI), SB has slightly stronger impact than internalisation (IN), which means that moral action is a better indicator to online pro-brand CCB.
- Members with brand dis-identification (BD) may have stronger pro-social motive than members with brand identification (BI).
- The overall effect of pro-social motive is weak.

For online anti-brand community (OABC),

- Internalisation (IN), symbolisation (SB), and positive brand emotion (BE+) are the three most important determinants that drive online anti-brand CCB.
- Regarding moral identity (MI), IN is found slightly stronger than SB which shows that moral thought is a better indicator to online anti-brand CCB.
- Members with brand dis-identification (BD) and negative brand emotion (BE-) may show weak sign of pro-social motive (brand adversary).

- Members with brand identification (BI) and BE+ may show strong sign of pro-social motive (brand supporter).
- There is no clear dominance of one member type over another.

7. Managerial Implications

Overall, this study not only reinforces our current understanding of online pro-brand CCB but also helps uncover some mysteries about online anti-brand CCB. One important finding is that members of OABC tend to have stronger internalisation (IN) than those of OBC. It implies that one may need more inner triggers to oppose the brand rather than supporting. Joining OABC may be one way of confirming one's self-concept through interaction with the like-minded people (Hollenbeck and Zinkhan, 2010). Brand identification (BI), brand dis-identification (BD) together with brand emotion (BE+/BE-) would be used to identify two types of OABC members: one with weak pro-social motive (brand adversary) and another with strong pro-social motive (brand supporter). From the managerial perspective, OABC administrator must make sure that any anti-brand content is genuine and justified in order to promote online anti-brand CCB. Otherwise, anti-brand action is merely seen as business activities initiated by competitors rather than act of rightfulness which conforms to the internalisation especially from the perspective of OABC members with weak pro-social motive (brand adversary). On another hand, OBC administrator would uncover opportunities from OABC content especially from the perspective of OABC members with strong pro-social motive (brand supporter) so as to promote online pro-brand CCB. Since both CCBs can co-exist, OBC and OABC should not be managed following zero sum strategy.

It is well-known that member (or brand) engagement can be positively or negatively valenced (Hollebeek and Chen, 2014). However, it is not clear how such engagement can be defined. To address this, another important finding of our study suggests that positive brand emotion (BE+) would drive both online pro-brand and anti-brand CCBs. In other words, people who feel good about the brand would be part of OBC making pro-brand comments. They can also join OABC making anti-brand comments but hope that the brand can be improved. It means that anti-brand action does not always lead to negative brand engagement. Hence, the research model developed in this paper could be used to define and improve brand engagement. This enables OBC/OABC administrator to gain more control over online pro-brand/anti-brand CCB. As a result, OBC/OABC can be better managed to support its own purpose.

8. Conclusion

In order to fill the three research gaps, we re-define CCB, consider brand related determinants, and develop a research model to examine the relationship between determinants and formations of community citizenship behaviour (CCB) in the context of online community. To overcome the inherent limitations of multivariate analysis, a two-stage approach is implemented to uncover new observations from the empirical data. The first stage of the proposed approach is to identify the interplay among determinants using fsQCA method while the second stage is to measure the relative importance of determinants in each interplay using ANN method. Analysis results show that the six determinants exhibit different degrees of influence towards online pro-brand and anti-brand CCBs. In general, moral identity and positive brand emotion are the two most influential determinants driving both online pro-brand and anti-brand CCBs. There are two main distinctions between pro-brand and anti-brand groups. The first distinction is the impact of internalisation/symbolisation and the second is the effect of pro-social motive which helps identify two member types in OABC. However, no member type dominates.

As one of the few studies investigating both online pro-brand and anti-brand CCBs, we uncover some new observations which help manage OBCs and OABCs. However, there are some limitations of the current search: (i) analysis results are highly data-driven, thus the generalisation may be limited. Future research should expand the scale and diversity of the dataset; (ii) the research model does not consider mediators and moderators which are mostly specific to online pro-brand CCB. Future work should examine their impact on both online pro-brand and anti-brand CCBs. Some mediators and moderators will need to be modified in the context of online anti-brand CCB; and (iii) the effect of pro-social motive and other relevant motives will be further examined for both online pro-brand and anti-brand CCBs.

Appendix

Table A1: Survey design

Item Code	Item
Moral identity	
Internalisation	
IN1	It would make me feel good to be a person who has these characteristics.
IN2	Being someone who has these characteristics is an important part of who I am.
IN3	I would be ashamed to be a person who had these characteristics. (Reverse scale)
IN4	Having these characteristics is NOT really important to me. (Reverse scale)
IN5	I strongly desire to have these characteristics.
Symbolisation	
SB1	I often wear clothes that identify me as having these characteristics.
SB2	The types of things I do in my spare time (e.g., hobbies) clearly identify me as having these characteristics.
SB3	The kinds of books and magazines that I read identify me as having these characteristics.
SB4	The fact that I have these characteristics is communicated to others by my membership in certain organizations.
SB5	I am actively involved in activities that communicate to others that I have these characteristics.
Brand identification	
BI1	This brand's successes are my successes.
BI2	If someone praises this brand, it feels like a personal compliment.
BI3	If someone criticizes this brand, it feels like a personal insult.
Brand dis-identification	
BD1	The brand's failures are my successes.
BD2	When someone praises this brand, it feels like a personal insult.
BD3	When someone criticizes this brand, it feels like a personal compliment.
Brand emotion	
BE1	Affectionate
BE2	Friendly
BE3	Loved
BE4	Peaceful
BE5	Passionate
BE6	Delighted
BE7	Captivated
BE8	Connected

BE9	Bonded
BE10	Attached
BE11	Sad
BE12	Sorrowful
BE13	Distressed
BE14	Irritated
BE15	Angry
BE16	Annoyed
BE17	Offended
BE18	Depressed
Community citizenship behaviour	
Making recommendation	
MR1	Recommend this online community to my family.
MR2	Recommend this online community to my peers.
MR3	Recommend this community to people interested in the community/brand content.
Helping members	
HM1	Assist other members in finding information.
HM2	Help others with their information research.
HM3	Teach someone how to use the online community correctly.
Providing feedback	
PF1	Provide helpful feedback to the host.
PF2	Provide information when surveyed by the online community.
PF3	Inform the host about the great information or support received by an individual member.
Making moderation	
MM1	Explain to other members how to use the online community correctly.
MM2	Report to the owner/webmaster misuse/abuse in the community.
MM3	Draw participants to good quality interaction (e.g., discussion)
Sharing knowledge	
SK1	I intend to post information in this online community regularly in the future.
SK2	I will try to share my comments with members of this online community in the future.
SK3	I will always make an effort to provide feedback to members of this online community.

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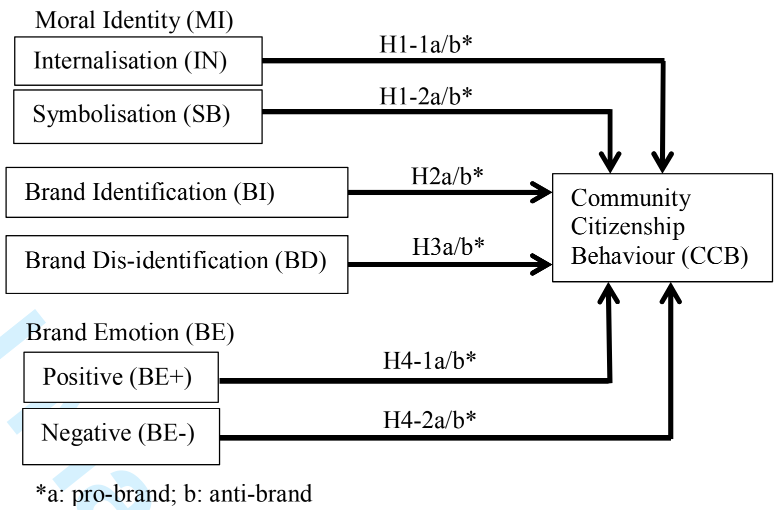


Figure 1: The research model

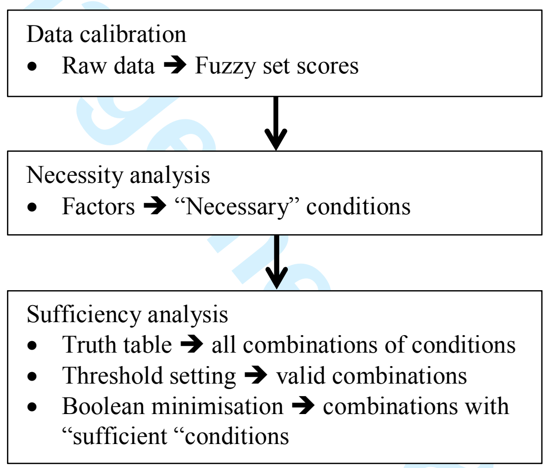
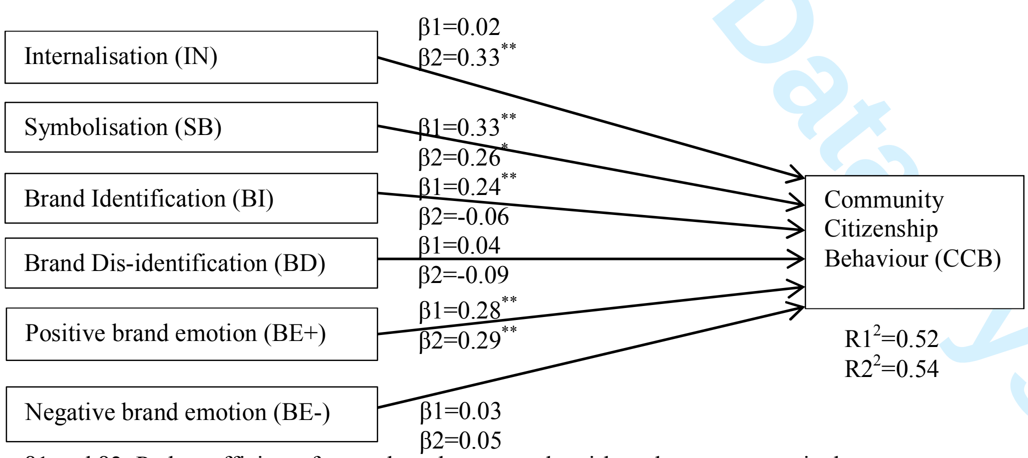


Figure 2: Procedures of fsQCA



β1 and β2: Path coefficients for pro-brand group and anti-brand group respectively
$R1^2$ and $R2^2$: Coefficients of determinations for pro-brand group and anti-brand group respectively
** and *: Significance levels at 0.1% and 1% respectively

Figure 3: Assessment of the inner models

Table 1: A summary of measurement scales used

Construct	Measurement Scale
Moral identity (MI)	
Internalisation (IN) Symbolisation (SB)	Aquino and Reed (2002)
Brand identification (BI)	Mael and Ashforth (1992)
Brand dis-identification (BD)	Elsbach and Bhattacharya (2001)
Brand emotion (BE)	
Positive brand emotion (BE+) Negative brand emotion (BE-)	Thomson et al. (2005) Burke and Edell (1989)
Community citizenship behaviours (CCB)	
Making recommendation (MR) Helping members (HM) Providing feedback (PF)	Groth (2005) Organ et al. (2005)
Making moderation (MM)	He and Kwok (2011)
Sharing knowledge (SK)	Lin (2007)

Table 2: Assessment of the outer models

Construct	Pro-brand			Anti-brand		
	α	CR	AVE	α	CR	AVE
BD	0.958	0.971	0.917	0.962	0.975	0.93
BI	0.93	0.955	0.877	0.956	0.971	0.919
BE+	0.932	0.942	0.62	0.972	0.976	0.802
BE-	0.974	0.979	0.884	0.968	0.974	0.863
PF	0.943	0.964	0.898	0.966	0.978	0.937
HM	0.949	0.967	0.907	0.962	0.975	0.929
IN	0.881	0.926	0.808	0.924	0.952	0.868
SK	0.944	0.964	0.899	0.953	0.97	0.914
MM	0.886	0.929	0.814	0.935	0.958	0.884
MR	0.889	0.932	0.821	0.932	0.957	0.881
SB	0.862	0.901	0.645	0.926	0.944	0.773

Table 3: Necessary analysis for online pro-brand and anti-brand CCBs

Condition	Group	Community Citizenship Behaviour	
		Consistency	Coverage
IN	Pro-brand	0.946478	0.737846
	Anti-brand	0.938819	0.750657
SB	Pro-brand	0.913103	0.838673
	Anti-brand	0.853144	0.815859
BI	Pro-brand	0.800096	0.869841
	Anti-brand	0.694836	0.830650
BD	Pro-brand	0.365337	0.969097
	Anti-brand	0.681794	0.796285
BE+	Pro-brand	0.919202	0.830886
	Anti-brand	0.805535	0.812513
BE-	Pro-brand	0.393640	0.954311
	Anti-brand	0.676704	0.802162

Table 4: Conditions leading to online pro-brand CCB

Solutions	IN	SB	BI	BD	BE+	BE-	Consistency	Raw coverage	Unique coverage
1	●	●	○	●	●		0.98	0.32	0.02
2	●	●	●	○	●		0.93	0.70	0.04
3	●	●			●	○	0.88	0.77	0.10
Note: ● presence of condition; ○ absence or negation of condition									
Solution coverage: 0.82; solution consistency: 0.89									
Algorithm: Quine-McCluskey; frequency cutoff: 4.0; consistency cutoff: 0.90									

Table 5: Conditions leading to online anti-brand CCB

Solutions	IN	SB	BI	BD	BE+	BE-	Consistency	Raw coverage	Unique coverage
1	●	●	●		●	○	0.95	0.52	0.06
2	●	●	○		●	●	0.94	0.44	0.02
3*	●	●	●	●	●		0.94	0.50	0.0009
4	●	●		●	●	●	0.94	0.45	0.03
Note: ● presence of condition; ○ absence or negation of condition; * excluded									
Solution coverage: 0.64; solution consistency: 0.93									
Algorithm: Quine-McCluskey; frequency cutoff: 4.0; consistency cutoff: 0.94									

Table 6: Performance of ANNs with varying P

ANNs	Perf.	P														
		2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
ANN-1	Ave.	9.10	***8.87***	8.90	9.03	8.90	9.13	9.08	9.25	9.03	9.03	9.13	9.15	9.15	8.97	9.05
	SD	0.79	***0.72***	0.81	0.55	0.94	0.79	0.94	0.96	0.75	1.01	0.70	0.84	0.50	0.53	0.58
ANN-2	Ave.	9.18	9.21	8.82	9.10	8.73	***8.62***	9.00	9.21	9.01	8.83	8.93	9.16	9.11	8.96	8.99
	SD	1.04	1.04	1.00	0.79	0.84	***0.78***	0.88	0.81	1.04	0.98	0.67	0.68	0.83	0.51	0.83
ANN-3	Ave.	8.62	***8.61***	9.00	8.73	8.64	8.82	8.97	8.73	8.69	8.98	8.76	8.67	8.86	9.04	9.03
	SD	0.98	***0.94***	0.73	0.82	0.77	0.80	0.77	0.49	0.69	0.49	0.67	0.57	0.86	0.95	0.39
ANN-4	Ave.	8.94	9.16	8.96	8.88	9.02	8.42	9.16	8.94	8.85	***8.35***	8.96	8.98	9.38	9.12	8.67
	SD	0.59	0.86	0.94	0.74	0.68	0.69	0.60	0.98	0.89	***0.87***	0.69	0.79	1.10	0.53	0.82
ANN-5	Ave.	9.29	9.03	***8.55***	9.03	9.36	9.14	9.19	9.10	8.90	9.16	9.16	9.30	8.95	8.78	9.36
	SD	0.88	0.62	***0.68***	0.89	0.77	1.13	1.03	0.71	0.74	0.95	0.49	0.66	0.75	0.92	0.75
ANN-6	Ave.	9.12	8.98	9.52	9.39	9.15	9.30	9.01	9.05	9.20	9.31	9.20	9.16	9.20	***8.41***	9.10
	SD	0.62	0.86	0.92	0.84	0.76	0.78	0.95	0.75	0.97	0.72	0.81	0.87	0.99	***0.57***	0.57

Table 7: Relative importance of conditions

Group	Solutions	ANNs	IN	SB	BI	BD	BE+	BE-
Pro-brand	1	ANN-1	0.18	***0.29***	-	0.12	***0.41***	-
	2	ANN-2	0.17	***0.20***	0.11	-	***0.52***	-
	3	ANN-3	0.22	***0.28***	-	-	***0.50***	-
Anti-brand	1	ANN-4	***0.30***	***0.27***	0.15	-	***0.28***	-
	2	ANN-5	***0.38***	***0.25***	-	-	***0.22***	0.15
	4	ANN-6	0.19	0.16	-	***0.23***	***0.20***	***0.22***

Table 8: Results of hypothesis testing

Group	Hypothesis	Path	Multivariate analysis	fsQCA analysis
Pro-brand	H1-1a	IN➔CCB		✓
	H1-2a	SB➔CCB	✓	✓
	H2a	BI➔CCB	✓	*
	H3a	BD➔CCB		*
	H4-1a	BE+➔CCB	✓	✓
	H4-2a	BE-➔CCB		✓
Anti-brand	H1-1b	IN➔CCB	✓	✓
	H1-2b	SB➔CCB	✓	✓
	H2b	BI➔CCB		*
	H3b	BD➔CCB		✓
	H4-1b	BE+➔CCB		
	H4-2b	BE-➔CCB		*

✓: Accepted
*: Mutually exclusive, i.e. one hypothesis is accepted while another must be rejected