

## **Building customers' resilience to negative information in the airline industry**

**Mário Augusto** (Email: [maugusto@fe.uc.pt](mailto:maugusto@fe.uc.pt))

**Pedro Godinho** (Email: [pgodinho@fe.uc.pt](mailto:pgodinho@fe.uc.pt))

**Pedro Torres** (Email: [pedro.torres@uc.pt](mailto:pedro.torres@uc.pt))

CeBER and Faculty of Economics, University of Coimbra  
Av. Dias da Silva, 165  
3004-512 Coimbra - Portugal

Corresponding author: Pedro Torres

### **Abstract**

This study aims to model the conditions that lead to existing customers' resilience to negative information in the context of the airline industry. In doing so, the study examines the role of electronic word-of-mouth, considering the commitment-consistency principle. Fuzzy-set qualitative comparative analysis is employed along with structural equation modeling. Interaction effects are also studied. The structural equation modeling results show that electronic word-of-mouth influences resilience to negative information directly and indirectly (through the mediation of customer-brand identification). The results of the fuzzy-set qualitative comparative analysis show that customer-brand identification must be combined with electronic word-of-mouth to achieve high resilience to negative information. The combination of self-brand congruity with electronic word-of-mouth can also be sufficient to obtain this outcome. The interaction analysis provides additional support for the amplifying effect of electronic word-of-mouth.

**Keywords:** Resilience to negative information, electronic word-of-mouth, customer-brand identification, self-brand congruity, memorable brand experiences, brand social benefits

This is a pre-copyedit version of an article published in the Journal of Retailing and Consumer Services.

© 2019. This manuscript version is made available under the CC-BY-NC-ND 4.0 license <http://creativecommons.org/licenses/by-nc-nd/4.0/>.

This is a pre-copyedit version of an article published in the Journal of Retailing and Consumer Services. The final version of the article is available online at: <https://doi.org/10.1016/j.jretconser.2019.05.015>

## **1. Introduction**

Previous research has noted that airlines should place a stronger focus on the brand value proposition to remain viable entities in a highly competitive industry (e.g., So et al., 2017). In fact, building and managing the brand identity has become a strategic imperative for airline companies (Balmer et al., 2009; So et al., 2018). However, creating and developing strong service brands is challenging, given the intangible nature of services (Becker et al., 1992). In this context, relationship-building is an important issue (Javalgi et al., 2006). Customer-brand identification has been considered an indicator of the customer-brand relationship (So et al., 2018), which can be enhanced by social media (Wang et al., 2012).

With the emergence of online social media, social networking sites (e.g., Facebook) and microblogging sites (e.g., Twitter) in particular, customer daily routines have changed. Customers often post travel experiences on social media platforms (Xiang & Gretzel, 2010), and it has been suggested that travelers have a strong desire to share their experiences with others (Kim & Fesenmaier, 2017). Airline companies often see these online platforms as effective means to communicate and reinforce their brand identity and to build customer rapport (So et al., 2018). Thus, electronic word-of-mouth has been promoted by airlines. Nevertheless, social media also presents challenges to airlines because customers no longer have to accept service dissatisfaction quietly. Therefore, building resilience to negative information, which is closely related to the customer-brand relationship, has become increasingly important for airlines. In fact, negative information has a greater impact on brand evaluation than does positive information (Skowronski et al., 1998). Moreover, travel incidents that have gone wrong tend to be strongly recalled by travelers (Lee & Park, 2010), and service failures often occur in air travel (Park & Park, 2016).

By adopting the novel perspective of focusing on existing customers, this study claims that positive electronic word-of-mouth may complement customer-brand identification in building

resilience to negative information. If customers take a public position through electronic word-of-mouth, then they are likely to align their attitudes in the direction of that position (Cialdini, 1971). Furthermore, the study suggests that positive electronic word-of-mouth can reinforce customer-brand identification for the sender. Hence, the main objective of this research is to identify the conditions that lead to existing customers' resilience to negative information and to investigate the role of electronic word-of-mouth in this process. In doing so, electronic word-of-mouth is integrated into the customer-brand identification approach.

Focusing on existing customers, this research postulates that customers' engagement in electronic word-of-mouth will directly and indirectly affect resilience to negative information based on the relationship between commitment and consistency. These effects are tested using structural equation modeling, which is also used to compare alternative models and identify the most correct relations among constructs. Furthermore, considering the complex relations among the constructs and taking into account that customer-brand identification alone may not be sufficient to build high resilience to negative information, an application of fuzzy-set qualitative comparative analysis (fsQCA) is performed. In addition to customer-brand identification, electronic word-of-mouth, and resilience to negative information, self-brand congruity is also considered in this analysis. Finally, to complement the fsQCA analysis and to explore the amplifying effect of electronic word-of-mouth, interaction effects are analyzed.

The fsQCA approach adds two interesting dimensions: the ability to puzzle out complex relations between constructs, such as equifinality (Grofman & Schneider, 2009), and the ability to identify configurations that reflect the necessary and sufficient conditions to achieve an outcome of interest (Ordanini et al., 2014). Previous studies have noted that qualitative comparative analysis studies in tourism are scarce, but they have also highlighted its suitability to deal with complexity

in this sector (Papatheodorou & Pappas, 2016). Inspired by Haumann et al. (2014), this research focuses on the airline industry because *i*) airline companies are prototypical companies with which customers can identify (Berry, 2000; Bhattacharya & Sen, 2003); *ii*) building and maintaining successful customer-brand relationships is critical in the airline industry (Grewal et al., 2010); *iii*) given the previous argument, considering the intense competitive environment (So et al., 2017) and the importance of building and managing the brand identity (Balmer et al., 2009; So et al., 2018), the promotion of positive electronic word-of-mouth and the reinforcement of customer-brand identification can be suitable marketing strategies; and *iv*) this context has been used in past research, which provides a suitable basis to advance the customer-relationship literature. Additionally, the airline industry faces specific challenges for which building resilience to negative information can have particular importance. As highlighted by Migacz et al. (2017), such challenges include the impact of certain failures (e.g., flight delays) on large groups of people; the significant loss caused by certain failures (time and/or money) in proportion to other services; and the feeling of lack of control associated with flying that stresses passengers' feelings of vulnerability and hopelessness.

The impact of customer-brand identification on resilience to negative information remains unclear (So et al., 2018). Resilience to negative information has been considered an extra-role behavior (Elbedweilhy et al., 2016) that corresponds to the extent to which customers do not allow negative information about a company to diminish their general view of the company (Bhattacharya & Sen, 2004; Eisingerich et al., 2011). Such behavior tends to occur when customers experience an enhanced fit with the company's identity (Bhattacharya & Sen, 2003). Identification is likely to lead to extra-role customer behaviors (Bhattacharya & Sen, 2003), driving customers to benefit a brand without thinking purely of their own self-interest (O'Reilly & Chatman, 1986).

However, despite the importance of customer-brand identification, the results obtained in recent research suggest that customer-brand identification alone may not be sufficient to build resilience to negative information (So et al., 2018).

Customer satisfaction and customer-brand identification have been acknowledged as two of the most important concepts in relationship marketing (Haumann et al., 2014), but identification is gaining more importance because it is increasingly difficult to compete on the basis of customer satisfaction (Homburg et al., 2009). While the confirmation/disconfirmation paradigm provides theoretical support to customer satisfaction development, social-identity theory provides theoretical support to customer-brand identification (Haumann et al., 2014). Identification can have a positive long-term impact on customer-brand relationship (Popp et al., 2017). Customer-brand identification corresponds to “a consumer’s psychological state of perceiving, feeling, and valuing his or her belongingness with a brand” (Lam et al., 2013, p. 235), and identification with an organization is the foundation of “deep, committed, and meaningful relationships” (Bhattacharya & Sen, 2003, p. 76).

Furthermore, previous research that examined the effect of word-of-mouth for the sender found that word-of-mouth can be effective in retaining customers (Garnefeld et al., 2011). This result suggests that the customer-brand relationship can be enhanced by electronic word-of-mouth. Hence, because customer-brand identification reflects the customer-brand relationship, electronic word-of-mouth can also improve customer-brand identification. Electronic word-of-mouth includes, for example, social media, online reviews, and forums (Pan & Zhang, 2011; Kozinets et al., 2010; Ordenes et al., 2017; Motyka et al., 2018), which offer greater convenience, anonymity, many-to-many communications and have fewer constraints regarding time and space. Thus, the potential impact of word-of-mouth has significantly increased (Migacz et al., 2017). The

intangibility and inseparability of services make electronic word-of-mouth even more important because customers often resort to external information to help when making purchase decisions (Tsao et al., 2015). However, despite the growing body of literature on the antecedents and outcomes of word-of-mouth, the impact of word-of-mouth on the communicator has been neglected (Garnefeld et al., 2011).

Considering the aforementioned arguments, this study draws upon social identity theory (Turner, 1975; Tajfel & Turner, 1985, 2001), cognitive dissonance theory (Festinger, 1957), and self-perception theory (Bem, 1965, 1967) to address three important research gaps. First, there is a lack of research on resilience to negative information, which has become an important outcome, particularly for airlines that face new challenges with the emergence of social media. Second, the impact of customer-brand identification on resilience to negative information remains unclear. Third, research that focuses on existing customers has been scarce, and the impact of electronic word-of-mouth on the communicator has been neglected.

By addressing these gaps, this study makes four important contributions to the literature: i) it advances customer-brand identification research by clarifying the effect of customer-brand identification on resilience to negative information; ii) it provides a model for resilience to negative information; iii) it identifies the influence of electronic word-of-mouth in the process that leads to resilience to negative information; and iv) it identifies two alternative solutions for achieving high resilience to negative information, suggesting that this outcome can be achieved with a combination of electronic word-of-mouth with either customer-brand identification or self-brand congruity. Thus, the importance of electronic word-of-mouth is emphasized. These results have important theory and marketing practice implications, which are highlighted in the final section of the paper.

Following this introduction, Section 2 provides a literature review and presents the research hypotheses informing the conceptual framework. In Section 3, the data, measures, and methods employed in this study are presented. Section 4 presents the results of the measurement model, the structural equation model, the comparative model analysis, the fuzzy-set qualitative comparative analysis, and the interaction analysis. Finally, in Section 5, the results are discussed in relation to the literature, and conclusions are drawn. Theoretical contributions and practical implications are highlighted, limitations are presented, and future research is suggested.

## **2. Literature Review**

This section starts with a literature review of customer-brand identification, emphasizing the role of its affective-based drivers, especially brand social benefits and memorable brand experiences. These antecedent conditions, grounded in social identity theory (Turner, 1975; Tajfel & Turner, 1985, 2001), have been well established in previous research (e.g., Stokburger-Sauer et al., 2012; So et al., 2017; Torres et al., 2017). Social identity theory claims that an individual's self-concept encompasses a personal identity, including idiosyncratic characteristics such as abilities and interests, and a social identity that involves salient group classifications (Tajfel & Turner, 1985). The social identity is key in shaping various social interactions and behaviors (So et al., 2017).

However, despite the recognized importance of affective-based drivers, it has also been noted that cognitive-based drivers (such as self-brand congruity) can be more important in sustaining customer-brand identification (Lam et al., 2013). Self-brand congruity is a symbolic driver that refers to the matching process between the symbolic attributes of brands and the customer's own self-image (Sirgy, 1985). Self-brand congruity reflects the notion of identity similarity (Bhattacharya and Sen, 2003). The extent to which a customer's personality overlaps

with a brand's personality influences customer behavior (e.g., Kuenzel & Halliday, 2010). Thus, it is also hypothesized that self-brand congruity can have a direct influence on resilience to negative information. Taking into account its possible effect on resilience to negative information, self-brand congruity is addressed in a different subsection. Likewise, because electronic word-of-mouth can be a driver of resilience to negative information, it is presented in a different subsection. Taking into consideration cognitive dissonance theory (Festinger, 1957), when existing customers engage in positive electronic word-of-mouth, then resilience to negative information is likely to increase because the communicator strives to act consistently with the advocated position.

The conceptual model presented in Figure 1 was defined to guide this research. This conceptual model proposes a direct effect of self-brand congruity, electronic word-of-mouth, and customer-brand identification on resilience to negative information. Indirect effects of brand social benefits, memorable brand experiences, self-brand congruity, and electronic word-of-mouth on resilience to negative information through the mediation of customer-brand identification are also expected. Unlike past research, besides main effects, the necessary and sufficient conditions to achieve high resilience to negative information are also examined, keeping in mind the potential amplifying effect of electronic word-of-mouth. It is assumed that none of the antecedents to resilience to negative information alone will be sufficient to achieve high resilience to negative information, despite the effect they may have on that resilience. In the following subsections, these constructs are defined, and the hypotheses are theoretically developed.

*(Insert Figure 1 about here)*

## **2.1. Customer-brand identification**



Social identity is considered an integral part of one's self-concept along with personal identity (Elbedweihy et al., 2016). Brands can facilitate social identity creation (Stokburger-Sauer et al., 2012). Individuals search for brands that are consistent with their self-concept and avoid brands that could threaten their sense of self (this idea is implicit in the marketing literature; see, for example, Escalas & Bettman, 2003). Companies that have socially meaningful identities are possible targets for identification because that can partially fulfill customers' self-definitional needs (Bhattacharya & Sen, 2003). The feeling of oneness with an organization not only affects the individuals' perception toward it but also influences their reactions to new information about the organization (Zavyalova et al., 2016). Customers that identify themselves with a brand are more likely to defend it when negative brand information is made public (Eisingerich et al., 2011). Furthermore, because customer satisfaction levels are already high, it is difficult to compete on this basis, and identification is becoming more important (Homburg et al., 2009). Therefore, the ability to create meaningful associations is also becoming increasingly important (Chernev et al., 2011), particularly brand values that help customers verify and maintain their self-concept (Tuškej et al., 2013). To build customer-brand identification, the more affective-based drivers are considered relatively more important in comparison to more-cognitive drivers (Torres et al., 2017). In this study, two affective-drivers are considered: memorable brand experiences and brand social benefits. These constructs are influenced by customers' interactions with the brand and with other brand customers; they are considered core to achieving customer-brand identification in the case of experiential brands such as airlines (So et al., 2017).

Identification is suggested to be more closely related to extra-role behaviors (Riketta, 2005) such as citizenship behaviors (Bergami & Bagozzi, 2000). Resilience to negative information can be considered an extra-role behavior. Inspired by Eisingerich et al. (2011), we defined resilience

to negative information as the extent to which customers do not allow negative information about a given brand to diminish their general view of the brand. In the presence of strong customer-brand relationships, resilience to negative information tends to be higher (e.g., Aaker et al., 2004), and customer-brand identification reflects the strength of the customer-brand relationship (So et al. 2018). Therefore, a relationship between customer-brand identification and resilience to negative information is not out of order.

Identification with a brand improves customer willingness to tolerate defects and forgive mistakes (Wu & Tsai, 2008), and prior research has found evidence of a direct effect of customer-brand identification on resilience to negative information (e.g., Elbedweilhy et al., 2016). Customers that identify with a brand are more likely to support the brand and defend it when the brand is exposed to negative information (Eisingerich et al., 2011). Because customer-brand identification helps customers satisfy their self-definitional needs, they are more likely to be resilient when exposed to negative information about the brand. Therefore, the following hypothesis was formulated:

**Hypothesis 1.** The higher the customer-brand identification, the higher resilience to negative information tends to be.

### **2.1.1. Memorable brand experiences**

Brand experiences correspond to “subjective, internal consumer responses (sensations, feelings, and cognitions) and behavioral responses evoked by brand-related stimuli that are part of a brand’s design and identity, packaging, and environments” (Brakus et al., 2009, p. 53). Brand experiences involve sensory perceptions, brand affect, and the participatory experiences that a customer may seek with a brand (Schmitt, 2012). The creation of brand-related stories and narratives contributes

to the self-referencing process and produces affect-laden and easily retrievable memories that contribute to the strengthening of customer-brand connections (Escalas 2004). Previous research noted that brands can leave a strong, affectively charged mark on the customer's consciousness, even if such brands are infrequently used (e.g., Stokburger-Sauer et al., 2012). Brands that provide memorable brand experiences are more likely to develop customer-brand identification (Stokburger-Sauer et al., 2012). In the case of airlines, memorable brand experiences are likely to play a central role in shaping customers' perceptions, considering that the evaluation of service brands relies on the service encounter experience (Grace & O'Cass, 2004). The delivery of memorable tourism experiences has recently emerged as an important issue that can guide the development of tourism programs (e.g., Kim & Jang, 2016; Kim & Ritchie, 2014). Previous studies (e.g., Harmeling et al., 2015) also suggest that transformational relationship events induce emotional and cognitive responses that affect customers' psychological identification with the seller and/or the brand. Among the experiential factors, Kim et al. (2012) highlighted the following: hedonism, novelty, knowledge, involvement, meaningfulness, local culture, and refreshment.

### **2.1.2. Brand social benefits**

Another important driver of customer-brand identification is brand social benefits. Stokburger-Sauer et al. (2012) defined brand social benefits as the social interaction opportunities provided by a brand, suggesting that customers' perception that a brand provides brand social benefits will likely lead to customer-brand identification. Brands carry social and cultural meanings (Thompson et al., 2006) that enable the development of social reference groups. Social interactions between the customer and the brand, and with other brand customers, can lead to the formation of brand

communities (Muniz & O'Guinn, 2001). These interactions also contribute to the development of brand associations (Escalas & Bettman, 2003). If positive attitudes toward a brand are created, then customers will tend to behave in such a way as to sustain those positive attitudes (Raghunathan et al., 2006). Extant studies consider brand social benefits a driver of customer-brand identification (e.g., Torres et al., 2017).

## **2.2. Self-brand congruity**

Self-brand congruity has been acknowledged as a driver of customer-brand identification (e.g. Kuenzel & Halliday, 2010; Torres et al., 2017), and it is a conceptually different construct. While customer-brand identification corresponds to “a consumer’s psychological state of perceiving, feeling, and valuing his or her belongingness with a brand” (Lam et al., 2013, p. 235), self-brand congruity corresponds to the matching of a brand’s personality with a customer’s personality. The brand personality refers to the human characteristics that can be linked to a brand, and an individual personality can be defined as “a set of points falling along several behavioral dimensions, each corresponding to a trait, resulting in a unique profile, different from other individuals” (Pervin, 1989, p. 7).

The need for self-continuity is a key driver of individuals’ choice of organizations to identify with (Pratt, 1998) in their effort to build viable, cognitively consistent social identities (Heider, 1958). Following Bhattacharya and Sen (2003), this need is mainly justified for two reasons. First, individuals find company identities that are similar to their own easier to focus on, process, and retrieve (Markus & Wurf, 1987). Second, the company identity can enable individuals to maintain and express their sense of who they are, that is, their traits and values (Pratt, 1998). Thus, self-brand congruity is an important antecedent of customer-brand identification (Kuenzel

& Halliday, 2010). However, it is not by itself sufficient to achieve high customer-brand identification (Torres et al., 2017). Therefore, self-brand congruity and customer-brand identification are related, but they are conceptually different.

Through customer-brand identification, self-brand congruity is expected to influence resilience to negative information. As noted before, individuals that identify with a brand tend to overlook and downplay any negative information they may receive about it (Bhattacharya & Sen, 2003). Nevertheless, while some authors have suggested that the relationship between self-brand congruity and customer behavior is mediated by customer-brand identification (e.g., Bhattacharya & Sen, 2003), the results obtained in subsequent studies suggest that this relationship could be more direct (e.g., Sirgy et al., 2008). In fact, it is generally accepted in the marketing literature that the greater the match between a customer's self-concept and brand personality, the more favorable the customer behavior toward the brand tends to be (Kuenzel & Halliday, 2010). Self-congruity with a brand, that is, the overlap between customers' self-image and the symbolic attributes of the brand (Sirgy, 1985), can influence important outcomes such as brand loyalty (e.g., Sirgy et al., 2008). Thus, it is reasonable to postulate that it can have a direct effect on resilience to negative information. On this basis, the conceptual model guiding this research proposes that

**Hypothesis 2.** The higher the self-brand congruity, the higher resilience to negative information tends to be.

### **2.3. Electronic word-of-mouth**

The diffusion of the Internet and the emergence of social platforms have completely changed how customers interact with each other and with brands. Customer routines were changed by social media, such as social networking sites (e.g., Facebook), microblogging sites (e.g., Twitter), photo

sharing sites (e.g., Instagram), and video sharing sites (e.g., YouTube). Electronic word-of-mouth occurs essentially through social media (Levy & Gvili, 2015), and its influence on customer behavior has been recognized (Wang et al., 2012). Because of its convenience, scope, source, and the speed of interactions, electronic word-of-mouth is considered the most powerful form of word-of-mouth. Electronic word-of-mouth can be defined as “any positive or negative statement made by potential, actual, or former customers regarding a product or company, which is made available to a multitude of people and institutions via the Internet” (Hennig-Thurau et al., 2004, p. 39). Positive and negative electronic word-of-mouth have a significant influence on tourism-related businesses because they usually involve intangible services that are difficult to evaluate prior to purchase (Cantalops & Salvi, 2014). That description is true of the travel sector. Therefore, individuals look for unbiased information (Vermeulen & Seegers, 2009). In particular, social networking sites can have significantly positive implications for travel companies (Casaló et al., 2010; Xiang & Gretzel, 2010). To gather information and minimize uncertainty, individuals often rely on the online comments of other customers who have already experienced a service (Ye et al., 2011; Hess & Ring, 2016). In fact, online customer reviews are one of the most important sources of information for travelers (Book et al., 2015).

Participation in travel communities is a key driver of electronic word-of-mouth (Qu & Lee, 2011). Individuals tend to make purchase decisions based on information collected from other customers (e.g., Cheung et al., 2008). Thus, considering the strong impact of online reviews, many companies are developing their own review platforms to facilitate electronic word-of-mouth (Filiari, 2015). Previous research has also stressed that travel companies should promote the use of social media to allow customers to write and read opinions and reviews (Bigné et al., 2015). Customers who engage in electronic word-of-mouth are often seen as co-creators of value (Kao et

al., 2016), and their interactions with other customers can enrich the purchase experience (Wu & Fang, 2010). Nevertheless, social media presents challenges to airlines because it becomes difficult to control their online image (So et al., 2018), and negative brand information can have a greater impact than positive information has (Skowronski et al., 1998). When existing customers engage in electronic word-of-mouth, they become agents that amplify (or undermine) the impact of marketing actions (Lamberton & Stephen, 2016).

It has been suggested that customers engage in communication about their consumption activities to express their self-concept and attract attention to themselves (Saenger et al., 2013). Extant marketing studies have acknowledged that self-enhancement is a strong motivation for customer engagement in electronic word-of-mouth (e.g., Hars & Ou, 2002; Hennig-Thurau et al., 2004). Self-enhancement is one of the key needs that drives identification (Stokburger-Sauer et al., 2012). Thus, it is likely that electronic word-of-mouth affects customer-brand identification. The self-perception theory (Bem, 1965, 1967) theoretically supports this link, which was also empirically supported in recent studies (e.g., Augusto & Torres, 2018; Torres et al., 2018).

Past research also suggests that customer-brand identification drives electronic word-of-mouth (e.g., Popp & Wopratschek, 2017; So et al., 2018). However, considering the focus of the present study on existing customers, it makes sense to consider the effect of electronic word-of-mouth on customer-brand identification. That is not to say that customer-brand identification does not drive electronic word-of-mouth but rather to examine the relationship between these constructs by adopting a different perspective. Sharing and posting positive brand information is a means to express and improve one's own self-identity (Arnett et al., 2003). The literature supports that the interaction between the customer and the brand drives symbolic meanings that customers can use to build their own identities (Belk, 1988). In fact, one of the key functions that is fulfilled with

word-of-mouth is impression management, which relates to identity-signaling and self-enhancement motives, and the social bonding involves the reinforcement of shared values (Berger, 2014). Thus, customer-brand identification can be reinforced by positive electronic word-of-mouth.

Furthermore, electronic word-of-mouth can influence resilience to negative information directly. Self-perception theory (Bem, 1965, 1967) postulates that people learn by their inner states by observing their own behavior and the context in which it occurs. According to the social psychology literature, when people take a public position, they tend to align their attitudes in the direction of that position (Cialdini, 1971), that is, commitment arises (Kiesler, 1971). This commitment is justified by the person's desire to be internally consistent (Garnefeld et al., 2013). Furthermore, according to cognitive dissonance theory, inconsistency between the individual's thoughts and behaviors creates psychological tension and distress (Festinger, 1957). Thus, individuals are strongly motivated to align their thoughts and behaviors. One approach to doing so is to ignore information that contradicts the individual's behavioral commitment (So et al., 2018). Therefore, by engaging in word of mouth, the customer takes a public position that is difficult to change (Garnefeld et al., 2013). The magnitude of such commitment depends on the extent to which the advocacy is public (Cialdini, 1971). Positive advocacy tends to make the communicator's attitude more extreme (Higgins & Rholes, 1978). Studies have already acknowledged the effect of positive electronic word-of-mouth on resilience to negative information (e.g., So et al., 2018), a point particularly relevant in the case of existing customers.

Thus, consistent with the above arguments, the following hypotheses were formulated:

**Hypothesis 3.** The higher the level of electronic word-of-mouth, the higher resilience to negative information tends to be.



**Hypothesis 4.** The higher the level of electronic word-of-mouth, the higher customer-brand identification tends to be.

Following the aforementioned arguments, electronic word-of-mouth can have a central role in achieving resilience to negative information because it can complement and amplify the effect of customer-brand identification and self-brand congruity. The results of past research also suggest that customer-brand identification alone is not sufficient to obtain high resilience to negative information (e.g., So et al., 2017). Therefore, it is hypothesized that the combination of electronic word-of-mouth with either customer-brand identification or self-brand congruity can be sufficient to achieve high resilience to negative information. This formulation suggests that customer-brand identification and self-brand congruity could act as substitutes. Thus, taking a configurational approach, a final hypothesis is proposed:

**Hypothesis 5.** High resilience to negative information can be achieved through the combination of electronic word-of-mouth with either self-brand congruity or customer-brand identification, meaning that electronic word-of-mouth complements and amplifies the effect of self-brand congruity and customer-brand identification.

### **3. Data, Measures and Methods**

#### **3.1. Data and measures**

The data for the present study were collected through an online survey. The questionnaire was sent to a database of professional people that use the TAP airline service. The answers were received between the 17<sup>th</sup> of January and the 17<sup>th</sup> of March 2017. Of 2,000 distributed questionnaires, we received 329 responses, 49 of which were deleted due to incompleteness, resulting in a final sample of 280 responses, corresponding to a response rate of 16.45%. Following the procedure

recommended by Armstrong and Overton (1977) to test the nonresponse bias, which is widely used (e.g., Alayo et al, 2019), the means obtained for each scale item from the first fifty answers were compared with the means of the last fifty answers. The *t*-test for equality of means was used. The results of the *t*-test show, with two exceptions, no significant differences at the conventional significance level (5%) between the means of the two groups of the 19 items used to measure the model constructs. The same result was obtained when considering the first seventy and the last seventy answers. Thus, nonresponse bias is not a major problem in this study.

The respondents were mainly females (approximately 64%) and highly educated; 97.5% held at least a university degree (25% held a university degree, 61.4% held a postgraduate or master's degree, and approximately 11% held a PhD). In terms of age, most respondents were in the age range of 35-44 (36.4%) or 25-34 (36.1%). Approximately 15.4% were between 45 and 54 years old, 5.7% were 55 years old or more, and approximately 6.4% were 24 years old or less. Because millennials, that is, those born between 1980 and 2000, are avid users of social media (Nusair et al., 2013), the sample was considered appropriate to examine the role of electronic word-of-mouth in the airline industry.

The questionnaire items used to measure the constructs (memorable brand experiences, brand social benefits, self-brand congruity, customer-brand identification, electronic word-of-mouth, and resilience to negative information) were based on pre-existing scales validated in prior studies. The scales were adapted and pre-tested in a pilot sample. A Likert-type 7-point scale was used, ranging from 1 ("strongly disagree") to 7 ("strongly agree"). Self-brand congruity was measured using the scale of Lam et al. (2013), which is an adaptation of Aaker's (1997) brand personality scale. The items used to measure memorable brand experiences, brand social benefits, and customer-brand identification were based on the scales of Stokburger-Sauer et al. (2012) with

minor modifications. For instance, following Torres et al. (2017), the scale used to measure brand social benefits includes an additional item: “(Brand X) creates warm feelings among its users”. The scale of Park and Kim (2014) was used to measure electronic word-of-mouth. Resilience to negative information was measured using the scale employed by Elbedweihy et al. (2016).

### **3.2. Methods**

To examine the relationships among the constructs and to fully investigate the necessary and sufficient conditions to achieve high resilience to negative information, the data analysis incorporated both structural equation modeling and fsQCA. Structural equation modeling was performed using AMOS 25.0 software, and the fsQCA employed version 3.0 of this software. In the structural equation modeling approach, the two-step procedure recommended by Anderson and Gerbing (1988) was performed, that is, the measurement model was first formulated and evaluated; the proposed hypotheses were then tested using a structural equation model. The maximum likelihood estimation method was used.

fsQCA is a technique that belongs to a general approach usually termed qualitative comparative analysis (Rihoux et al., 2011). fsQCA applications in management are more recent than are those of structural equation modeling, but they have seen a rapid growth in recent years (see, for example, Berger, 2016). While regression-based methods are based on the principle of symmetry, i.e., higher values of an independent variable will either increase or decrease the outcome of interest, qualitative comparative analysis techniques are based on the principle that the configurations are what matter. In fact, more-established methods, such as linear regression models, clustering algorithms, latent class analysis, and the deviation score approach have notable limitations with complex, high-order interactions (Frösén et al., 2016).

Qualitative comparative analysis techniques examine the relationships between the outcome and all possible combinations of the binary states (i.e., presence or absence) of its predictors, performing a systematic cross-case analysis. In doing so, qualitative comparative analysis allows the identification of configurations that reflect the necessary and sufficient conditions to achieve an outcome of interest (Ordanini et al., 2014). Thus, such techniques account for situations in which there are significant main effects of the independent variable but, simultaneously, there is a nonnegligible number of contrarian cases – cases that contradict the main effects (e.g., Woodside 2014, 2016). Qualitative comparative analysis techniques consider that the effects of the variables may be asymmetric; in some configurations, the presence of a given condition may contribute to reaching the outcome but, in other contexts, it may be its absence that leads to the outcome. Using the expression in the title of the paper of Ordanini et al. (2014), we can say that in qualitative comparative analysis, “...the recipe is more important than the ingredients.”

### **3.3. Calibration**

fsQCA is based on fuzzy numbers that represent degrees of membership in sets defined by conditions. These degrees of membership are also referred to as fuzzy scores, and they belong to the [0,1] interval. The process used for obtaining these degrees of membership is termed *calibration*. Ragin (2008), chapter 5, presents a method, termed the *direct method*, for determining these degrees of membership when the range of values of the variables is continuous or the number of possible values is very large. This method maps the original values of the variables into fuzzy scores based on the specification of three thresholds: a full membership threshold, a nonmembership threshold, and a crossover point. The full membership and nonmembership

thresholds specify the limits beyond which we consider a case to be virtually a full member of the set or virtually outside the set, respectively (Ragin, 2008, p. 88). The crossover point is the value for which there is most ambiguity concerning whether a case is more in or more out of the set (Ragin, 2008, p. 90).

Each of these thresholds translates into a specific fuzzy value – it is standard to use fuzzy values of 0.95, 0.05 and 0.50 for the full and nonmembership thresholds and for the crossover point, respectively (e.g., Ragin, 2008, chapter 5). In the absence of external standards that could be used to define these values, many authors resort to percentiles of the distribution of the original values of the variables. The 90<sup>th</sup>, 10<sup>th</sup> and 50<sup>th</sup> percentiles of the values of the original distribution are commonly used to define the full membership and nonmembership thresholds and the crossover point, respectively (e.g., Ho et al., 2016; Navarro et al., 2016). In this research, we used this method, with these percentiles, to obtain the membership degrees for resilience to negative information, customer-brand identification, self-brand congruity, and electronic word-of-mouth.

### **3.4. Consistency and frequency thresholds**

The analysis of sufficient conditions with fsQCA requires the definition of two thresholds: a frequency threshold and a consistency threshold. The frequency threshold establishes the minimum number of cases that should belong to a given causal combination for it to be included in the causal analysis. A higher frequency threshold means that a smaller number of combinations is considered to obtain the results but, at the same time, it allows researchers to avoid low-frequency combinations that might represent random forces or measurement errors. Therefore, the choice of a frequency threshold is based on a trade-off between the potential for deductive analysis and the inclusion of rare combinations (Emmenegger et al., 2014). The number of causal

combinations that can be included in the analysis depends on the number of antecedent conditions. In this study, we used three antecedent conditions for resilience to negative information. Potential combinations are defined by the presence or absence of these antecedent conditions, so we have eight ( $2^3$ ) combinations. The larger the number of combinations, the smaller the number of cases that fall into each one; in this study, the smaller number of cases was ten. The minimum number of ten cases is quite high, significantly reducing the possible influence of randomness. Therefore, we chose to use a frequency threshold of ten for the analysis of sufficient conditions.

The consistency threshold is the minimum consistency that is required to consider that a given configuration leads to the presence of the outcome in the causal analysis. For the choice of a consistency threshold, several authors recommend avoiding values less than 0.75, preferably using values of 0.80 or greater (e.g., Ragin, 2009, p. 121). To choose a specific value, the most recommended procedure consists of identifying substantial gaps in the range of the consistency scores for the combinations to be used in the causal analysis (e.g., Ragin 2009, p. 121). In this study, a sizeable gap in the consistency scores could be found at 0.80; there is a gap between 0.797 and 0.866, which is the largest gap in the range of reasonable values for the consistency threshold. Therefore, the value of 0.80 was used for this threshold. Additionally, a consistency threshold of 0.80 is common in the literature (e.g., Navarro et al., 2016).

## **4. Results**

### **4.1. Structural equation modeling analysis**

A two-step procedure was used to estimate and evaluate the proposed structural equations model. In the first step, the measurement component of the completed model was estimated and evaluated. In the second step, the structural component of the model was estimated.

#### **4.1.1. Measurement model**

The maximum likelihood method assumes the multinormality of the distribution of the observed variables. Following Kline (2017), the skewness and kurtosis were used to assess the departures from normality. The skewness ranged from -1.13 to 0.62, and the kurtosis ranged from -0.94 to 1.08; thus, according to the thresholds reported by Kline (2017) (skewness < 3.0 and kurtosis < 20.0), the departure from multinormality is not a major problem.

As usual, before the estimation, a preliminary analysis was performed to purify the scale, and some items were deleted. First, regarding the brand social benefits scale (Lam et al., 2013), the “Rugged” dimension was deleted. Second, from the scales used for brand social benefits, memorable brand experiences and customer-brand identification, which were based on Stokburger-Sauer et al. (2012), one item was deleted in the memorable brand experiences scale (“I have had a lot of memorable experiences with brand X”), and two items were eliminated in the customer-brand identification scale (“Brand X embodies what I believe in”; and “Brand X is like a part of me”). Third, regarding electronic word-of-mouth (Park & Kim, 2014), the item “I have recommended (brand X) to lots of people” was deleted. The remaining scales include all the items of the original scales, which were adapted to the context of the present study. Although dropping items used in the original scales may have drawbacks (e.g., doing so could hinder the correct measure of all the components that a construct encompasses, and it is more difficult to compare the results with previous research), the scales that were used capture the essence of the respective constructs.

Deleting two of five items from the customer-brand identification scale could make it more difficult to cover the cognitive, affective and evaluative components of this construct, an approach

proposed in previous research (e.g., Lam et al., 2010; Lam et al., 2013), but such an approach is consistent with Stokburger et al.'s (2012) conceptualization. The latter considers that customer-brand identification mostly has a cognitive representation, despite the profusion of emotional associations. This conceptualization is consistent with Bergami and Bagozzi (2000), who advocate a separation between the emotional component of identification and the stage of identification. Hence, following Stokburger et al. (2012), "brand social benefits" is considered an antecedent condition of customer-brand identification rather than part of the construct of identification. In the same vein, the evaluation component is considered an input to customer-brand identification rather than being an integral part of it. Stokburger et al. (2012) regard positive brand evaluations as conceptually different from customer-brand identification because the latter encompasses both the perceived brand identity and the customer self-identity. Thus, the items that were used to measure customer-brand identification reflect the extent to which an individual has incorporated a brand into his/her self-concept, capturing the conceptualization of the construct that has been proposed by Stokburger et al. (2012).

After purifying each scale, an exploratory factor analysis was used to test the unidimensionality of each construct. The results of the exploratory factor analysis for each construct show that all items used to measure a particular construct belong to one factor, thereby confirming that the scale used to measure each construct is unidimensional. Table 1 shows the items used in the analysis, the standardized loadings, the *t-values*, and the squared multiple correlations ( $R^2$ ). The final measurement model presents an adequate global fit to the data, complying with thresholds suggested in the literature. Despite the chi-square ( $\chi^2$ )=402.49, with *df* = 137, being statistically significant ( $p < 0.01$ ), the other global fit indexes suggest that the measurement model has an acceptable fit [goodness of fit index (GFI) = 0.87, normed fit index



(NFI) = 0.92, incremental fit index (IFI) = 0.95, Tucker-Lewis index (TLI) = 0.93, comparative fit index (CFI) = 0.95, and root mean square error approximation (RMSEA) = 0.08]. Next, the particular aspects of the model fit were analyzed. For this purpose, three aspects were considered: individual item reliability, the convergent validity of the items related to individual constructs, and discriminant validity. The individual item reliability was assessed through both standardized factor loadings and the  $R^2$ . All the standardized factor loadings exceeded the 0.5 threshold, so they were highly significant ( $p < 0.01$ ) (Bagozzi & Yi, 1988). The  $R^2$  reported for each observed variable indicates the extent to which it adequately measures the respective underlying construct. For example, the  $R^2$  for the item “Sincere (e.g., Down-to-earth, honest, genuine)” indicates that 62% of its variance can be explained by the construct “Self Brand Congruity”. The  $R^2$  values were all above the 0.20 threshold (Hooper et al., 2008); thus, the individual item reliability is supported.

*(Insert Table 1 about here)*

Table 2 presents additional particular aspects of the measurement model. The Cronbach’s alpha values were all above 0.70, and the composite reliability of each scale also exceeded the 0.70 threshold, indicating that the scales are internally consistent (Fornell & Larcker, 1981). Discriminant validity of the measured constructs was also tested using the procedure suggested by Fornell and Larcker (1981). For this purpose, the square of the correlations among the constructs was compared with the average variance extracted for the corresponding constructs. The average variance extracted of each construct must be greater than the square of the correlations among the corresponding constructs to support discriminant validity. Table 2 shows that the squares of the correlations among the constructs do not surpass the average variance extracted values. In summary, the constructs are unidimensional and show acceptable levels of reliability, convergent validity, and discriminant validity.

(Insert Table 2 about here)

#### **4.1.2. Common method variance**

Common method variance arises when the variance of the responses is systematically attributable to the single measurement method used (Podsakoff et al., 2003; Podsakoff et al., 2012). The present study uses self-reported data from the same respondents to measure the model constructs, so it is acknowledged that common method bias can occur. However, as noted by Fuller et al. (2016, p. 3193), the “common method variance, should it even exist, may not produce changes in effect sizes and significance levels, may change them trivially, or may change them in an amount that is practically meaningless”. Nevertheless, to attend to this potential bias, *ex ante* and *ex post* procedures were employed.

*Ex ante*, following the recommendations of Podsakoff et al. (2003), several control procedures were used, including the following: the survey was pre-tested to define ambiguous terms and avoid vague concepts and complex syntax, double-barreled questions were avoided, and each question was kept simple, specific, and concise; and in the first page of the questionnaire, we ensured that the answers are anonymous and informed respondents that there are no right or wrong answers to each question. *Ex post*, common method variance can be tested using different techniques, such as Harman’s single factor test, confirmatory factor analysis test, correlational marker technique, single unmeasured latent method factor, and multiple method factors (see Podsakoff et al., 2003, for a synthesis of these techniques). If the variance of the responses is systematically attributable to the single measurement method used, both a simple measurement model (e.g., single-factor model) and a more complex one should fit the data (Stevens et al., 2015).

A model in which all 19 observed variables used were allowed to load onto a single factor revealed a very poor fit ( $\chi^2 = 2,193.80$  with  $df = 153$  and  $p < 0.01$ , GFI = 0.52, NFI = 0.56, IFI = 0.58, TLI = 0.53, CFI = 0.58, and RMSEA = 0.219). Following Baldauf et al. (2009) and So et al. (2013), we compared the single-factor measurement model (with all 19 used items loaded on a single common factor) with the CFA results of the proposed measurement model, which include 6 constructs. To compare the single-factor measurement model ( $\chi^2 = 2,193.80$ ,  $df = 153$ ) and the proposed measurement model ( $\chi^2 = 402.49$ ,  $df = 137$ ), the chi-square difference test was used. The results show that the proposed measurement model fits better than the single-factor measurement ( $\Delta\chi^2 = 1,791.31$ ,  $df = 16$ ,  $p < 0.01$ ). Thus, based on both *ex ante* and *ex post* procedures used, the CMV is not a major issue in this study.

#### **4.1.3. Structural model**

After the measurement model was established, we proceeded with the estimation of the structural model to test the hypotheses outlined in the conceptual model (see Figure 1). Table 3 presents the structural parameter estimates and the global model fit statistics. The different goodness-of-fit statistics indicate an adequate model fit to the data collected ( $\chi^2 = 405.87$ ,  $df = 139$ ,  $p < 0.01$ , GFI = 0.86, NFI = 0.92, IFI = 0.95, TLI = 0.93, CFI = 0.94, and RMSEA = 0.08). Considering the structural path coefficients, it can be concluded that a majority of the relationships received statistical support (6 of 7), with only one path not being significant (i.e., Self-Brand Congruity → Customer-Brand Identification). Additionally, an inspection of the modification indices revealed that no other path was significant at the conventional significance levels (1% and 5%); this point also supported the robustness of the hypothesized model.

The results show that customer-brand identification has a positive impact on resilience to negative information. They also reveal a positive impact of self-brand congruity and electronic word-of-mouth on resilience to negative information. Both have a similar effect on resilience to negative information. Furthermore, the results indicate that electronic word-of-mouth influences customer-brand identification, which is consistent with recent studies (e.g., Augusto & Torres, 2018; Torres et al., 2018). The importance of electronic word-of-mouth on resilience to negative information is highlighted because it has the path with the higher coefficient (0.39), and it also has an indirect effect through customer-brand identification. However, it also shows that electronic word-of-mouth is not as important to achieve customer-brand identification (the path coefficient is only 0.08), compared to memorable brand experience and brand social benefits.

*(Insert Table 3 about here)*

#### **4.1.4. Alternative models**

Although both the literature review and the global fit indices support the proposed model, to further enhance the robustness of our results, two alternative models were also considered (see Figure 2). The alternative models are similar to the proposed model but with different relationships among the constructs (Model A is equal to the proposed model plus the direct effects of brand social benefits and memorable brand experiences on resilience to negative information; in Model B, the direct effects of self-brand congruity and electronic word-of-mouth on resilience to negative information were dropped).

*(Insert Figure 2 about here)*

To test the difference between the proposed model and the alternative models, a chi-square difference test was conducted. In comparing Model A with the proposed model, no difference was

obtained ( $\Delta\chi^2 = 3.38$ ,  $\Delta df = 2$ ,  $p > 0.05$ ), and Model A is less parsimonious than the proposed model. This result was expected, because an inspection of the modification indices of the proposed model reveals that no other path is significant at the conventional significance levels. Regarding Model B, the fit is significantly worse than the proposed model (Model B vs. Proposed Model:  $\Delta\chi^2 = 62.46$ ,  $\Delta df = 2$ ,  $p < 0.01$ ). Table 4 provides a synthesis of the model comparison and the most popular goodness-of-fit statistics of each model. Based on these results, the alternative models were rejected in favor of the proposed model.

*(Insert Table 4 about here)*

## **4.2. Fuzzy-set qualitative comparative analysis**

fsQCA was applied to identify the necessary and sufficient conditions to obtain resilience to negative information. The methodological options used in the analysis are described in the previous section. As usual in fsQCA analyses, the values of *consistency* and *coverage* are presented. Consistency is a measure of how closely a perfect subset relation is approximated (Ragin, 2008, p. 44), that is, of how much the data agree with the relation being considered. Coverage is a measure of the empirical relevance of a given relation (Ragin, 2008, p. 44) according to the data. The values of both consistency and coverage range between zero and one.

Following other studies (e.g., Xu et al., 2016), the predictive validity of the models was also analyzed using a method based on the division of the sample into two random subsamples, identification of the sufficient conditions for each subsample, and application of the obtained models to the other subsample.

### **4.2.1. Analysis of necessary conditions**

In the analysis of necessary conditions, whether an antecedent is necessary for a given outcome is analyzed. A summary of the results is presented in Table 5.

*(Insert Table 5 about here)*

It is usually recommended that the consistency threshold used to assess necessary conditions should be larger than the one used for sufficient conditions. In this study, we use a threshold of 0.9 (see, for example, Schneider et al., 2010). Table 5 shows that all the considered antecedents show consistency levels below this threshold. Therefore, neither of the antecedents can be considered necessary for achieving resilience to negative information.

#### **4.2.2. Configurational analysis**

The aim of the configurational analysis is to find configurations of conditions that are sufficient to attain the outcome – resilience to negative information. Three types of solutions may be produced by such an analysis, according to how the logical remainders are used to simplify the configurations: i) a “complex” solution, in which no logical remainders are incorporated into the solution; ii) a “parsimonious” solution, in which all logical remainders are used; and iii) an “intermediate” solution, in which only the plausible logical remainders are incorporated into the solution (Ragin, 2009). Intermediate solutions are often considered superior to the complex and parsimonious ones (see, e.g., Ragin, 2009).

In this work, we followed Fiss (2001) who considers both the intermediate and the parsimonious solutions. For the intermediate solution, we assumed that just the presence of self-brand congruity, electronic word-of-mouth, and customer-brand identification may plausibly lead to resilience to negative information. In all cases, we obtained intermediate solutions identical to

the parsimonious ones, so we just present one solution, which is simultaneously the intermediate and the parsimonious one.

The configurational analysis was based on the conceptual framework presented in Figure 1, taking into account the direct relations considered in this framework. The notation used in the tables follows Fiss (2011): black circles (“●”) indicate the presence of a condition, and blank spaces indicate a situation in which the condition may be either present or absent; there is no case in which the absence of a condition is part of a configuration. The configurations obtained for achieving resilience to negative information are presented in Table 6.

*(Insert Table 6 about here)*

In Table 6, we have two configurations, both with two antecedents and both with the presence of electronic word-of-mouth. Both configurations exhibit a consistency close to 0.84 and coverage of at least 0.597. The overall coverage indicates that the combined models account for approximately 68% of membership in the outcome of interest (resilience to negative information), with an overall consistency of 0.817. These results indicate that, to ensure that resilience to negative information is obtained, a high level of electronic word-of-mouth should be attained, accompanied by either customer-brand identification or self-brand congruity.

There are two interesting aspects in these analyses. First, the model attains a large overall consistency but at the cost of limited coverage. In other words, although the presented configurations lead to resilience to negative information, there is a nonnegligible number of cases in which this outcome is obtained without the presence of any of these configurations (remember that these configurations are sufficient, but not necessary, to obtain the outcome). Second, although electronic word-of-mouth is not necessary for achieving resilience to negative information, it is present in all the configurations. This result is, in fact, consistent with the low overall coverage of

the model; this limited overall coverage indicates that, in a nonnegligible number of cases, resilience to negative information is obtained without the presence of any of these configurations and, therefore, electronic word-of-mouth is not necessary for achieving resilience to negative information.

#### **4.2.3. Predictive validity**

As stated by Wu et al. (2014), a good model fit does not necessarily mean that the model offers good predictions. To test for predictive validity, the sample was split into a modeling subsample and a holdout subsample, as suggested in previous research (e.g., Xu et al., 2016). Additionally, the roles of the subsamples were reversed, with the latter treated as the modeling subsample and the former as the holdout subsample. The assignment of the observations to the subsamples was completely random, and it was performed in such a way that the two subsamples would have the same number of observations. The objective of the analysis is to determine whether the model obtained from subsample 1 has high predictive ability in subsample 2, and vice versa. If that is true, the models obtained from each subsample should perform well in the other one, showing high consistency and coverage.

Table 7 shows the configurations obtained using the two subsamples. The levels of consistency and coverage do not change much when the models obtained from one subsample are applied to the other subsample. These results provide support for predictive validity. Additionally, the models obtained with the subsamples are not very different from the model obtained using the whole sample. In fact, the subsample 2 model is identical to the model from the whole sample, and the subsample 1 model just adds a configuration (containing customer-brand identification and self-brand congruity), which also reinforces the predictive validity.



*(Insert Table 7 about here)*

In summary, the results presented in Table 7 indicate that models obtained with one subsample behave well when applied to the other and are not very different from the models obtained with the whole sample, pointing to the existence of predictive validity.

#### **4.3. Interaction analysis**

The sufficient conditions to achieve resilience to negative information, obtained with fsQCA, all include electronic word-of-mouth. Therefore, we also wanted to determine whether electronic word-of-mouth amplifies the impact of the other variables on resilience to negative information. Therefore, the sample was split into two subsamples: a subsample with high electronic word-of-mouth (higher than or equal to the median value of electronic word-of-mouth) and a subsample with low electronic word-of-mouth (lower than the median). Resilience to negative information was then regressed for each subsample on customer-brand identification and on self-brand congruity. The fuzzy values of the variables were used (the same procedure was also applied with the original values of the variables, with similar results). The regression results are shown in Table 8, and the linear regression lines are plotted in Figure 3.

*(Insert Table 8 about here)*

*(Insert Figure 3 about here)*

As expected, the high electronic word-of-mouth linear regression line always lies above the low electronic word-of-mouth line, showing that electronic word-of-mouth has a positive effect on resilience to negative information. Regarding the interaction between electronic word-of-mouth and the other variables (customer-brand identification and self-brand congruity), the regression coefficient of the variables is larger for the high electronic word-of-mouth subsample; therefore,

the slope is higher for this subsample. This result shows that electronic word-of-mouth amplifies the effect of the other variables on resilience to negative information; higher values of electronic word-of-mouth make resilience to negative information more sensitive to changes in customer-brand identification and self-brand congruity.

This interaction was also checked using an interaction plot (see Figure 4). To do that, not only electronic word-of-mouth was classified into high and low but also customer-brand identification and self-brand congruity were similarly classified (comparing the values with the median, as was done with electronic word-of-mouth). The impact of the interactions on the average resilience to negative information was then analyzed using fuzzy values of resilience to negative information (this procedure was also applied to the original values of resilience to negative information, leading to the same conclusions). The interaction plot shows that a high level of electronic word-of-mouth leads to a higher increase in the average resilience to negative information (lines with higher slope in Figure 4), confirming that electronic word-of-mouth amplifies the impact of customer-brand identification and self-brand congruity on resilience to negative information.

*(Insert Figure 4 about here)*

## **5. Discussion and conclusions**

### **5.1. Theoretical contributions**

With the emergence of social media, airlines are increasingly exposed to negative information, and it becomes more difficult to control the online brand image. Therefore, resilience to negative information is even more important. However, despite its importance, resilience to negative information has not received much research attention (with few exceptions). The conceptual model

proposed and tested in this study (see Figure 1) sheds light on the sequence of causality among the constructs leading to higher resilience to negative information.

Unlike past research, this study focuses on existing customers. The study builds on social-identity and examines the relationship between customer-brand identification and resilience to negative information, which was still unclear. Moreover, drawing upon cognitive dissonance and self-perception theories, it is shown that identification and word-of-mouth are effective marketing strategies to build resilience to negative information in social media environments. Therefore, this study contributes to advance the customer-relationship literature, in particular, the customer-brand identification and electronic word-of-mouth streams of research. Based on the conceptual model, several hypotheses were considered. Table 9 presents a summary of the tested hypotheses. All hypotheses were supported.

*(Insert Table 9 about here)*

It has been suggested that interactions with other users contribute to the enrichment of the purchase experience (Wu & Fang, 2010). The results obtained in this study support this idea and emphasize the importance of electronic word-of-mouth to achieve marketing outcomes. The results also show that identification can lead to extra-role customer behaviors, such as resilience to negative information, as suggested in previous research (e.g., Bhattacharya & Sen, 2003; Riketta, 2005).

Using configurational analysis, two alternative paths to achieve resilience to negative information were identified: the joint presence of electronic word-of-mouth with either self-brand congruity or customer-brand identification. The two solutions require the presence of electronic word-of-mouth, indicating that electronic word-of-mouth is key to obtaining resilience to negative information. Hence, customer-brand identification is not sufficient to achieve resilience to negative

information; it must be combined with electronic word-of-mouth. Furthermore, because there is more than one solution, it can be concluded that none of the solutions is necessary. The results of the interaction analysis show that electronic word-of-mouth amplifies the effect of self-brand congruity and customer-brand identification. Because customer-brand identification helps customers satisfy their self-definitional needs, they are more likely to be resilient when exposed to negative brand information. The need for self-continuity is a key driver of individual's choice of organizations to identify with (Pratt, 1998) in their effort to build viable, cognitively consistent social identities (Heider, 1958). By taking a public position through electronic word-of-mouth, existing customers tend to align their attitudes in the direction of that position, and commitment arises (Kiesler, 1971). This commitment is justified by a person's desire to be internally consistent (Garnefeld et al., 2013). Thus, customers will be more willing to give the brand another chance if something negative happens, to disregard negative information about the brand, and to forgive the brand when it makes mistakes if they post online positive opinions or recommendations about it.

The effect of customer-brand identification on resilience to negative information is clarified, and a model to build resilience to negative information is provided. The results of the configurational analysis suggest that resilience to negative information can be achieved with a combination of electronic word-of-mouth with either customer-brand identification or self-brand congruity. Electronic word-of-mouth complements and amplifies the effects of these constructs. These insights can be useful in guiding marketing strategies for airlines.

## **5.2. Managerial contributions**

The results show that the overlap of customers' personality with brand personality can yield positive results for airlines if other customers' positive evaluations and reviews of service brands are posted on digital platforms. Thus, airlines should encourage customer participation on social media platforms. Because it is more difficult to control the online brand image on social media platforms, airlines should build resilience to negative information and try to project an attractive brand identity. One approach to doing so is to communicate values that are a good match to customers' values. Moreover, airline brand managers should effectively manage electronic word-of-mouth. For example, the use of gamification techniques may help airlines promote and manage customer engagement in electronic word-of-mouth activities. This approach will also enable airlines to better understand targeted customers' lifestyles and expectations. Consequently, airlines could adjust their offering according to customers' preferences and use these platforms to communicate and project elements of identity that match customers' lifestyles.

### **5.3. Limitations and future research**

As with any research, this study is not without limitations, some of which will be addressed in future research. First, the study was conducted on the airline industry and considered only one brand. Second, the study was limited to Portuguese travelers. Therefore, any generalization of the findings should be made with caution. The proposed model should also be tested in other service sectors, using different samples and brands. Common method variance may be a problem in a study such as this one; it is important that future studies incorporate further safeguards against it. As recommended by Hulland et al. (2018), future studies should use a priori methods for dealing with common method variance. Finally, the sample is skewed towards younger and highly educated customers. We advocate further study to investigate the model relationships among other

demographics. We also recommend that future research uses different approaches, such as experimental analysis.

## **Acknowledgements**

The authors gratefully acknowledge the useful comments and suggestions of the reviewers, which helped to significantly improve the article. The authors also acknowledge the assistance of Catarina Pinto in the design of an initial version of figures.

## **References**

- Aaker, J., Fournier, S., Brasel, S.A. 2004. When good brands do bad. *Journal of Consumer Research* 31, 1–16.
- Aaker, J.L. 1997. Dimensions of brand personality. *Journal of Marketing Research* 34, 347-356.
- Alayo, M., Maseda, A., Iturralde, T., Arzubiaga, U. 2019. Internationalization and entrepreneurial orientation of family SMEs: The influence of the family character. *International Business Review* 28, 48-59.
- Anderson, J.C., Gerbing, D.W. 1988. Structural equation modelling in practice: A review and recommended two-step approach. *Psychological Bulletin* 103, 411-413.
- Armstrong, J.S., Overton, T.S. 1977. Estimating nonresponse bias in mail surveys. *Journal of Marketing Research* 14, 396-402.
- Arnett, D.B., German, S.D., Hunt, S.D. 2003. The identity salience model of relationship marketing success: the case of Nonprofit marketing. *Journal of Marketing* 67, 89–105.
- Augusto, M., Torres, P. 2018. Effects of brand attitude and eWOM on consumers’ willingness to pay in the banking industry: Mediating role of consumer-brand identification and brand equity. *Journal of Retailing and Consumer Services* 42, 1-10.
- Bagozzi, R. P., Yi, Y. 1988. On the evaluation of structural equation models. *Journal of the Academy of Marketing Science*, 16, 74-94.
- Baldauf, A., Cravens, K.S., Diamantopoulos, A., Zeugner-Roth, K.P. 2009. The impact of product-country image and marketing efforts on retailer-perceived brand equity: An empirical analysis. *Journal of Retailing* 85, 437-452.
- Balmer, J.M., Stuart, H., Greyser, S.A. 2009. Aligning identity and strategy: Corporate branding at British Airways in the late 20th century. *California Management Review* 51, 6-23.
- Becker, B.W., Berry, L.L., Parasuraman, A. 1992. Marketing services: Competing through quality. *Journal of Marketing* 56, 132-134.

- Belk, R.W. 1988. Possessions and the extended self. *Journal of Consumer Research* 15, 139-168.
- Bem, D. 1965. An Experimental Analysis of Self-Persuasion. *Journal of Experimental Social Psychology* 1, 199-218.
- Bem, D. 1967. Self Perception: An Alternative Explanation for Dissonance Phenomena,” *Psychological Bulletin* 74, 183-200.
- Bergami, M., Bagozzi, R.P. 2000. Self-categorization, affective commitment, and group self-esteem as distinct aspects of social identity in the organization. *British Journal of Social Psychology* 39, 555–577.
- Berger, E.S. 2016. Is Qualitative Comparative Analysis an Emerging Method?—Structured Literature Review and Bibliometric Analysis of QCA Applications in Business and Management Research,” In *Complexity in Entrepreneurship, Innovation and Technology Research, Applications of Emergent and Neglected Methods*, edited by E. S. C. Berger and A. Kuckertz, 287-308, Springer International Publishing.
- Berger, J. 2014. Word of mouth and interpersonal communication: a review and directions for future research. *Journal of Consumer Psychology* 24,586-607.
- Berry, L.L. 2000. Cultivating service brand equity. *Journal of the Academy of Marketing Science* 28, 128–37.
- Bhattacharya, C.B., Sen, S. 2003. Consumer-company identification: A framework for understanding consumers’ relationships with companies. *Journal of Marketing* 67, 76–88.
- Bhattacharya, C.B., Sen, S. 2004. Doing better at doing good: When, why and how consumers respond to corporate social initiatives. *California Management Review* 47, 9-24.
- Bigné, E., Ruiz, C., Andreu, L., Hernandez, B. 2015. The role of social motivations, ability, and opportunity in online know-how exchanges: Evidence from the airline services industry. *Service Business* 9, 209-232.
- Book, L.A., Tanford, S., Chen, Y-S. 2015. Understanding the impact of negative and positive traveler reviews: Social influence and price anchoring effects. *Journal of Travel Research* 55, 993-1007.
- Brakus, J.J., Schmitt, B.H., Zarantonello, L. 2009. Brand experience: What is it? How is it measured? Does it affect loyalty? *Journal of Marketing* 73, 52-68.
- Cantalops, A.S., Salvi, F. 2014. New consumer behavior: A review of research on eWOM and Hotels. *International Journal of Hospitality Management* 36, 41-51.
- Casaló, L.V., Flavián, C., Guinalú, M. 2010. Determinants of the intention to participate in firm-hosted online travel communities and effects on consumer behavioral intentions. *Tourism Management* 31, 898-911.
- Chernev, A., Hamilton, R., Gal, D. 2011. Competing for consumer identity: Limits to self-expression and the perils of lifestyle branding. *Journal of Marketing* 75, 66-82.
- Cheung, C., Lee, M.K.O., Rabjohn, N. 2008. The impact of e-WOM - The adoption of online opinions in online customer communities. *Internet Research* 18, 229–247.
- Cialdini, R.B. 1971. Attitudinal advocacy in the verbal conditioner. *Journal of Personality and Social Psychology* 17, 350–58.

- Eisingerich, A.B., Rubera, G., Seifert, M., Bhardwaj, G. 2011. Doing good and doing better despite negative information? The role of corporate social responsibility in consumer resistance to negative information. *Journal of Service Research* 14, 60-75.
- Elbedweihy, A., Jayawardhena, C., Elsharnouby, M.H., Elsharnouby, T.H. 2016. Customer relationship building: The role of brand attractiveness and consumer-brand identification. *Journal of Business Research* 69, 2901-2910.
- Emmenegger, P., Schraff, D., Walter, A. 2014. QCA, the truth table analysis and large-N survey data: The benefits of calibration and the importance of robustness tests. Compass working paper 2014-79, available at <http://www.compass.org/wpseries/EmmeneggerSchraffWalter2014.pdf> (Accessed 18.01.2018).
- Escalas, J. 2004. Narrative processing: Building consumer connections to brands. *Journal of Consumer Psychology* 14, 168–180.
- Escalas, J.E., Bettman, J.R. 2003. You are what they eat: The influence of reference groups on consumers' connections to brands. *Journal of Consumer Psychology* 13, 339–348.
- Filieri, R. 2015. What makes online reviews helpful? A diagnosticity-adoption framework to explain informational and normative influences in e-WOM. *Journal of Business Research* 68, 1261-1270.
- Fiss, P.C. 2011. Building better causal theories: A fuzzy set approach to typologies in organization research,” *Academy of Management Journal* 54, 393-420.
- Fornell, C., Larcker, D.F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research* 18, 39-50.
- Frösén, J., Luoma, J., Jaakkola, M., Tikkanen, H., Aspara, J. 2016. What counts versus what can be counted: The complex interplay of market orientation and marketing performance measurement. *Journal of Marketing* 80, 60-78.
- Fuller, C.M., Simmering, M.J., Atinc, G., Atinc, Y., Babin, B.J. 2016. Common methods variance detection in business research. *Journal of Business Research* 69, 3192-3198.
- Garnefeld, I., Eggert, A., Helm, S.V., Tax, S.S. 2013. Growing existing customers' revenue streams through customer referral programs. *Journal of Marketing* 77, 17-32.
- Garnefeld, I., Helm, S., Eggert, A. 2011. Walk your talk: An experimental investigation of the relationship between word-of-mouth and communicators' loyalty. *Journal of Service Research* 14, 93-107.
- Grace, D., O'Cass, A. 2004. Examining service experiences and postconsumption evaluations. *Journal of Services Marketing* 18, 450-461.
- Grewal, R., Chandrashekar, M., Citrin, A.V. 2010. Customer satisfaction heterogeneity and shareholder value. *Journal of Marketing Research* 47, 612–626.
- Grofman, B., Schneider, C.Q. 2009. An introduction to crisp set QCA, with a comparison to binary logistic regression. *Political Research Quarterly* 62, 662-672.
- Harmeling, C.M., Palmatier, R.W., Houston, M.B., Arnold, M.J., Samaha, S.A. 2015. Transformational relationship events. *Journal of Marketing* 79, 39-62.



- Hars, A., Ou, S. 2002. Working for free? Motivations for participating in open-source projects. *International Journal of Electronic Commerce* 6, 25-39.
- Haumann, T., Quaiser, B., Wieseke, J., Mario Rese, M. 2014. Footprints in the sands of time: A comparative analysis of the effectiveness of customer satisfaction and customer–company identification over time. *Journal of Marketing* 78, 78-102.
- Heider, F. 1958. *The psychology of interpersonal relations*. New York: John Wiley & Sons.
- Hennig-Thurau, T., Gwinner, K., Walsh, G., Gremler, D.D. 2004. Electronic word-of-mouth via consumer-opinion platforms: What motivates consumers to articulate themselves on the Internet? *Journal of Interactive Marketing* 18, 38-52.
- Hess, R.L., Ring, L. 2016. The influence of the source and valence of word-of-mouth information on post-failure and post-recovery evaluations. *Service Business* 10, 319-343.
- Higgins, E.T., Rholes, W.S. 1978. Saying is believing: Effects of message modification on memory and liking for the person described. *Journal of Experimental Social Psychology* 14, 363–78.
- Ho, J., Plewa, C., Lu, V.N. 2016. Examining strategic orientation complementarity using multipleregression analysis and fuzzy set QCA. *Journal of Business Research* 69, 2199–2205.
- Homburg, C., Wieseke, J., Hoyer, W.D. 2009. Social identity and the service-profit chain. *Journal of Marketing* 73, 38–54.
- Hooper, D., Coughlan, J., Mullen, M. R. 2008. Structural equation modelling: Guidelines for determining model fit. *The Electronic Journal of Business Research Methods*, 6, 53-60.
- Hulland, J., Baumgartner, H., & Smith, K. M. 2018. Marketing survey research best practices: evidence and recommendations from a review of *JAMS* articles. *Journal of the Academy of Marketing Science*, 46(1), 92-108.
- Javalgi, R.J., Martin, C.L., Young, R.B. 2006. Marketing research, market orientation and customer relationship management: A framework and implications for service providers. *Journal of Services Marketing* 20, 12-23.
- Kao, T.Y., Yang, M.H., Wu, J.T.B., Cheng, Y.Y. (2016). Co-creating value with consumers through social media. *Journal of Services Marketing* 30, 141-151.
- Kiesler, C.A. 1971. *The Psychology of Commitment: Experiments Linking Behavior to Belief*. New York: Academic Press.
- Kim, J-H., Jang, S. 2016. Memory retrieval of cultural event experiences: Examining internal and external influence. *Journal of Travel Research* 55, 322-339.
- Kim, J-H., Ritchie, J.R.B. 2014. Cross-cultural validation of memorable tourism experience scale (MTES). *Journal of Travel Research* 53, 323-335.
- Kim, J-H., Ritchie, J.R.B., McCormick, B. 2012. Development of a scale to measure memorable tourism experiences. *Journal of Travel Research* 51, 12-25.
- Kim, J., Fesenmaier, D.R. 2017. Sharing tourism experiences: The posttrip experience. *Journal of Travel Research* 56, 28–40.

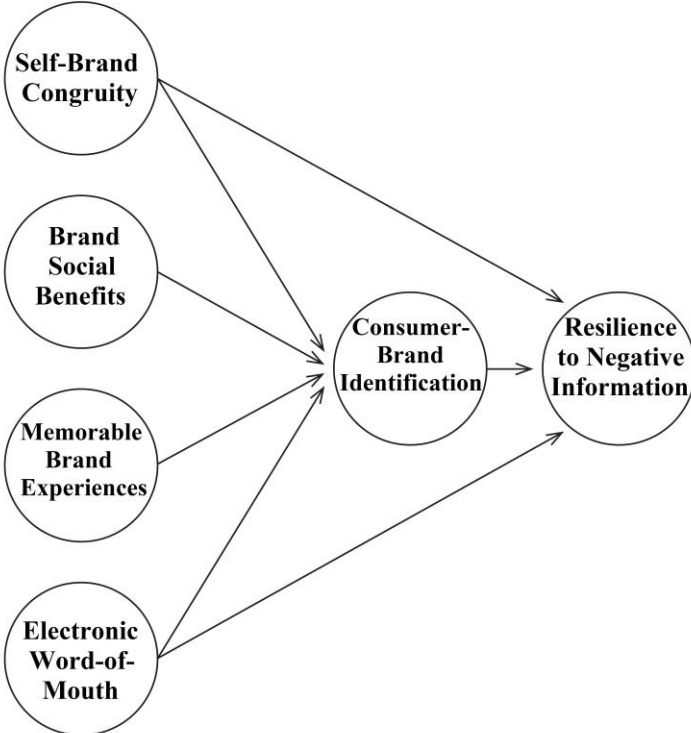
- Kline, R.B. 2017. *Principles and practice of structural equation modeling*. 3rd ed. The New York: Guildford Press.
- Kozinets, R.V., De Valck, K., Wojnicki, A.C., Wilner, S.J. 2010. Networked narratives: Understanding word-of-mouth marketing in online communities. *Journal of Marketing* 74, 71–89.
- Kuenzel, S., Halliday, S.V. 2010. The chain of effects from reputation and brand personality congruence to brand loyalty: The role of brand identification. *Journal of Targeting, Measurement and Analysis for Marketing* 18, 167–176.
- Lam, S.K., Ahearne, M., Hu, Y., Schillewaert, N. 2010. Resistance to brand switching when a radically new brand is introduced: A social identity theory perspective. *Journal of Marketing*, 74, 128-146.
- Lam, S.K., Ahearne, M., Mullins, R., Hayati, B., Schillewaert, N. 2013. Exploring the dynamics of antecedents to consumer–brand identification with a new brand. *Journal of the Academy of Marketing Science* 41, 234–252.
- Lamberton, C., Stephen, A. 2016. A thematic exploration of digital, social media, and mobile marketing: Research evolution from 2000 to 2015 and an agenda for future inquiry. *Journal of Marketing* 80, 146-172.
- Lee, S., Park, S. 2010. Financial impacts of socially responsible activities on airline companies. *Journal of Hospitality & Tourism Research* 24, 185-203.
- Levy, S., Gvili, Y. 2015. How credible is E-Word of Mouth across Digital-Marketing channels – The roles of social capital, information richness, and interactivity. *Journal of Advertising Research* 55, 95–109.
- MacInnis, D.J. 2011. A framework for conceptual contributions in Marketing. *Journal of Marketing* 75, 136-154.
- Markus, H.R., Wurf, E. 1987. The dynamic self-concept: A social-psychological perspective. *Annual Review of Psychology* 38, 299-337.
- Migacz, S.J., Zou, S., Petrick, J.F. 2017. The “terminal” effects of service failure on airlines: Examining service recovery with justice theory. *Journal of Travel Research* 57, 83-98.
- Motyka, S., Grewal, D., Aguirre, E., Mahr, D., de Ruyter, K., Vezels, M. 2018. The emotional review-reward effect: How do reviews increase impulsivity? *Journal of the Academy of Marketing Science* 46, 1032-1051.
- Muniz, A.M., T. O'Guinn, C. 2001. Brand community. *Journal of Consumer Research* 27, 412-432.
- Navarro, S., Llinares, C., Garzon, D. 2016. Exploring the relationship between cocreation and satisfaction using QCA. *Journal of Business Research* 69, 1336–1339.
- Nusair, K., Bilgihan, A., Okumus, F., C. Cobanoglu, C. 2013. Generation Y travelers' commitment to online social network websites. *Tourism Management* 35, 13-22.
- O'Reilly, C.A., Chatman, J. 1986. Organizational commitment and psychological attachment: The effects of compliance, identification, and internalization on prosocial behaviour. *Journal of Applied Psychology* 71, 492–499.

- Ordanini, A., Parasuraman, A., Rubera, G. 2014. When the recipe is more important than the ingredients a Qualitative Comparative Analysis (QCA) of service innovation configurations. *Journal of Service Research* 17, 134-149.
- Ordenes, F., Ludwig, S., De Ruyter, K., Grewal, D., Wetzels, M. 2017. Unveiling what is written in the stars: Analyzing explicit, implicit, and discourse patterns of sentiment in social media. *Journal of Consumer Research* 43, 875–894.
- Pan, V., Zhang, J.Q. 2011. Born unequal: a study of the helpfulness of user-generated product reviews. *Journal of Retailing* 87, 598-612.
- Papatheodorou, A., Pappas, N. 2016. Economic recession, job vulnerability, and tourism decision making: A qualitative comparative analysis. *Journal of Travel Research* 56, 663-677.
- Park, H., Kim, Y.-K. 2014. The role of social network websites in the consumer-brand relationship. *Journal of Retailing and Consumer Services* 21, 460–467.
- Park, J., Park, J. 2016. Investigating the effects of service recovery quality elements on passengers' behavioural intention. *Journal of Air Transport Management* 53, 235-241.
- Pervin, L.A. 1989. *Goal concepts in personality and social psychology*. NJ: Lawrence Erlbaum Associates, Inc, Hillsdale.
- Podsakoff, P.M, MacKenzie, S.B., Lee, J.-Y., Podsakoff, N.P. 2003. Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology* 88, 879-903.
- Podsakoff, P.M., MacKenzie, S.B., Podsakoff, N.P. 2012. Sources of method bias in social science research and recommendations on how to control it. *Annual Review of Psychology*, 63, 539-569.
- Podsakoff, P.M., Organ, D.W. 1986. Self-reports in organizational research: Problems and prospects. *Journal of Management* 12, 531–544.
- Popp, B., Woratschek, H. 2017. Consumers' relationships with brands and brand communities – The multifaceted roles of identification and satisfaction. *Journal of Retailing and Consumer Services* 35, 46–56.
- Pratt, M.G. 1998. To be or not to be: Central questions in organizational identification. In *Identity in organizations: Building theory through conversations*, edited by Whetten, D.A. and Godfrey, P.C., 171-207. Thousand Oaks: Sage Publications.
- Qu, H., Lee, H. 2001. Travelers' social identification and membership behaviors in online travel community. *Tourism Management* 32, 1262-1270.
- Raghunathan, R., Naylor, R.W., Hoyer, W.D. 2006. The unhealthy = tasty intuition and its effects on taste inferences, enjoyment, and choice of food products. *Journal of Marketing* 70, 170-184.
- Ragin, C.C. 2008. *Redesigning social inquiry: Fuzzy sets and beyond*. Chicago: University of Chicago Press.
- Ragin, C.C. 2009. Qualitative comparative analysis using fuzzy sets (fsQCA). In *Configurational comparative methods: Qualitative comparative analysis (QCA) and related techniques*, edited by C.C. Ragin and B. Rihoux, 87–122. Los Angeles: Sage.

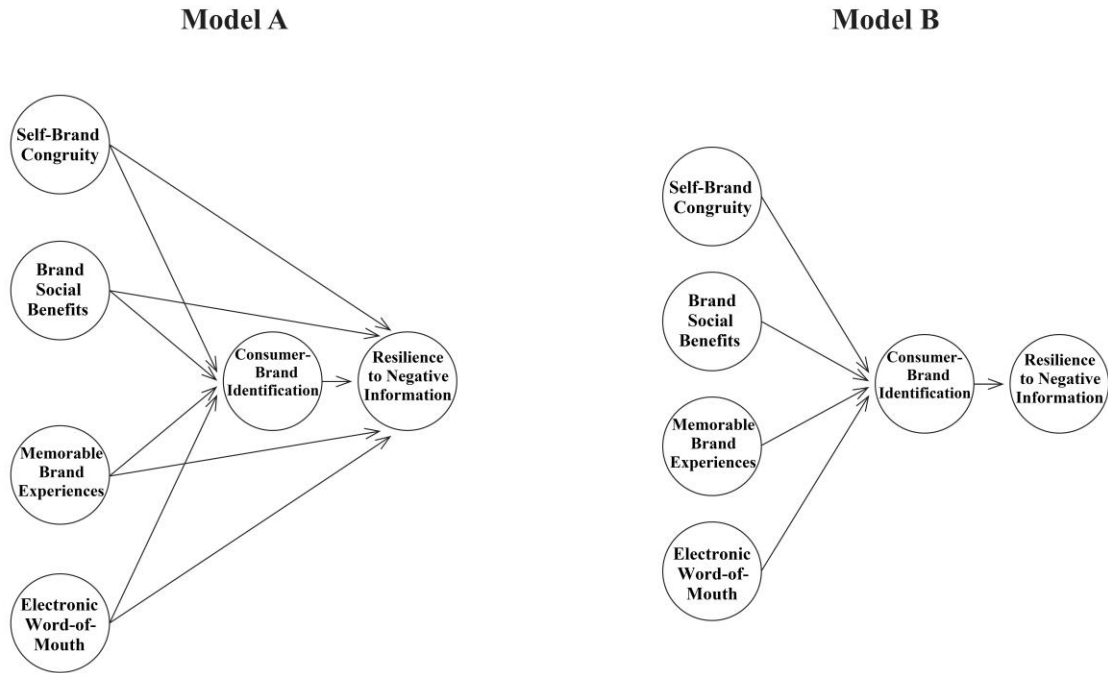
- Rihoux, B., Rezsöházy, I., Bol, D. 2011. Qualitative comparative analysis (QCA) in public policy analysis: An extensive review. *German Policy Studies* 7, 9-82.
- Riketta, M. 2005. Organizational identification: A meta-analysis. *Journal of Vocational Behavior* 66, 358–384.
- Saenger, C., Thomas, V.L., Johnson, J.W. 2013. Consumption-focused self-expression word of mouth: A new scale and its role in consumer research. *Psychology & Marketing* 11, 959–70.
- Schmitt, B. 2012. The consumer psychology of brands. *Journal of Consumer Psychology* 22, 7–17.
- Schneider, M.R., Schulze-Bentrop, C., Paunescu, M. 2010. Mapping the institutional capital of high-tech firms: A fuzzy-set analysis of capitalist variety and export performance. *Journal of International Business Studies* 41, 246-266.
- Sirgy, M.J. 1985. Using self-congruity and ideal congruity to predict purchase motivation. *Journal of Business Research* 13, 195–206.
- Sirgy, M.J., Lee, D.-J., Johar, J. S., Tidwell, J. 2008. Effect of self-congruity with sponsorship on brand loyalty. *Journal of Business Research* 61, 1091–1097.
- Skowronski, J.J., Carlston, D.E., Mae, L., Crawford, M.T. 1998. Spontaneous trait transference: Communicators take on the qualities they describe in others. *Journal of Personality and Social Psychology* 74, 837-848.
- So, K.K.F., King, C., Hudson, S., Meng, F. 2017. The missing link in building customer brand identification: The role of brand attractiveness. *Tourism Management* 59, 640-651.
- So, K.K.F., Wu, L., Xiong, L., King, C. 2018. Brand management in the era of social media: Social visibility of consumption and customer brand identification. *Journal of Travel Research* 57, 727-742.
- Stevens, R., Moray, N., Bruneel, J. 2015. The social and economic mission of social enterprises: Dimensions, measurement, validation, and relation. *Entrepreneurship Theory and Practice* 39, 1051-1082.
- Stokburger-Sauer, N., Ratneshwar, S., Sen, S. 2012. Drivers of consumer–brand identification. *International Journal of Research in Marketing* 29, 406–418.
- Tajfel, H., Turner, J. 2001. An Integrative theory of intergroup conflict.” In *Intergroup relations: Essential readings: Key readings in social psychology*, edited by M.A. Hogg and D. Abrams, 94–109. New York: Psychology Press.
- Tajfel, H., Turner, J.C. 1985. The social identity theory of intergroup behaviour. In *Psychology of intergroup relations*, edited by S. Worchel and W.G. Austin, 7–24. Chicago: Nelson-Hall.
- Thompson, C.J., Rindfleisch, A., Arsel, Z. 2006. Emotional branding and the strategic value of the doppelgänger brand image. *Journal of Marketing* 70, 50–64.
- Torres, P., Augusto, M., Godinho, P. 2017. Predicting high consumer-brand identification and high repurchase: Necessary and sufficient conditions. *Journal of Business Research* 79, 52-65.

- Torres, P., Augusto, M., Wallace, E. 2018. Improving consumers' willingness to pay with social media activities. *Journal of Services Marketing* 32, 880-896.
- Tsao, W-C., Hsieh, M.-T., Shih, L.-W., Lin, T.M.Y. 2015. Compliance with eWOM: The influence of hotel reviews on booking intention from the perspective of consumer conformity. *International Journal of Hospitality Management* 46, 99-111.
- Turner, J.C. 1975. Social comparison and social identity: Some prospects for intergroup behaviour. *European Journal of Social Psychology* 5, 1-34.
- Tuškej, U., Golob, U., Podnar, K. 2013. The role of consumer-brand identification in building brand relationship. *Journal of Business Research* 66, 53-59.
- Vermeulen, I.E., Seegers, D. 2009. Tried and tested: The impact of online reviews on consumer consideration. *Tourism Management* 30, 123-127.
- Wang, X., Yu, C., Wei, Y. 2012. Social media peer communication and impacts on purchase intentions: A consumer socialization framework. *Journal of Interactive Marketing* 26, 198-208.
- Woodside, A.G. 2014. Embrace\*perform\*model: Complexity theory, contrarian cases analysis, and multiple realities. *Journal of Business Research* 67, 2495-2503.
- Woodside, A.G. 2016. The good practices manifesto: Overcoming bad practices pervasive in current research in business. *Journal of Business Research* 69, 365-381.
- Wu, P.L., Yeh, S.S., Woodside, A.G. 2014. Applying complexity theory to deepen service dominant logic: Configurational analysis of customer experience-and-outcome assessments of professional services for personal transformations. *Journal of Business Research* 67, 1647-1670.
- Wu, S., Fang, W. 2010. The effect of consumer-to-consumer interactions on idea generation in virtual brand community relationships. *Technovation* 30, 570-581.
- Wu, W.Y., Tsai, C.H. 2008. The empirical study of CRM: Consumer-company identification and purchase intention in the direct selling industry. *International Journal of Commerce and Management* 17, 194-210.
- Xiang, Z., Gretzel, U. 2010. Role of social media in online travel information search. *Tourism Management* 31, 179-188.
- Xu, B., Zheng, H., Xu, Y., Wang, T. 2016. Configurational paths to sponsor satisfaction in crowdfunding. *Journal of Business Research* 69, 915-927.
- Ye, Q., Law, R., Gu, B., Chen, W. 2011. The influence of user-generated content on traveler behavior: An empirical investigation on the effects of e-word-of-mouth to hotel online bookings. *Computers in Human Behavior* 27, 634-639.
- Zavyalova, A., PFarrer, M.D., Reger, R.K., Hubbard, T.D. 2016. Reputation as a benefit and a burden? How stakeholders' organizational identification affects the role of reputation following a negative event. *Academy of Management Journal* 59, 253-276.

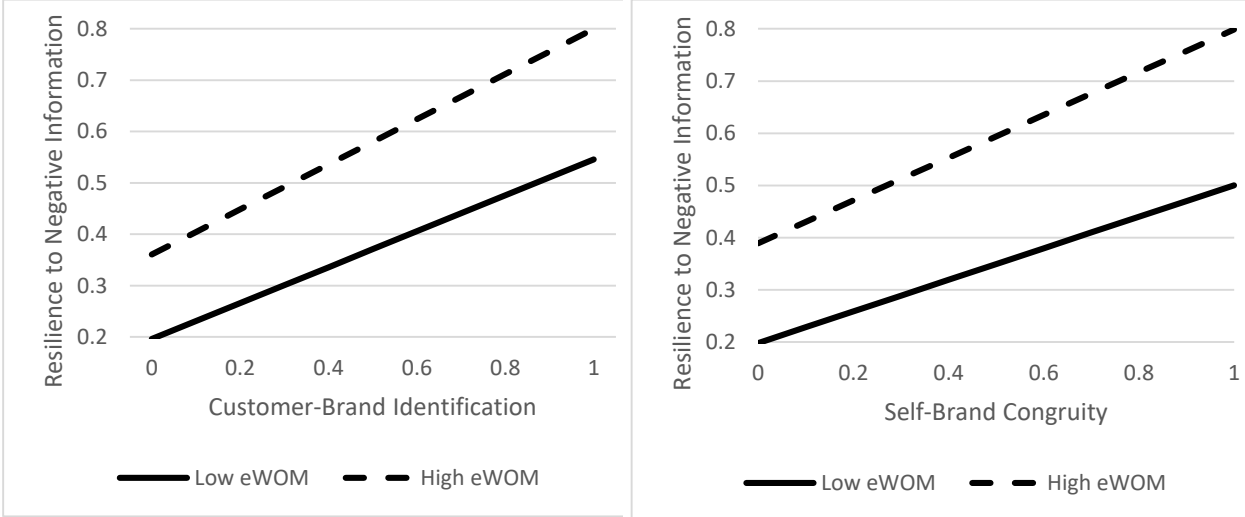
**Figure 1:** Conceptual framework



**Figure 2:** Specification of alternative models



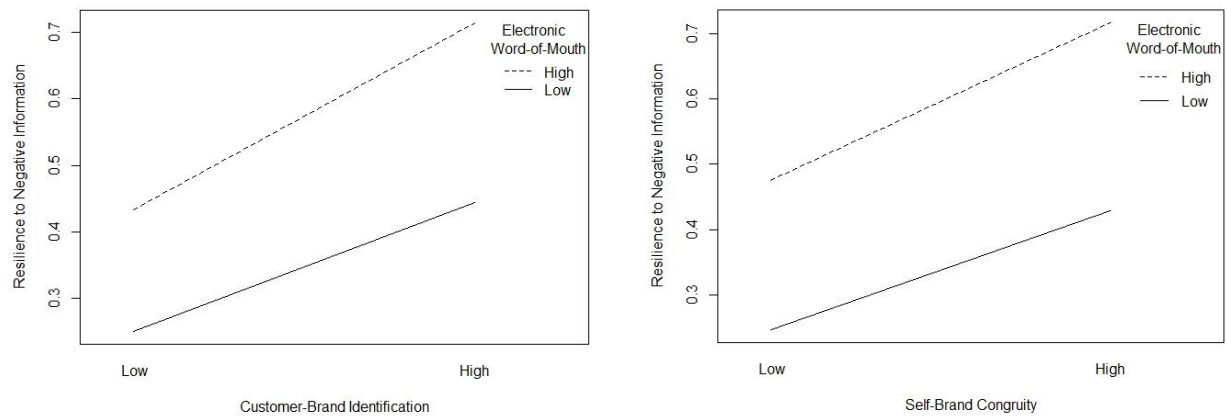
**Figure 3:** Regression lines for Resilience to Negative Information as a function of Customer-Brand Identification and Self-Brand Congruity, for high and low values of Electronic Word-of-Mouth



**Legend:** High eWOM: Higher electronic word-of-mouth than or equal to the median; Low eWOM: Lower electronic word-of-mouth than the median. Fuzzy values of the variables are used.



**Figure 4:** Impact on Resilience to Negative Information of the interaction between Electronic Word-of-Mouth and customer-brand identification, and between Electronic Word-of-Mouth and Self-Brand Congruity



**Legend:** High values: Higher than or equal to the median; Low values: Lower than the median. Fuzzy values of the resilience to negative information are used.

**Table 1:** Standardized parameter estimates, critical ratio, and R<sup>2</sup> for the measurement model

Construct	Items	Stand. loads.	t-value	R <sup>2</sup>
<b>Self-Brand Congruity</b>	Sincere (e.g., Down-to-earth, honest, genuine)	0.79	--- <sup>(a)</sup>	0.62
	Exciting (e.g., Daring, spirited, young, up-to-date)	0.76	13.18	0.58
	Competent (e.g., Reliable, efficient, leader)	0.84	14.80	0.71
	Sophisticated (e.g., Glamorous, charming, upper class)	0.79	13.83	0.63
	<i>Source: Lam et al. (2013)</i>			
<b>Brand Social Benefits</b>	(Brand X) offers me the opportunity to socialize	0.82	--- <sup>(a)</sup>	0.68
	I feel a sense of kinship with other people who use (brand X)	0.83	16.40	0.70
	I gain a lot from interactions with other customers/users of (brand X)	0.89	18.11	0.80
	(Brand X) creates warm feelings among its users	0.88	17.80	0.78
	<i>Source: Stokburger-Sauer et al. (2012)</i>			
<b>Memorable Brand Experiences</b>	Thinking of (brand X) brings back good memories	0.96	--- <sup>(a)</sup>	0.92
	I have fond memories of (brand X)	0.97	34.66	0.94
	<i>Source: Stokburger-Sauer et al. (2012)</i>			
<b>Electronic Word-of-Mouth</b>	I 'talk up' the (brand X) online pages to my friends.	0.87	--- <sup>(a)</sup>	0.76
	I try to spread the good word about the (brand X) online pages	0.90	21.55	0.81
	I give the (brand X) online pages lots of positive word-of-mouth advertising.	0.95	23.70	0.91
	<i>Source: Park and Kim (2014)</i>			
<b>Customer-Brand Identification</b>	I feel a strong sense of belonging to (brand X)	0.92	--- <sup>(a)</sup>	0.85
	I identify strongly with (brand X)	0.97	32.38	0.95
	(Brand X) has a great deal of personal meaning to me	0.84	21.23	0.70
	<i>Source: Stokburger-Sauer et al. (2012)</i>			
<b>Resilience to Negative Information</b>	If (brand X) did something I didn't like, I would be willing to give it another chance.	0.77	--- <sup>(a)</sup>	.59
	I will disregard any negative information that I hear or read about (brand X).	0.68	11.02	.47
	I will forgive (brand X) when it makes mistakes.	0.84	13.28	.70
	<i>Source: Elbedweihy et al. (2016)</i>			

**Legend:** Stand. loads = standardised loads. R<sup>2</sup> = squared multiple correlation; <sup>(a)</sup> The path is fixed at 1.0 to set the metric of the construct.

**Model fit:** Chi-square ( $\chi^2$ ) = 402.49; *df* = 137; goodness of fit index (GFI) = 0.87; normed fit index (NFI) = 0.92; incremental fit index (IFI) = 0.95; Tucker-Lewis index (TLI) = 0.93; comparative fit index (CFI) = 0.95, and root mean square error approximation (RMSEA) = 0.08.

**Table 2:** Correlation matrix of constructs, reliability estimates, and variance extracted estimates

<b>Construct</b>	SBC	BSB	MBE	eWOM	CBI	RNI	CR	AVE
SBC	<b>0.87</b>						0.87	0.63
BSB	0.63	<b>0.90</b>					0.92	0.73
MBE	0.65	0.55	<b>0.96</b>				0.97	0.93
eWOM	0.45	0.62	0.40	<b>0.93</b>			0.93	0.82
CBI	0.66	0.74	0.78	0.54	<b>0.93</b>		0.94	0.84
RNI	0.64	0.66	0.59	0.66	0.66	<b>0.79</b>	0.81	0.59

**Legend:** Diagonal entries (highlighted) are Cronbach's alpha coefficients. SBC = Self-Brand Congruity; BSB = Brand Social Benefits; MBE = Memorable Brand Experiences; eWOM = Electronic Word-of-Mouth; CBI = Customer-Brand Identification; RNI = Resilience to Negative Information; CR = composite reliability; AVE = average variance extracted.

**Table 3:** Results of the structural model

Path	<i>Stand. coeff.</i>	<i>t-value</i>
Self-Brand Congruity → Customer-Brand Identification	0.05	0.85
Self-Brand Congruity → Resilience to Negative Information	0.30	4.07**
Brand Social Benefits → Customer-Brand Identification	0.38	6,37**
Memorable Brand Experiences → Customer-Brand Identification	0.51	10.21**
Electronic Word-of-Mouth → Customer-Brand Identification	0.08	1.71*
Electronic Word-of-Mouth → Resilience to Negative Information	0.39	6.10**
Customer-Brand Identification → Resilience to Negative Information	0.26	3.49**

**Legend:** Stand. coeff. = standardised coefficient; one-tailed significant testing: \*\*, \* Significant at the 1% and the 5% level, respectively. R<sup>2</sup>: Customer-Brand Identification : 0.75; Resilience to Negative Information : 0.62.

**Model global fit:** Chi-square ( $\chi^2$ ) = 405.87, *df*= 139, goodness of fit index (GFI) = 0.86, normed fit index (NFI) = 0.92; incremental fit index (IFI) = 0.95, Tucker-Lewis index (TLI) = 0.93, comparative fit index (CFI) = 0.94, and root mean square error approximation (RMSEA) = 0.08.

**Table 4:** Model comparison

Fit estimates	$\chi^2$	$df$	$\Delta\chi^2$	$\Delta df$	NFI	GFI	IFI	TLI	CFI	RMSEA
Proposed Model	405.87	139	Base comparison		0.92	0.87	0.95	0.93	0.95	0.08
Model A	402.49	137	3.38	2	0.92	0.87	0.95	0.93	0.95	0.08
Model B	468.33	141	62.46*	2	0.91	0.85	0.93	0.92	0.93	0.09

**Legend:** \* Significant at the 1% level; NFI = Normed fit index; GFI = Goodness of fit index; IFI = Incremental fit index; TLI = Tucker-Lewis index; CFI = Comparative fit index; RMSEA = Root mean square error approximation.

**Table 5:** Analysis of necessary conditions for achieving Resilience to Negative Information

	Resilience to Negative Information	
	Consistency	Coverage
Self-Brand Congruity	0.736	0.718
Electronic Word-of-Mouth	0.750	0.742
Customer-Brand Identification	0.746	0.741

**Table 6:** Configurations for achieving Resilience to Negative Information

Configuration	Solution	
	1	2
Customer-Brand Identification	●	
Self-Brand Congruity		●
Electronic Word-of-Mouth	●	●
Consistency	0.844	0.838
Coverage	0.620	0.597
Unique coverage	0.086	0.063
Overall consistency	0.817	
Overall coverage	0.682	

**Legend:** Black circles indicate the presence of a condition; blank spaces indicate “don’t care”. The solution is simultaneously the parsimonious and the intermediate one.

**Table 7:** Configurations for achieving Resilience to Negative Information in random subsamples

Configuration	Configurations obtained from subsample 1			Configurations obtained from subsample 2		
	Solution			Solution		
	1	2	3	1	2	
Customer-Brand Identification	●	●			●	
Self-Brand Congruity		●	●	●		
Electronic Word-of-Mouth	●		●	●	●	
	Performance in subsample 1			Performance in subsample 2		
Consistency	0.816	0.802	0.832	0.845	0.877	
Coverage	0.633	0.646	0.609	0.584	0.607	
	Overall consistency		0.774	Overall consistency		0.831
	Overall coverage		0.786	Overall coverage		0.674
	Performance in subsample 2			Performance in subsample 1		
Consistency	0.877	0.811	0.845	0.832	0.816	
Coverage	0.607	0.611	0.584	0.609	0.633	
	Overall consistency		0.768	Overall consistency		0.804
	Overall coverage		0.774	Overall coverage		0.691

**Legend:** Black circles indicate the presence of a condition. Blank spaces indicate “don’t care”. The solutions are simultaneously the parsimonious and the intermediate ones.



**Table 8:** Regression of Resilience to Negative Information on Customer-Brand Identification and on self-brand congruity, with different models estimated for high and low values of electronic Word-of-Mouth

Dependent variable: Resilience to Negative Information				
	High eWOM	Low eWOM	High eWOM	Low eWOM
Constant	0.3604** (6.979)	0.1960** (5.941)	0.3894** (8.454)	0.1983** (5.315)
Customer-Brand Identification	0.4394** (5.803)	0.3501** (5.051)		
Self-Brand Congruity			0.4093** (5.984)	0.3022** (4.061)
R <sup>2</sup>	0.1906	0.1610	0.2003	0.1103
Adjusted R <sup>2</sup>	0.1850	0.1547	0.1947	0.1036
F-statistic	F(1,143)=33.68**	F(1,133)=25.52**	F(1,143)=35.81**	F(1,133)=16.49**

\*\* , \* Significant at the 1% and the 5% level, respectively. *t*-statistics are shown in parenthesis, below the coefficients. High eWOM: Higher electronic word-of-mouth than or equal to the median; Low eWOM: Lower electronic word-of-mouth than the median. Fuzzy values of the variables are used.

**Table 9:** Summary of hypotheses testing

<b>Propositions</b>	<b>Result</b>
H1. The higher the customer-brand identification, the higher resilience to negative information tends to be.	Supported
H2. The higher the self-brand congruity, the higher resilience to negative information tends to be.	Supported
H3. The higher the level of electronic word-of-mouth, the higher resilience to negative information tends to be.	Supported
H4. The higher the level of electronic word-of-mouth, the higher customer-brand identification tends to be.	Supported
H5. High resilience to negative information can be achieved through the combination of electronic word-of-mouth with either self-brand congruity or customer-brand identification.	Supported