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TITLE PAGE

Eliciting Brand Association Networks: A New Method using Online Community Data

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Eliciting Brand Association Networks: A New Method Using Online Community Data

Abstract

This study explores a new methodology called *community-aided brand concept map* (CA-BCM) for eliciting brand association networks using data collected from technology-enabled online communities. NVivo software is used to qualitatively code these data to 1) uncover how users associate themselves with a brand and 2) use content analysis to quantify each of these associations, leading to the elicitation of a comprehensive network of brand associations and their relationships. Using the example of a movie brand, the new tool CA-BCM effectively uncovers 1) the core, secondary, and tertiary brand associations and 2) classifies the brand associations into strong, favorable, and unique associations. Finally, 3) using these brand association classification data and the brand awareness level, customer brand equity is measured. Pearson correlation is used to provide external validity to the CA-BCM technique, which shows a significant and positive relationship between customer brand equity and market performance. The implications and limitations of this study are presented.

Keywords – brand associations; brand concept maps; brand equity; user-generated data; online community

Eliciting Brand Association Networks: A New Method Using Online Community Data

1. Introduction

Brand associations are consumers' perceptions of a brand held in consumer memory, which contains the meaning of the brand for consumers, and these associations come in all forms and may reflect characteristics of the product or aspects independent of the product (Keller, 2013). Customers form beliefs (associations) about the brand attribute and brand benefits, however, but they also form beliefs from a variety of other sources outside of the brand itself and/or form brand associations in a variety of ways other than marketing activities, such as from direct experience, word of mouth, by assumptions and inferences about the brand itself, brand elements, etc. While brand awareness is important for brand recognition and brand recall performance, creating a positive brand image or association that is strong, favorable, and unique, and not shared with competing brands enables a company to create a differential response that creates customer brand equity (Keller, 1993, 2013). Krishnan (1996) pointed out that the ideal situation for high brand equity is to have a large number of shared associations to be correctly and quickly classified as a member of that product category but also possess some unique associations that enable it to stand out from the product category.

Consumers store brand information in the form of associative networks (Brandt et al., 2011; John et al., 2006; Keller, 1993; Krishnan, 1996; Schnittka et al., 2012; Teichert & Schöntag, 2010), and this association network forms a brand's image, identifying the brand's uniqueness and value to consumers (Aaker, 1996). The graphical representation of such a brand memory is often referred to as a brand concept map (BCM), and John et al. (2006) differentiated direct (core brand associations) from indirect brand associations. *Core brand associations are associations that are directly linked to the brand and the brand's meaning, and indirect brand associations are not linked directly but rather indirectly to the brand through direct brand associations.* For brand managers, it is very important to be able to elicit both intended and unintended association networks around their brands to gain actionable, strategic insight into competitive positioning (Till et al., 2011).

1.1 Review of current methodologies for eliciting brand association networks

Various tools and methodologies are available for eliciting brand association networks, such as Zaltman's metaphor elicitation technique (Zaltman & Coulter, 1995), brand concept maps

(BCMs) by John et al. (2006), and advanced brand concept maps (advanced BCMs) by Schnittka et al. (2012). These strategic tools help brand managers in a variety of ways, such as to understand *core brand associations* from a consumer's perspective, to use as a diagnostic tool to look for early signals of any negative associations, to understand unique associations that are not shared with competitors, to check whether brand extension products reflect the original brand's associations, and to check whether a firm's intended brand associations match those perceived by consumers. The above-mentioned tools and methodologies used to elicit brand association networks can be classified under two categories of techniques based on the way the brand maps are derived (John et al., 2006): Analytical techniques using network analysis (Henderson et al., 1998) and Consumer mapping techniques (advanced BCM (Schnittka et al., 2012) and Zaltman's metaphors elicitation technique (Zaltman and Coulter, 1995)).

1.1.1 Analytical mapping technique

In the analytical mapping technique, Henderson et al. focused on the breadth of applicability of existing network representations (of Aaker (1996), Peter and Olson (1993), Kelly (1955)) by focusing on their network properties and applying network methods to see how such mapping tools can aid in the sophistication of the analysis for the brand manager beyond just eye-ball analysis. The authors improved the performance of the existing mapping methods by integrating both intra-network (centrality, cohesion, position) and inter-network analyses (density, equivalence). By developing an aggregate network representation (figure 1) of perceived associations among seven brands of sports cars using pairwise similarities judgments, they mapped an array of ten branding effects such as branded features, driver brands, complements, co-branding, cannibalization, brand parity, from intra-network analysis and brand dilution, brand confusion, counter brands, and segmentation from inter-network analysis (for more details, see (Henderson et al., 1998)). Moreover, this method is less labor-intensive owing to the use of quantitative data compared to the use of lengthy personal interviews in other mapping methods like ZMET. However, knowledge of statistical techniques and network analysis methods is important to use the analytical mapping technique, especially since the latter is mostly unfamiliar in marketing research firms (John et al., 2006).

The primary intention of the analytical mapping technique is not to elicit the core and tertiary brand associations or their strength, favorability, or uniqueness, but instead to demonstrate whether a brand manager should look within a single brand network or compare

between different networks, to investigate the above mentioned ten consumer-perceived branding effects, and to develop strategies accordingly. Moreover, brand associations first need to be uncovered through consumer surveys for the incumbent brand as well for competitors before analytical methods such as network analysis (intra- and inter-network analysis) can be applied to uncover the above-mentioned ten branding effects (Henderson et al., 1998).

Analytical mapping technique: Aggregate sports car network (see Henderson, Iacobucci, & Calder, 1998, p. 323)

(Aggregate sports car network: (N = 10))

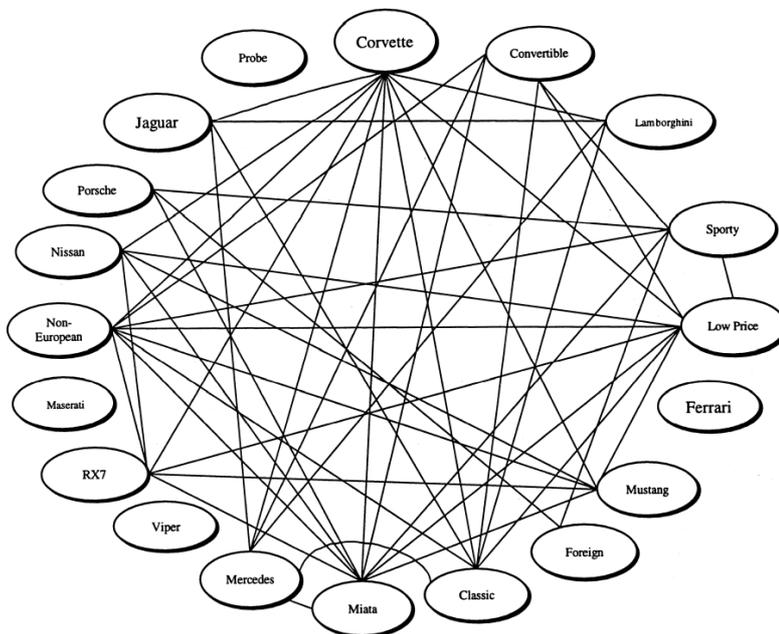


Figure 1. Analytical mapping technique: Aggregate sports car network incorporating pairwise similarities data (Source of Figure 1: Henderson, Iacobucci, & Calder, 1998, p. 323)

1.1.2 Consumer mapping techniques

In consumer mapping techniques, individual brand association networks are elicited directly from consumers whereby respondents reveal how the brand associations relate to the brand, and thereafter researchers can aggregate information to produce a consensus brand association network (John et al., 2006; Schnittka et al., 2012; Zaltman and Coulter, 1995). Schnittka et al. (2012) developed an advanced brand concept mapping approach (advanced BCM) for evaluating the ‘favorability’ dimension of brand association networks using two lab experiments involving Volkswagen Golf (Figure 2) and Adidas brands. Brand associations were

elicited using surveys and in-depth interviews, and after selecting the top 25 associations to create an association set, it is used in the mapping stage by asking respondents to indicate their evaluative judgment and importance of each association to develop an individual map. These individual maps are aggregated based on a set of rules to obtain a consensus map for the brand. Unlike the analytical method, marketers do not require specialized knowledge such as network analysis and other advanced statistical techniques to use this method and are easy to administer. Moreover, the advanced BCM methods help to uncover the favorability of brand associations, unlike BCM (John et al., 2006) and the analytical mapping method (Henderson et al., 1998).

Consensus mapping technique: Advanced-BCM of Volkswagen Golf (see Schnittka, Sattler, & Zenker, 2012, p. 270)

(Advanced-BCM (N = 111))

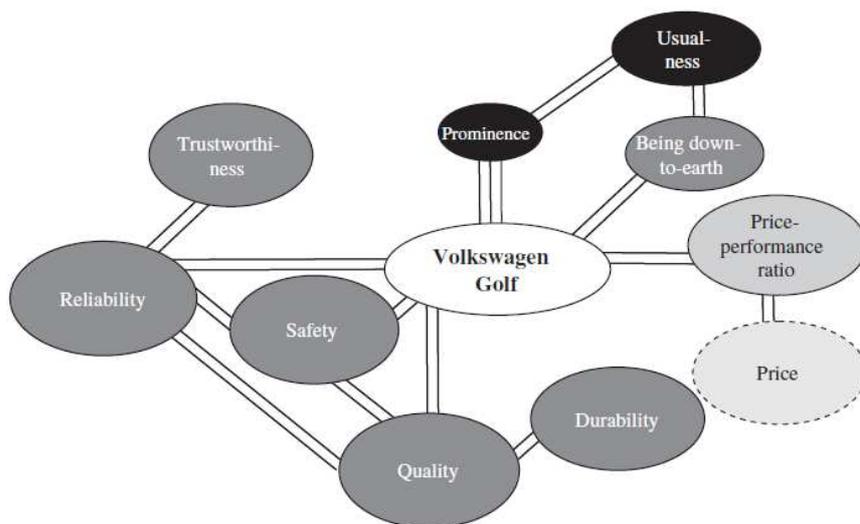


Figure 2. Consumer mapping technique: Advanced-BCM of Volkswagen Golf (Source of Figure 2: Schnittka, Sattler, & Zenker, 2012, p. 270)

Both of the above techniques (consumer mapping techniques and analytical techniques) rely on consumer self-reports for collecting brand association data. For example, consumer mapping techniques use qualitative approaches such as in-depth interviews and focus groups for eliciting brand association maps, while analytical techniques uncover brand association maps using quantitative surveys (attribute rating scales, brand personality inventories) (Henderson et al., 1998; John et al., 2006; Schnittka et al., 2012). Several studies have highlighted reliability and validity problems with self-reports or survey-based data collection methods that most

prominently present themselves through *common method bias*, *social desirability bias*, *selection bias*, *measurement bias* (such as instrumental bias, insensitive measure bias, expectation bias, recall bias, attention bias), *discriminant validity and consistency motifs* (Craighead et al., 2011; Doty & Glick, 1998; Fisher, 1993; Podsakoff et al., 2003; Podsakoff & Organ, 1986; Siemsen et al., 2010).

Moreover, these approaches (consumer mapping techniques and analytical techniques) are quite tedious, especially at the data collection stage, and are cumbersome when there is a need to repeat the process at frequent intervals. Both of these approaches are useful only after brands are launched and cannot elicit brand associations before launch. Moreover, it is very difficult for brand managers to measure brand associations for a newly launched product since brand associations are just beginning to form in consumers' minds, and hence it is difficult to identify at an early stage those few early (potential) consumers who have already developed brand associations from a large population (market). Hence, both consumer mapping techniques and analytical techniques are not useful to elicit brand association networks before the product is launched. Moreover, these techniques are static in nature, i.e., brand associations can be elicited for a specific time point during the brand's lifetime and hence are not useful when brand managers have to regularly monitor brand strength. While the two approaches are useful in eliciting strong and/or favorable brand associations, they **do not help identify unique brand associations** in the context of competitors, i.e., based on actual competitor data¹, which is important to fully understand their competitive advantage (point of difference and point of parity).

1.2 A new methodological and data solution to overcome the above challenges

All the above-identified issues highlight the requirement for a new method that 1) is not tedious or at least less tedious; 2) is easy to repeat at frequent intervals or, as and when needed (i.e., dynamic); 3) can help to elicit brand associations not just after product release but also long before release, and 4) can elicit not only the strength and favorability of brand associations but also their unique brand associations. Any new method that will fulfill these requirements, if it still

¹ Instead, these techniques (BCM and Advanced BCM) provide information on uniqueness of association in terms of the magnitude of brand-specific association in the brand map thereby assuming that additional associations in the brand map increase the probability that associations are unique in comparison with competitors (Schnittka et al., 2012)

relies on researcher or marketer-assisted self-reported data such as interviews, online surveys, focus groups, etc., will still not be able to overcome the biases associated with self-reports that were identified in the earlier paragraphs. Hence, 5) a new method that is independent or non-reliant on self-reports is needed. This highlights the need for a new type of data required for the new method that includes: 1) a readily available source of data that is free of bias, and it should not be difficult to collect; 2) data that *can be accessed* at any given point in time during a brand's lifetime starting from the time when the preannouncement of an upcoming new product is made, through its launch and the completion of the lifecycle of that product in the market; 3) data that provides insights into customers' mind in terms of their opinions, attitudes, feelings, preferences, dislikes, etc., toward the brand; 4) readily accessible competitors' brand association data that are required to elicit unique brand associations, and finally; 5) data that are created not based on self-reports, i.e., without researcher's intervention so that biases can be minimized.

A solution that meets the above-mentioned data-related requirements is user-generated data (UGD) or user comments, which are created by consumers when they participate in discussions in technology-enabled online communities. While UGC itself is a self-report, it is created **voluntarily** by the users *without any researcher or marketer influence or interference*, and UGC exists irrespective of whether this data is used for marketing purposes or not. This voluntariness of UGC makes it **unique and different** from the *involuntary or marketer/researcher-induced self-reports* which are often subjected to interviewer bias, measurement bias, etc. Brand associations are purely subjective, and such associations reside in the mind of consumers and include their opinions, feelings, preferences, attitude, attachments, dislikes, aspirations, etc., all of which are subjective and hence vary from one person to another. Practitioners, when they measure brand associations, are in fact measuring such personal opinions, and these opinions are formed based on the brand advertisements and any other brand information that the potential consumer is exposed to. This brand association information gets contaminated by the presence of various types of biases that are usually inherent in interviewing, surveying, focus groups, measurements, etc. However, in the case of UGC used in the CA-BCM method, there is no requirement for interviewing, surveying, focus groups, etc., and hence their associated biases are absent, which makes UGC less contaminated and therefore, provides a more truthful representation of brand associations held in consumer memory..

Using UGD collected from online communities, this study develops a new method called community-aided brand concept maps (CA-BCMs) for eliciting brand association networks for a new product. This is a new method for the following reasons: 1) unlike previous methods, the CA-BCM can be used not only after product launch but also **long before product launch**; 2) This method is **quick or less tedious**; 3) it can be repeated at frequent intervals (**not cumbersome**), 4) it helps to unravel not only the strength and favorability of brand associations but also the **uniqueness of brand associations**; and finally 5) this method **does not rely on self-reports** but instead uses UGD, which is less problematic or less biased than self-reports. The details about how to use or implement this new method are explained in detail in the methodological introduction in *Section 2*, which is followed by a demonstration with an example in *Section 2.1*.

Online brand communities *bring together people with shared interests and passion for a specific product* (e.g., iPhone, Harry Porter, Porsche, etc.), *even though they may be geographically distributed* across different cities or even countries (Füller et al., 2008; Jang et al., 2008). According to Armstrong and Hagel III (1996), people join online communities to fulfill their needs, such as the need for information, transactions, relationships, and fantasies. Every time a consumer posts a message online, a digital footprint is left behind, providing information such as the date and time when the message is posted. Consumers participate in online discussions at different points in time, leaving a continuous and dynamic supply of user-generated data.

1.3 Online user comment data for predicting movie success

User comments are often conceptualized as online word of mouth (e-WOM). Several studies in the past have investigated the role of e-WOM (i.e., the volume of e-WOM and/or valence of e-WOM) on sales, and this is more common in the motion picture industry, where the role of e-WOM in predicting box office sales is investigated (Chintagunta et al., 2010; Divakaran & Nørskov, 2016; Duan et al., 2008; Karniouchina, 2011b; Lipizzi et al., 2016; Moon et al., 2010). For example, Lipizzi et al. (2016) used Twitter conversations to show that conversational analysis could significantly explain opening weekend box office sales. Another study by Karniouchina (2011b) demonstrated that starbuzz has a positive impact on movie revenues. Wang et al. (2010) conceptualized user comments as word-of-mouth, which influences movie market performance by positively affecting imitation and innovation. This study, however, did not

examine the qualitative aspect of user comments (valence). Moon and his coauthors (2010) found that negative reviews hurt movie performance more than positive reviews help movie performance, thereby providing evidence for negative bias. In their study, they used summary ratings, and they did not analyze the content of the textual reviews. A study by Duan et al. (2008) showed that a movie's box office and WOM valence significantly influence WOM volume, which in turn leads to higher box office sales. In their study, user reviews were conceptualized as word-of-mouth, but the valence was calculated at a daily and cumulative level instead of at each individual user review level. Liu (2006) found that only WOM volume but not WOM valence correlated with box office sales. In their study, the valence of word-of-mouth depends on the overall positivity or negativity of each user comment.

In many of the above studies, e-WOM valence is conceptualized by a superficial or broad classification of whether a user comment is positive, negative, or neutral but not based on a more in-depth qualitative analysis of each user comment (Basuroy et al., 2003; Duan et al., 2008; Eliashberg & Shugan, 1997; Liu, 2006; Moon et al., 2010), and their measure of user comment valence did not have any direct effect on box office sales. However, in the current study, by considering the brand associations from each user comment, the valence of each user comment is shown to have a significant correlation with box office sales (details in Table 2). Thus, by analyzing user comment valence from a branding perspective, the current study makes an important contribution by providing external validity to user comments' valence.

As consumers' participation in online discussions is voluntary, the number of participants in discussions for any product or movie gives a good measure of awareness level for that product (Liu, 2006). Comparing the number of participants in online discussions for different upcoming new product brands indicates their respective awareness levels. Using information such as brand awareness and the strength, favorability, and uniqueness of brand associations (elicited using the CA-BCM technique), customer brand equity is measured in the current study (discussed in Section 3.1). Pearson correlation is used to provide external validity to the CA-BCM technique, which shows a significant and positive relationship between customer brand equity and market performance (discussed in Section 3.2).

2. Methodological Introduction: Community-aided brand concept map - A new method for eliciting brand association networks

As brand associations include anything that is deep-rooted in consumers' minds, there are several factors that contribute to the development of brand associations, such as advertisements, product quality, product category, word of mouth, celebrity association, etc. (Koll & von Wallpach, 2014). Brand associations are the brand image that resides in a consumer's mind, which includes their personal opinion, feelings, preferences, attitude, attachment, etc. Such brand associations reflect the rational values (i.e., based on product attributes) and/or emotional values of the brand. The number of different types of brand associations (diversity), their frequency, favorability (positive or negative), uniqueness, etc., are important factors that determine and differentiate a strong brand from a weak brand. Brand associations are very subjective in nature, and online communities provide a platform to understand these personal brand associations.

In the new elicitation technique called the *community-aided brand concept map* (CA-BCM) proposed in the current study, the focus is on online communities and the brand-related user comments generated in such online communities for eliciting brand association networks. Using this CA-BCM technique, one can infer not only the core brand associations but also the secondary (or second-order) and tertiary (or third-order) brand associations. In addition, the brand association network elicited by this new technique helps to identify the three brand association characteristics, such as strength, favorability, and uniqueness of brand associations. For the purpose of explaining this new methodology, a movie-based online community is chosen. Thereafter, user comments are downloaded for any brand of interest (e.g., the movie brand *The Princess and the Frog*) from the chosen community for which the brand association network needs to be elicited. The number of user comments generated varies from one brand to another (or movie to another) depending on whether it is a well-known brand (a strong brand) or not. The user comments for the chosen brand are then coded using NVivo software, and the coding process is guided by the branding theories and literature. It is important to note *that each user comment may be composed of one or (mostly) several brand associations*, and the current study considers all the associations that are present in each user comment and are coded using NVivo.

A content analysis framework was developed to code the collected data related to each movie from the online community. To code the collected data, category systems were developed both inductively (which shows the exploratory nature of the study) and deductively (based on

existing theories and insights from branding literature, e.g., to categorize the strength, favorability, and uniqueness of brand associations). The deductive section was constructed prior to the data collection, and the following theories and models, such as the associative network memory model (Anderson, 1983; John et al., 2006; Keller, 2013; Srull, 1989), customer brand equity (Keller, 1993) and brand concept map (John et al., 2006), served as a basis for the deductive component of *customer brand equity characteristics such as brand awareness and brand associations (strength, favorability, and uniqueness)*. According to Keller (2013), the associative network memory model developed by psychologists provides an insightful way to represent how brand knowledge exists in consumer memory. This model views memory as a network of nodes and connecting links in which nodes represent stored information or concepts, and links represent the strength of association between the nodes and that any type of information, whether it is verbal, abstract, or contextual, can be stored in the memory network (Anderson, 1983; John et al., 2006; Keller, 2013; Srull, 1989). Using the associative network memory model, brand knowledge can be thought of as consisting of a brand node in memory with a variety of associations attached to it, which is defined as a brand concept map earlier in this paper (i.e., the graphical representation of brand memory). Finally, the brand concept map (John et al., 2006) provided the basis for understanding the constituents of a brand map from a brand equity perspective.

Using the above approach during the coding process, and based on brand-related knowledge and based on the insights found in each user comment, they are classified into different types, such as positive comments, negative comments, and others (mixed, neutral, or irrelevant). In branding and particularly in measuring brand equity, brand image or brand associations is what determines whether the brand equity is strong or weak for a product (Christodoulides et al., 2006; Keller, 1993; King & Grace, 2010). Such brand associations have to be strong, favorable (i.e., positive), and unique in order to create strong brand equity (Keller, 1993, 2013, 2020). Unfavorable (i.e., negative) brand associations lead to weak brand equity. In other words, it is important to classify brand associations into positive or negative. User comments which are neither positive nor negative do not contain any positive or negative associations, and in most cases, these comments are irrelevant and unfocused and hence not useful in eliciting brand associations. Moreover, user comments for a total of 43 movies were collected and coded not only for their positive and negative comments but also for the other

categories (i.e., neutral, mixed, or irrelevant). The findings further confirm that these other category comments hardly contain any brand associations in them and are not found to be useful. Simultaneously, for each user comment, any information such as their personal opinion, feelings, preferences, attitude, and attachment that reflects the image (rational or emotional values) of the brand are coded, and these are the brand associations. Thus, the current study takes a more in-depth look into the valence of each user comment.

Once all plausible brand associations are identified through coding using NVivo software, the next step is to categorize these coded brand associations into strong or weak, favorable or unfavorable, and unique brand associations. Some of these associations are grouped under a larger construct to form the **core brand associations** (first-order brand associations). Any other associations that are attached directly to the core brand associations are classified as **secondary brand associations**, and similarly, **tertiary brand associations** are associations that are attached to the secondary associations. NVivo helps to display the ‘diversity’ (or the variety of brand associations), and according to Keller (2013), the **strength of brand associations** is determined by the diversity of brand associations. When the number of brand associations (diversity) increases, the memory structure for that brand becomes richer but also more complex. Increasing the number of associations makes it easier to access a particular brand node from memory since these associations offer multiple pathways to the same brand node (Krishnan, 1996). If a brand has a wide variety of brand associations, it is said to have *strong brand associations*, and conversely, if the diversity of brand associations is small or fewer, then the movie is said to have *weak brand associations*. To summarize, consumers develop several opinions (wide variety or range of associations) toward certain brands (e.g., an Apple iPhone or MTV brand has a wide variety of brand associations), whereas there are also some brands for which consumers have fewer associations (e.g., less familiar brands, smaller brands, unsuccessful brands, local brands or newly launched brands). In other words, consumers have a wide variety or range of brand associations toward stronger brands, whereas consumers have less variety of brand associations toward weaker brands.

The NVivo software also displays the number of times (i.e., frequency) each of these diverse brand associations is coded. Moreover, frequently cited brand associations are classified into either *positive or negative* brand associations. From this information, the valence of associations is identified by their aggregate favorability (i.e., the number of positive minus

negative brand associations), which gives the overall **favorability of brand associations** for a product. If the number of positive associations is greater than the number of negative associations for the brand, then the brand is found to have an overall *favorable brand association*. Conversely, if the number of positive associations is less than the number of negative associations, then this brand is said to have an overall *unfavorable brand association*. In addition to the strength and favorability of brand associations, **unique brand associations** are important, as they contribute to the brand's image in a product category and are reflective of the brand's positioning in the consumer's mind (Keller, 1993; Krishnan, 1996). The uniqueness of brand association is identified by comparing the brand associations of this brand with its main competitors, and usually, such uniqueness is based on the value proposition or USP. Based on such a comparison, the *shared* brand associations (i.e., point of parity) and those who are not shared (i.e., point of difference) can be identified.

2.1 Applying the CA-BCM technique for eliciting a brand association network

2.1.1 Data collection and source

To demonstrate the proposed new technique called community-aided brand concept map (CA-BCM), a movie brand is chosen, and its brand association network is elicited using this technique. There is a strong precedent for treating a movie as a brand (Hennig-Thurau et al., 2009; Joshi & Mao, 2012; Karniouchina, 2011a; Sood & Dréze, 2006). Movies typically involve considerable investment in creating an identity for a movie, which is often extended through sequels and merchandising activities. Several movie-based online communities exist, where members post their opinions about specific movies that reflect their perceptions, attitudes, preferences, expectations, intentions, dislikes, etc. (Decker & Trusov, 2010; Duan et al., 2008; Finn et al., 2009; Liu & Lopez, 2014; McKinney et al., 2002; Punj, 2013; Risselada et al., 2015; Schreier et al., 2007). Online discussions related to upcoming and currently released movies create a time-series and cross-sectional archive of user-generated data that is easily accessible and publicly available (Dhar & Chang, 2009; Jensen et al., 2014; Khim-Yong et al., 2013; Smith et al., 2012). Prior studies have shown that in the movie sector, the behavior demonstrated in an online community is a good representation of market behavior (Divakaran, 2012); hence, the current paper argues that the CA-BCM elicited in this study is a good representation of the mass market. This argument finds support in the current study, which is presented later in this paper.

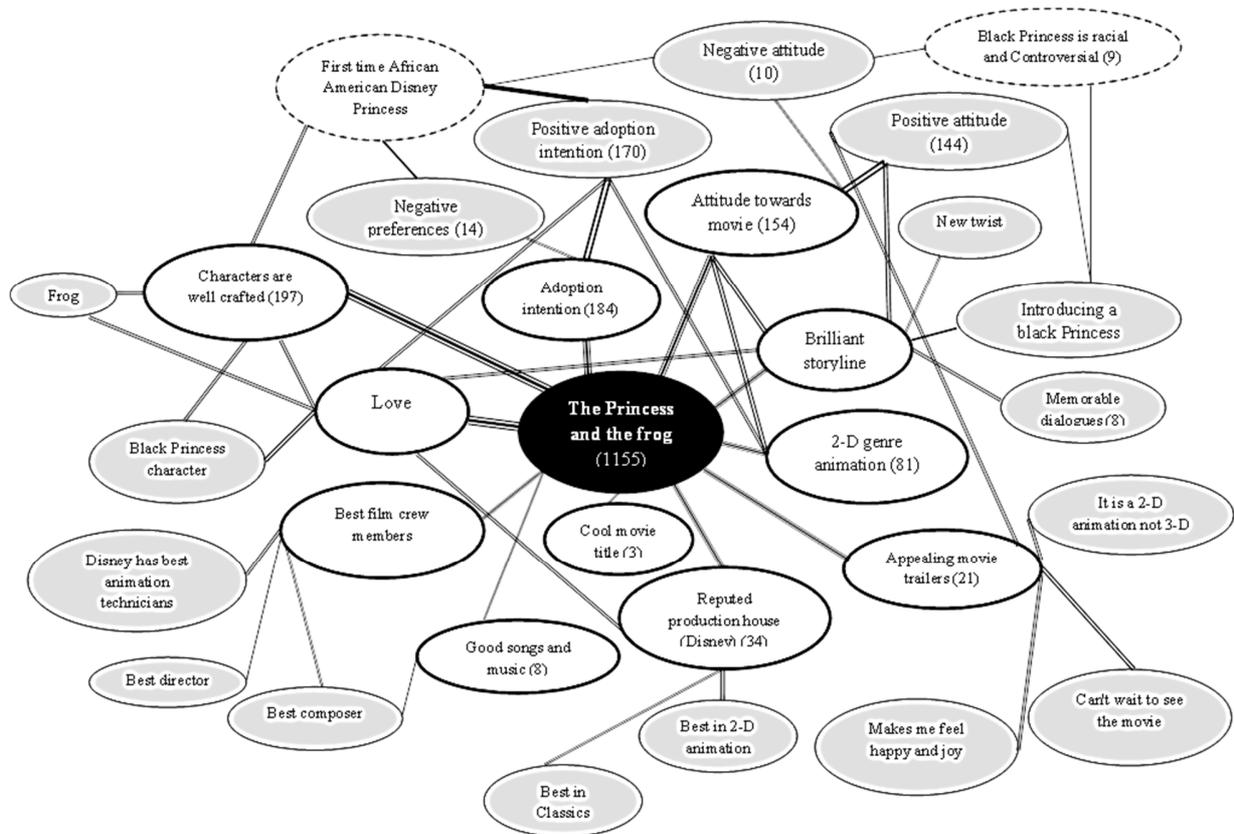
In this study, data were collected from only one movie-based online community. However, there are several movie-based online communities available on the internet. This study proposes to select one community with 1) the highest number of participants (registered members) to ensure that the community represents all types of moviegoers (different age groups, all genders, preferences for different genres, etc.) so that the findings represent the mass market; and 2) where there are active online discussions going on both before and after a movie's release. Usually, online discussions in a movie-based community start as soon as the preannouncement of an upcoming movie is made. Analyzing these discussions sheds light on their evolving associations with the upcoming movie.

User-generated data for the movie "The Princess and the Frog" are collected from a movie-based online community called Clevver movies². As soon as the Walt Disney Pictures (a production studio) preannounced the upcoming movie "The Princess and the Frog," it created a lot of excitement among community members of www.clevver.com, who then started participating in online discussions not only during the movie's prerelease period but also throughout its theatrical run. Such online discussions leave behind a trail of user-generated data (UGD), which is collected and then analyzed using analytical coding software such as NVivo to identify consumers' brand associations. *Each user comment is composed of one or several brand associations that are identified during the coding process and coded accordingly.* Thus, this coding process investigates each user's comments qualitatively and more in-depth for their valence by identifying one or several brand associations from each user's comments, and this process is guided by the branding literature. The current study differentiates itself from prior studies that focused on the valence of user comments in which they conceptualized only superficially by categorizing each user comment into either positive or negative but not going in-depth to understand their qualitative meanings.

Figure 3 below represents the brand association network for the movie "The Princess and the Frog" (premiered on 25 November 2009) created using this new CA-BCM technique, which is explained in Section 2.

² Source: <http://www.clevver.com/> and <https://www.youtube.com/user/ClevverMovies>

Figure 3: Community-aided brand concept map for the movie ‘The Princess and the Frog.’



Notes: In Figure 3, the numbers within brackets inside some of the circles indicate the number of times (frequency) the brand association was coded, and the number 1155 for the central brand node indicates the number of members who posted comments before release for this movie, which is a measure of awareness level. The circles with thick boundaries indicate core brand associations, the secondary brand associations (i.e., associations that are attached to the core brand associations) are displayed in circles that are shaded and that have thin boundary lines, and the tertiary brand associations (i.e., associations that are attached to the secondary associations) are highlighted by circles with dotted boundaries. The single, double, and triple lines linking the different circles represent weak, moderate, and strong links with the central brand node.

Source of Figure 3: Author’s own elaboration

After coding for all brand associations from each and every user comment for the movie “The Princess and the Frog,” some of these associations are grouped under a larger construct to form the core brand associations (“first-order brand associations”). In Figure 3, the *core brand associations* are depicted by circles with thick boundaries, examples being ‘brilliant storyline,’ ‘reputed production house,’ ‘best crew members,’ ‘attitude toward the movie,’ etc. Based on the CA-BCM technique, the movie “The Princess and the Frog” has very *strong brand associations* since a wide variety of associations (i.e., diversity is high) are identified for this movie.

Moreover, the movie “The Princess and the Frog” is found to have an overall *favorable brand association* since the number of positive associations is greater than the number of negative associations (Figure 3). In addition to the strength and favorability of brand associations, the uniqueness of brand association for “The Princess and the Frog” is identified by comparing the brand associations of this movie with other movies (competitors) that were scheduled to release on the same date (in this case, “Old Dogs,” “The Road,” and “Ninja Assassin”). Based on such a comparison, the *shared* brand associations (i.e., point of parity) are: ‘best film crew members’; ‘good trailers’; ‘brilliant story’; ‘positive adoption intention’; etc., while the *unique brand associations* of “The Princess and the Frog” which are not shared (i.e., points of difference) with other movies are: ‘first-time African American Disney Princess’; ‘black princess character’; ‘Disney has the best animation technicians’; ‘good songs and music’; etc. Moreover, according to Keller (2013), brand associations have either a *rational source* (based on product attributes) and/or an *emotional source* (based on brand benefits or the personal value and meanings and reflecting consumers' emotions toward the brand). This is evident in Figure 3, where for example, *rational brand associations* are: ‘best film crew members’; ‘Best Director’; ‘brilliant storyline’; ‘Reputed production house’; ‘Best in 2D animation,’ etc., and *emotional brand associations* are: ‘characters are well crafted’; ‘cool movie title’; ‘makes me happy and joy’; ‘love;’ etc. Consumers form beliefs about brand attributes (rational associations) which are the descriptive characteristics of a product or service, and such attributes evoke rational judgments from customers. Consumers also form beliefs about brand benefits (associations) that include the personal value and meaning they attach to a brand. Marketing campaigns that focus on the brand attributes (rational route), brand benefits (emotional route), or both (rational and emotional), accordingly help create rational or emotional or both brand associations in consumers’ minds. The result is that consumers form rational brand associations or emotional brand associations, or both, and this should be reflected when eliciting their brand concept maps. Applying elaboration likelihood model theory (Cacioppo & Petty, 1984; Petty et al., 1983; Petty & Cacioppo, 1984; Petty & Cacioppo, 1990; Petty & John, 1984), when brand attributes are presented, consumers are more likely to use the central route of information processing which requires high elaboration (higher motivation and ability required). Whereas a marketing campaign focuses on brand benefits, consumers are more likely to use the peripheral route of information processing which requires low elaboration (low motivation and ability required).

As consumers' participation in online discussions is voluntary, the number of participants in discussions for any product or movie gives a good measure of **awareness level** for that product (Liu, 2006). Comparing the number of participants in online discussions for different upcoming new products indicates relative awareness levels. According to the associative network memory model, the **central node** of brand association network is the brand node, and the **brand awareness** is related to the strength of this brand node or trace in memory (Keller, 2013). The strength of this central node determines how many brand association nodes can be attached to this central node. If the awareness level of a brand is too small (e.g., a newly launched brand or an old dying brand), then the number and variety of brand associations attached to it are very small. Hence, it is critical to discuss the brand maps in the context of this central brand node to get the full picture of the brand association map held in consumer memory. For the movie "The Princess and the Frog," 1155 consumers participated in online discussions before its release, and around the same time, its competitor movies "Old Dogs," "Ninja Assassin," and "The Road," attracted only 189, 625, and 407 participants, respectively. From these data, it is clear that the awareness level for the movie "The Princess and the Frog" was the highest compared with its competitors.

Thus, to summarize, the CA-BCM technique is used to elicit the brand association network for the movie "The Princess and the Frog," and from this network, one can infer not only the core brand associations but also the secondary (or second-order) and tertiary (or third-order) brand associations. In addition, the brand association network helped to identify the three brand association characteristics of strength, favorability, and uniqueness of brand associations, which are found to be *strong, favorable, and unique* for "The Princess and the Frog."

3. External Validity to CA-BCM method

If the findings based on the CA-BCM method are true, that is, if the brand associations are *strong, favorable, and unique* for "The Princess and the Frog," then one would expect that the market performance of this movie should be good, and better than that of its competitors. To validate this, both the box office revenues and the average rating given by those moviegoers who have seen these movies were analyzed. Thus, in the case of the movie "The Princess and the Frog," its gross box office revenue is *97,690,000 USD*, which is much higher than that of its competitors such as "Old Dogs" (48,157,000 USD), "The Road" (7,659,000 USD), and "Ninja

Assassin” (37,824,000 USD)³. Moreover, the average rating of the movie “The Princess and the Frog” was **4.25** on a scale of 5 stars⁴, higher than the three competitor movies as “Old Dogs” (3.69), “The Road” (3.34), and “Ninja Assassin” (3.61). This external validity provided by the box office revenues and average rating provides support for the initial assumption made in this paper that the brand association network elicited using online community data represents the overall market.

The CA-BCM methodology was further validated by two studies. In the first study (i.e., Study 2A or Section 3.1), **customer brand equity** is measured using the strength, favorability, and uniqueness of brand associations identified using the CA-BCM method and the brand awareness level for each movie. In the second study (i.e., Study 2B or Section 3.2), Pearson correlation is used to provide external validity to the CA-BCM technique by testing the relationship between customer brand equity and market performance (box office sales).

3.1 Measuring customer brand equity by first applying CA-BCM (Study 2A)

Customer brand equity is defined as the differential effect that brand knowledge has on consumer response to the marketing of the brand Keller (1993). Accordingly, a brand has positive customer brand equity when consumers react more favorably to a product and the way it is marketed when the brand is identified than when it is not. According to Keller (2013), customer brand equity occurs when the consumer has a high level of awareness and familiarity with the brand and holds some strong, favorable, and unique brand associations in memory.

3.1.1 Data Collection

The data collection for this study is from a movie-based online community called ComingSoon⁵, and user comments for different movies are collected (see Table 1a for the list of movies). All the movies (N=43) that are used in the study are released in the same year in the US but represent different movie genres (fantasy, adventure comedy, suspense/thriller, supernatural horror, drama, and action) and different MPAA ratings (G, PG-13, R). This diversity ensures that the user comments represent people with different preferences, which will enable us to investigate different types of brand associations that are generated for different movie brands.

³ Source: www.the-numbers.com

⁴ Source: www.fandango.com

⁵ ComingSoon.net is a property of CraveOnline Media, LLC. and CraveOnline is the source for all of the entertainment needs that young men have. Represented by some of the leading sites in film, gaming, sports and video, CraveOnline is the premier destination for in depth news, interviews and reviews. CraveOnline feeds the appetites of nearly 26 million unique visitors every month with information from the voices that matter to young men. (Source: www.ComingSoon.net and www.craveonline.com/about).

However, the method presented in this study should be suited for any type of movie, and the above criteria used for choosing movies are necessary only to ensure that the data can help to discover different types of brand associations. The following data were collected *for each movie*: 1) the number of members who participated in the online discussions (as a proxy for the community's *awareness level* for each movie), and 2) the number of comments or postings for each movie. Data related to movies' *market performance in terms of box office revenues* were also collected for the US domestic market from publicly available sources (e.g., variety.com and ERCboxoffice.com). Overall, there are no self-reports used in this study, and hence, all major sources of bias are circumvented or at least lessened by using user-generated data in this study.

3.1.2 Data analysis

Once the user comments are downloaded for each of the selected movies identified in Table 1a, the CA-BCM technique is then applied to elicit the different types of brand associations to determine their strength, favorability, and uniqueness by following the various steps illustrated in the previous section (i.e., in Section 2). For each of these movies, the number of members who participated in the online discussion was taken as a measure of the relative awareness level of each movie in the online community. Data analysis was performed using the software solution QSR NVIVO 10, in which data were imported, structured, coded, and linked. Statistical software IBM SPSS statistics 27 is used to analyze the relationship between customer brand equity and box office sales by performing Pearson's correlational analysis (Table 2).

3.1.3 Findings and Discussion

The findings from the content analysis are presented in Table 1. Brand knowledge has two components: Brand awareness and brand associations (Keller, 2013). Hence, **higher-order constructs** were created, such as (*brand*) *awareness level* (Column no. II in Table 1), *strength* of brand association (Column no. III), *favorability* (Column no. IV), and *uniqueness* of brand association (Column no. V) (Böger et al., 2017; Koll & von Wallpach, 2014; Michel & Donthu, 2014; Romaniuk & Gaillard, 2007). Column no. II in Table 1 (i.e., the total number of posts) shows the number of comments posted for each of the movies that are focused on in this study. It is interesting to note that the number of user comments or posts received for each movie is different for different movies within the online community. This difference might indicate something regarding the popularity or awareness level of each movie (Kim et al., 2013; Liu, 2006; Woodside & Wilson, 1985), and this question is answered by comparing this difference

with the actual market performance (box office sales) of each movie (which is shown in Section 3.3). Column no. III in Table 2 shows the strength of the association for each movie, and the strength is measured in terms of the diversity or the different types of brand associations. Moreover, strong brand associations can be either positive or negative; therefore, both positively and negatively strong brand associations are presented in two sub columns under column no. III. The diversity of ‘positive’ associations was found to be greater than the diversity of ‘negative’ associations, suggesting that at the community level, all the movies have overall strong positive brand associations, except M8 (“The Tourist”), which has *strong but negative* brand associations. Similarly, column no. IV in Table 1 shows the favorability of brand associations for each movie (measured in terms of ‘volume’ of positive and negative brand associations), and the *volume* of positive associations was found to be greater than the *volume* of negative associations for all movies except M8. This suggests that at the community level, except M8 (“The Tourist”), which has negatively *favorable or unfavorable* brand associations, all the other movies have overall positively *favorable* brand associations. Finally, the *uniqueness* of brand associations is listed in column no. V in Table 1, and only movies M5 and M7 have an overwhelmingly greater number of unique but negative brand associations than unique and positive associations.

A comparison of all the above-mentioned constructs related to brand equity reveals that one cannot use each of these constructs in isolation (for example, to make marketing decisions), as different movies score differently for each of the above-mentioned constructs. Hence, a second **higher-order construct** (called *customer brand equity*), which takes into account all of the above-mentioned constructs, might be a better indicator of each movie’s market performance represented by its gross box office sales (Romaniuk & Gaillard, 2007) (discussed in the next Section 3.2).

Table 1. Output from Quantitative Content Analysis

I. Movie ID	III. STRENGTH		IV. FAVORABILITY		V. UNIQUENESS*		VI. No. of Positive Comments*	VII. No. of Negative Comments	VIII. Comments which are NOT positive/negative (i.e., comments which are mixed/neutral/irrelevant)	
	II. Total no. of posts (Awareness-level)	Diversity of Positive associations	Diversity of Negative associations	Volume of Positive associations	Volume of Negative associations	Diversity of Unique associations				Volume of Unique associations
M1	201	18	8	213	13	1	2	125	10	66
M2	52	14	2	45	3	2	2	23	3	26
M3	24	4	2	5	3	1	2	7	6	11
M4	32	6	3	15	14	1	1	11	13	8
M5	17	4	1	12	1	2	5	7	5	5
M6	35	4	1	8	1	1	1	10	1	24
M7	12	5	0	11	0	4	15	7	0	5
M8	42	7	12	31	44	2	2	24	3	15
M9	31	7	3	30	3	2	4	15	3	13
M10	1	2	0	2	0	0	0	1	0	0
M11	26	7	1	21	3	1	2	12	3	11
M12	21	7	2	20	3	1	2	12	3	6
M13	25	7	1	23	1	1	3	14	1	10
M14	34	14	0	45	0	2	7	19	0	15
M15	43	6	4	15	44	1	2	7	19	17
M16	16	9	3	17	5	2	3	8	3	5
M17	5	3	0	7	0	0	0	5	0	0
M18	41	7	3	16	23	1	2	8	19	14
M19	46	10	4	72	11	4	7	28	5	13
M20	47	12	4	104	7	5	6	29	3	15
M21	20	8	2	24	8	2	3	10	7	3
M22	26	13	0	61	0	3	8	22	0	4
M23	81	20	9	221	20	7	14	56	5	20

M24	10	7	1	7	1	1	1	3	1	6
M25	127	10	6	137	51	6	12	51	28	48
M26	9	6	1	10	3	1	1	3	3	3
M27	36	12	1	60	1	4	7	24	1	11
M28	38	9	5	20	18	2	3	11	12	15
M29	8	1	1	4	1	0	0	4	1	3
M30	38	5	1	40	1	3	5	19	1	18
M31	17	6	2	18	4	1	2	8	3	6
M32	9	2	1	5	1	1	2	4	1	4
M33	3	2	0	2	0	0	0	2	0	1
M34	89	13	7	128	49	6	9	33	19	37
M35	131	11	6	200	54	8	12	64	24	43
M36	25	6	0	18	0	1	2	7	7	11
M37	46	10	5	107	12	6	11	33	8	5
M38	2	2	0	3	0	0	0	2	0	0
M39	21	1	2	2	12	0	0	2	9	10
M40	9	1	1	1	2	0	0	1	2	6
M41	35	9	2	46	2	4	9	21	1	13
M42	205	10	8	62	136	3	9	32	79	94
M43	5	4	0	7	0	0	0	4	0	1

*In our sample, we did not observe any unique associations which were negative. Only positive unique associations were observed

** Please note that by 'Comments' we mean, the entire posting of a user whereas 'Associations' are subset in a specific comment

Table 1a: List of movies whose data are used in this study*

ID	Movie Name	Release date	Movie genre	MPAA ratings
M1	Toy Story 3	18/06/2010	Adventure Comedy, Children's Fantasy, Family-Oriented Adventure, Fantasy, Children's/Family	G
M2	Inception	16/07/2010	Suspense/Thriller	PG-13
M3	Case 39	10-01-10	Supernatural Horror, Horror	R
M4	Social Network	10-01-10	Drama	PG-13
M5	127 Hours	11-05-10	Adventure Drama, Docudrama, Drama	R
M6	Unstoppable	11-12-10	Action/Adventure	PG-13
M7	Black Swan	12-03-10	Suspense/Thriller	R
M8	The Tourist	12-10-10	Drama, Suspense/Thriller	PG-13
M9	Shutter Island	19-02-2010	Psychological Thriller	R
M10	The Yellow Handkerchief	26-02-2010	Drama	PG-13
M11	The Crazies	26-02-2010	Drama, Horror	R
M12	Brooklyn's Finest	05-03-2010	Crime, Drama	R
M13	Remember Me	12-03-2010	Drama, Romance	PG-13
M14	She's Out of My League	12-03-2010	Comedy, Romance	R
M15	Our Family Wedding	12-03-2010	Comedy	PG-13
M16	Green Zone	12-03-2010	Thriller	R
M17	Hubble 3D	19-03-2010	Adventure, Documentary	G
M18	Repo Men	19-03-2010	Action, Thriller	R
M19	Diary of a Wimpy Kid	19-03-2010	Comedy, Family Action, Adventure, Animation,	PG
M20	How to Train Your Dragon	26-03-2010	Fantasy	PG
M21	Hot Tub Time Machine	26-03-2010	Comedy	R
M22	The Last Song Tyler Perry's Why Did I Get	31-03-2010	Drama	PG
M23	Married Too?	02-04-2010	Comedy, Drama	PG-13
M24	The Warlords	02-04-2010	Action, Drama, War	R
M25	Clash of the Titans	01-04-2010	Action, Fantasy	PG-13
M26	Letters to God	09-04-2010	Drama	PG
M27	Kick-Ass	15-04-2010	Action, Adventure	R
M28	Death at a Funeral	16-04-2010	Comedy	R
M29	Oceans	22-04-2010	Documentary	G
M30	The Back-up Plan	23-04-2010	Comedy, Romance	PG-13
M31	The Losers	23-04-2010	Action, Thriller	PG-13
M32	Furry Vengeance	03-04-2010	Comedy, Family	PG
M33	Babies	07-05-2010	Documentary	PG
M34	Robin Hood	14-05-2010	Action, Adventure	PG-13

M35	Shrek Forever After	21-05-2010	Animation, Comedy, Fantasy	PG
M36	MacGruber	21-05-2010	Action, Comedy	R
M37	Sex and the City 2	27-05-2010	Comedy, Romance	R
M38	Ondine	04-06-2010	Drama, Fantasy	PG-13
M39	Killers	04-06-2010	Action, Comedy	PG-13
M40	Marmaduke	04-06-2010	Comedy, Family	PG
M41	Get Him to the Greek	04-06-2010	Comedy	R
M42	The Karate Kid	11-06-2010	Action	PG
M43	The A-Team	11-06-2010	Action, Adventure	PG-13

3.2 Testing the relationship between customer brand equity and market performance (Study 2B)

Table 2 below provides the result from Pearson's correlation between customer brand equity and market performance. Column 'I' (gross box office sales) and Column 'Opening Week sales' are highlighted in gray to show the main results. The results show that there is a strong positive and significant correlation between brand **awareness** and the opening week as well as gross box office sales, i.e., market performance (see row no. II in Table 2). Such brand awareness is created by the advertising and promotion of movies, including movie trailers prior to the movie release and word of mouth, all of which eventually affect box office sales (Elberse & Anand, 2007; Gopinath et al., 2013; Joshi & Hanssens, 2009; Macdonald & Sharp, 2000; Thompson & Malaviya, 2013; Woodside & Wilson, 1985; Zufryden, 1996).

Similarly, the **strength** of brand association shows a *strong positive and significant* correlation with market performance (see row no. III and IV in Table 2), and this finding is in line with earlier research that shows the relationship between brand strength and market performance (Hennig-Thurau et al., 2009; Lwin & Morrin, 2012; Sood & Dréze, 2006). Moreover, as expected, the *strong and positive brand association* is positive and significant (see row no. III); however, the *strong but negative* brand association, which one would expect to be negative and significant, is also positive and significant (see row no. IV). This is explained by the fact that the diversity of positive associations was far greater than the diversity of negative associations for each movie, as explained in the earlier section, i.e., in almost all the movies, the number of negative associations was far less than the number of positive associations, and at the same time, when the number of negative brand associations was increasing from one movie to another, their respective positive brand associations were also increasing for the same movies.

Hence, the reason why the *strong but negative* brand association is positive and significant. Had the number of movies whose negative associations were higher than positives been equal to or greater than the number of movies whose positive associations were higher than negative associations, then the correlation analysis would have resulted in a strong, negative, and significant relationship with box office sales.

Table 2: Pearson's Correlations*

	Brand Associations	Variables	Opening Week sales (LogN)	I. Gross Box Office sales (LogN)	II	III	IV	V	VI	VII
Market Performance		I. Gross Box Office sales (LogN)	.919**							
		P-value	0.000							
Customer Brand Equity		II. Brand Awareness (LogN)	.750**	.739**						
		P-value	0.000	0.000						
	STRENGTH	III. Positive Brand Associations	.524**	.507**	.721**					
		P-value	0.000	0.001	0.000					
		IV. Negative Brand Associations	.505**	.482**	.698**	.552**				
		P-value	0.001	0.001	0.000	0.000				
	FAVORABILITY	V. Positively favorable (LogN)	.608**	.624**	.828**	.887**	.617**			
		P-value	0.000	0.000	0.000	0.000	0.000			
		VI. Negatively favorable or Unfavorable (LogN)	.524**	.473**	.729**	.409**	.861**	.525**		
		P-value	0.000	0.001	0.000	0.006	0.000	0.000		
UNIQUENESS	VII. No. of Unique and positive	.537**	.540**	.710**	.732**	.581**	.857**	.535**		
	P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000		
	VIII. Volume of Unique and positive (LogN)	.581**	.578**	.820**	.804**	.531**	.906**	.496**	.878**	
	P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	

*. Sample size (N) = 43

**.. Correlation is significant at the 0.01 level (2-tailed).

Similarly, the **favorability** of brand association shows a *strong positive and significant* correlation with market performance (see row nos. V and VI in Table 2). Moreover, as expected, the *positively favorable brand association* is positive and significant (see row no. V); however, the *negatively favorable or unfavorable* brand association, which one would expect to be negative and significant, is instead positive and significant (see row no. VI). This is explained by the fact that the volume of positive associations was far greater than the volume of negative associations for each movie, i.e., in almost all the movies, the number of negative associations was far less than the number of positive associations, and at the same time when the number of negative brand associations was increasing from one movie to another their respective positive brand associations were also increasing for the same movies. Finally, the correlation between the **uniqueness** of brand associations and market performance is strong, positive, and significant.

The above findings suggest that all of the components of customer brand equity (such as brand awareness, the strength of brand association (positive) and favorability of brand associations (positively favorable) and uniqueness of brand associations are *valid measures* of customer brand equity and that these measures can be used as a potential signal or predictor of box office sales. Moreover, this positive relationship between the components of customer brand equity and market performance is in line with prior studies that have highlighted the positive relationship between brand equity and market performance (E.g., Hennig-Thurau et al., 2009; Tolba & Hassan, 2009); therefore, the above results from Table 2 provide external validity to the CA-BCM technique.

4. Conclusion, implications, limitations, and further research

The CA-BCM method developed in this study provides a comprehensive network of the core, secondary, and tertiary brand associations, and the core brand associations are attached directly to the central brand (awareness) node. The overall strength of the brand (i.e., diversity of brand associations) as well the strength of each individual association (based on how many people share them) that are attached to the central node is determined in this study. The overall favorability of the brand (overall favorable or unfavorable) is determined, and CA-BCM also helps to visualize all the favorable and all the unfavorable associations. Moreover, the CA-BCM method also helps to identify the unique brand associations. Lastly, the CA-BCM method helps to identify and differentiate the rational from the emotional brand associations, both of which are

important in the context of creating brand resonance (Keller, 2013). Eliciting rational and or emotional brand associations will help marketing managers to see if their rational or emotional campaigns are working or not and will enable them to take informed corrective measures on specific brand associations.

With the help of CA-BCM technique, the current study measures customer brand equity by operationalizing its components, such as the strength, favorability, and uniqueness of brand associations, as well as brand awareness. Analyzing the relationship between customer brand equity and market performance concluded that there is a strong positive and significant association between the two variables. As the finding of this study is in line with prior studies that link customer brand equity and market performance (Erdem & Swait, 1998; Erdem et al., 2006), this study concludes that customer brand equity measured with online community data is a signal or predictor of future market performance.

4.1 Contribution to research.

The current study makes several contributions to both (1) brand measurement research and (2) brand management research.

4.1.1 Contribution to brand measurement research

First, the need for the use of various data collection methods such as interviews or focus groups or surveys in the *elicitation stages (first stage)* and using that information to elicit the individual brand maps in the *mapping stage (second stage)*, and finally *aggregating* all the individual maps to create the final consensus map of previous methods (ZMET, BCM or advanced BCM methods), are completely overcome (not required) in the new CA-BCM method developed in the current study, thus saving valuable cost, time, resource, and making it easier to administer. Several studies have reported reliability and validity problems that are associated with a marketer or researcher-initiated self-reported data, the most prominent being *common method bias, social desirability bias, selection bias, measurement bias, discriminant validity, and consistency motif*. This study, however, minimized these issues by relying on user-generated data collected from online communities instead of using self-reports. Unlike self-reports, which are used in current BCM elicitation methods, user-generated data are unobtrusive, more elaborate, less time-consuming, and less costly to collect. Issues associated with self-reporting do not rise

with user-generated data because researchers do not intervene or influence the creation of voluntarily contributed online postings. This is because UGC is publicly available and collected, and they are coded using NVIVO. While UGC itself is a self-report, it is created **voluntarily** by the users *without any researcher or marketer influence or interference*, and UGC exists irrespective of whether this data is used for marketing purposes or not. This voluntariness of UGC makes it unique and different from the **involuntary or marketer/researcher-induced** self-reports which are often subjected to interviewer bias, measurement bias, etc.

Second, the sample size used to elicit brand associations in the previous methods are very small and fixed (less than 120), and this may limit eliciting all potential associations; however, in the new CA-BCM method, there is no limit to the sample size, and it varies depending on the awareness level of the brand (in figure 3, the sample size is 1,155). According to the associative network memory model, the central node in the brand association network is the **brand node** itself, and the **brand awareness** is related to the strength of this brand node or trace in memory (Keller, 2013).

Third, the CA-BCM method can also be combined with other methods if necessary. For example, as the data used in this study is derived from social networks, the analytical mapping technique can be integrated with CA-BCM as the analytical mapping technique uses social network analysis and statistical techniques to derive the structure of brand Association through network algorithms (Henderson et al., 1998). Moreover, with the availability of big data, AI-based machine learning techniques can be applied to visualize the brand concept maps in the future. Latent Dirichlet Allocation topic modeling approach may also be used to identify trends and patterns to identify core and periphery brand image or associations. One of the challenges in UGC is when users adopt ironic expressions, which are subjective expressions to communicate an underlying meaning focusing on negative or humorous aspects, which is opposite to the one expressed (Reyes & Rosso, 2012)—in other words, expressing negative feelings using positive comments. In the CA-BCM method, coding of the user comments was done manually, which makes it easier to detect such ironic comments in the context of the ongoing discussions; however, this manual coding is helpful when the volume of UGC is not too large, unlike big data. In the future, with the availability of big data, this manual coding method can be replaced or

supplemented by integrating *automatic ironic processing methods* that are recently identified in the literature (Chia et al., 2021; Farías et al., 2020; Reyes & Rosso, 2012; Zhang et al., 2019).

Fourth, using CA-BCM method a brand map can be generated even before a product is launched in the market and before consumption, due to the dynamic nature of the data being used. Prerelease elicitation of brand association networks is applicable to products and industries where new-product announcements are prevalent, which helps to generate much excitement among potential users or customers who then share their opinions and feelings in online forums as user comments. Such early brand mapping allows brand managers to understand the evolution of brand associations and monitor them from a very early stage. Moreover, CA-BCM can be developed at any point in time before product release or after release. Therefore, CA-BCM can allow brand managers to map brand associations on a periodic basis, allowing them to understand the dynamics of the evolution of brand associations. Brand associations can change with time, and this new CA-BCM method helps to unravel these changes and new associations.

4.1.2 Contribution to brand management research

In addition to contributing to brand measurement literature, the current study makes the following specific contribution to **brand management** research as well as marketing literature. First, previous studies that elicited brand association maps did not explicitly identify the diversity of brand associations (Brandt et al., 2011; Henderson et al., 1998; John et al., 2006; Schnittka et al., 2012), and the current study fills this gap by demonstrating how to determine *the diversity of brand association* using CA-BCM. According to Keller (2013), the strength of brand associations is determined by the diversity of brand associations. When the number of brand associations (diversity) increases, the memory structure for that brand becomes richer but also more complex. Increasing the number of associations makes it easier to access a particular brand node from memory since these associations offer multiple pathways to the same brand node (Krishnan, 1996). If a brand has a wide variety of brand associations, it is said to have strong brand associations, and conversely, if the diversity of brand associations is small or fewer, then the brand is said to have weak brand associations (overall brand strength). After eliciting the core, secondary and tertiary associations, the **intensity** of each of these associations are identified based on the number of times they are cited (as strong associations are those that are shared by a majority of consumers (Keller, 2013)). Thus, the current study also contributes to the brand

equity literature by determining the (1) overall brand strength (at the overall brand level), and (2) the strength of each individual brand association (intensity of the individual brand association).

Second, while prior research eliciting brand association networks focused on core, secondary, and tertiary brand associations, only some of them went beyond identifying the strong from weak associations, and few studies have helped identify favorable associations (Schnittka et al., 2012). The current study fills this gap by both demonstrating and identifying favorable as well as unfavorable brand associations. At the overall brand level – the current study helps to determine whether the brand is perceived favorably or unfavorably (for example, if the number of favorable associations is greater than the number of unfavorable brand associations, then overall the brand is perceived favorably). Without the knowledge of whether the brand is perceived favorably or unfavorably, and without being able to identify the specific negative or unfavorable brand associations, marketing managers cannot take corrective measures when there is a negative image affecting their brands.

Third, eliciting brand associations is one thing, but the main challenges lie in identifying and categorizing these associations into *strong, favorable, and unique* associations. Prior studies that elicited brand concept maps (analytical methods, BCM, and advanced BCM methods) used qualitative interviews and/or survey to elicit the brand associations (Brandt et al., 2011; Henderson et al., 1998; John et al., 2006; Schnittka et al., 2012; Zaltman & Coulter, 1995). However, they have not explicitly demonstrated how to identify or measure *unique brand associations*, which are very critical to a brand's success as they give consumers a compelling reason to buy a brand unless the brand faces no competition (Doyle et al., 2021; Keller, 2013). Only the *analytical technique of Henderson et al. (1998)* took competitor brands into consideration in their brand mapping using consumer associative networks study. The current study fills this gap by demonstrating how to identify the unique brand associations from the brand concept map, and for this purpose, knowledge about competitors' brand associations is important.

Fourth, while no prior research has paid attention to this **duality of a brand** (Kang et al., 2021; Keller, 2009, 2013) while eliciting their brand concept maps, this study complements this area by recognizing the duality of a brand (rational and emotional associations) and explaining how to categorize them using the CA-BCM method. Eliciting rational and emotional brand associations will help marketing managers to see if their rational or emotional campaigns are

working or not, and it will also enable them to take informed corrective measures on specific brand associations. Hence, the current study provides empirical evidence to the emotional route and rational route to build brand loyalty and resonance, thus providing new additional external validity to the duality concept of strong brands (brand resonance model (Gautam & Kumar, 2012; Kakati & Choudhury, 2013; Keller, 2013, 2020)).

Fifth, according to the associative network memory model, the central node of brand association network is the brand node, and the **brand awareness** is related to the strength of this brand node or trace in memory (Keller, 2013). Prior studies that elicited brand maps did not discuss or mention much about this *central brand node*, to which brand associations are attached (Brandt et al., 2011; Henderson et al., 1998; John et al., 2006; Schnittka et al., 2012; Zaltman & Coulter, 1995). The current study addresses this issue and argues that the size of the central node of the brand map elicited using CA-BCM, depends on brand awareness level, and it is measured by the number of people who participated in the online discussions (UGC). If a brand is unknown, very few people will post comments, but if it is a famous brand, then a large number of people are likely to participate and post comments (Liu, 2006). In figure 3, there were 1,155 members (*central brand node size*) who participated in the online discussion for the movie ‘The Princess and the frog’ and around the same time, its competitor movies “Old Dogs,” “Ninja Assassin,” and “The Road,” attracted only 189, 625, and 407 participants, respectively. From this data, it is clear that the awareness level for the movie “The Princess and the Frog” was the highest compared with its competitors. In other words, the current study provides empirical support that the size of central brand node is determined by the brand awareness level (column II in Table 1) when eliciting the brand concept map (Keller, 2013).

Sixth, the current study makes an important contribution to word of mouth (WOM) literature by providing external validity to user comment valence. In prior studies, where user comments or reviews are conceptualized as word of mouth (Chakravarty et al., 2010; Divakaran et al., 2017; Jeong & Koo, 2015; Moon et al., 2010; Purnawirawan et al., 2015), their valence is determined by a superficial or broad classification of whether a user comment is positive, negative or neutral but not based on a more in-depth qualitative analysis of each user comment. Their measure of user comment valence did not have any direct effect on market performance (sales). However, in the current study, by considering the brand associations from each user

comment, the valence of each user comment is shown to have a significant correlation with box office sales (details in Table 2). Thus, by analyzing user comment valence from a branding perspective, the current study makes an important contribution by providing external validity to user comment (WOM) valence.

4.2 Limitations and future research

There are certain limitations in this study. This study has demonstrated the value of CA-BCM within the specific context of the movie industry and generalizing it to other sectors requires additional studies. Additionally, the CA-BCM tool relies on user-generated data, and hence, this method cannot be applied for those products for which little or no user data are available. This study provides only a crude first step method for eliciting brand association networks and has shown how data from online communities can be used as a diagnostic tool. Movies are short lifecycle products whose average run in theaters lasts approximately eight weeks, and hence, the findings of this study might be generalized or limited to such short lifecycle products. Moreover, movies generate a lot of buzz or excitement in online forums and social networks, and this study collected such buzz or user-generated data from online communities to elicit brand association maps. Hence, the findings of this study might be limited to those products that create a lot of buzz or excitement online, and examples of similar products include books (e.g., the Harry Potter series), computer programs (e.g., Windows Vista¹⁰), mobile technology (e.g., the iPhone and iPad), Hollywood movies, DVDs, and gaming. Moreover, eliciting brand association maps before product release requires the generation of such buzz before the product's market release as in the case of movies, and hence the findings of this study might be limited to those industries where new product preannouncement behaviors are noticed, such as in the case of movies, books, smartphones, gaming, etc., and such preannouncements trigger online buzz prior to product market launch. Future studies can repeat the CA-BCM technique using other online communities from other industries, which can help to determine the applicability of this method for durable products across different industries to improve the generalizability.

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