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TACKLING SOCIAL MEDIA DATA ANALYSIS: COMPARING AND CONTRASTING QSR NVIVO AND LEXIMANCER

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ABSTRACT

PURPOSE: This paper offers insights into the ways two computer-aided qualitative data analysis software (CAQDAS) applications (QSR NVivo and Leximancer) can be used to analyse big, text-based data taken from consumer-to-consumer (C2C) social media communication.

DESIGN/ METHODOLOGY/ APPROACH: This study used QSR NVivo and Leximancer, to explore 200 discussion threads containing 1,796 posts from forums on an Online Open Community and an Online Brand Community that involved Online Brand Advocacy. The functionality, in particular, the strengths and weaknesses of both programs are discussed. Examples of the types of analyses each program can undertake and the visual output available are also presented.

FINDINGS: This research found that, while both programs had strengths and weaknesses when working with big, text-based, online data, they complemented each other. Each contributed a different visual and evidence-based perspective; providing a more comprehensive and insightful view of the characteristics unique to online consumer brand advocacy.

RESEARCH IMPLICATIONS: Qualitative market researchers are offered insights into the advantages and disadvantages of using two different software packages for research projects involving big social media data. The 'visual-first' analysis, obtained from both programs can help researchers make sense of such data, particularly in exploratory research.

PRACTICAL IMPLICATIONS: The paper provides practical recommendations for analysts considering which programs to use when exploring big, text-based, online data.

ORIGINALITY/VALUE: This paper answered a call to action for further research and demonstration of analytical programs of big, online data from social media C2C communication and makes strong suggestions about the need to examine such data in a number of ways.

KEYWORDS

Big data, Online Brand Advocacy (OBA), CAQDAS, Leximancer, QSR NVivo, online community, online communication, online branding, qualitative method.

Introduction

Fuelled by a rise in consumer-to-consumer (C2C) online participation, consumer networks are becoming increasingly important to marketers as influencers of consumer behaviour (Chu and Kim, 2011; Adjei *et al.*, 2010; McAlexander *et al.*, 2002; Muniz and O'Guinn, 2001). As a result, marketing researchers are interested in investigating and understanding such online C2C interactions, especially those found in social media. However, these interactions create big text-based data that is characterised by high volume, velocity, and variety, thus presenting analytical challenges (McAfee and Brynjolfsson, 2012). Computer-aided qualitative discourse analysis software (CAQDAS) applications enable semi-automated analysis to be undertaken on such data, providing more visual results than was possible previously. When working with such big datasets, researchers need to decide which approach is most suitable for 'visual text analytics' or 'visual data mining' and which provides better insights into the data's 'patterns of relevance' (Angus *et al.*, 2013; Risch *et al.*, 2008).

The QSR NVivo and Leximancer programs are well-known options for such analysis (Crofts and Bisman, 2010; Hutchison *et al.*, 2010). However, their strengths and weaknesses are not well researched (Jones and Diment, 2010; Sotiriadou *et al.*, 2014). Clearly, there is a need to better understand which programs and approaches can be used to gain greater insight from the 'unstructured data' obtained from data-rich online environments such as social media platforms. Indeed, the Marketing Science Institute (2016) recently suggested determining how to integrate and synthesise insights from big data is a research priority. Here, QSR NVivo's and Leximancer's usefulness in analysing big data is discussed through an examination of their use in an exploratory study investigating Online Brand Advocacy (OBA).

Despite increasing interest in OBA (Leventhal *et al.*, 2014; Parrott *et al.*, 2015, Wallace *et al.*, 2012), which can be defined as the active promotion, support for or defence of a brand by a consumer to other consumers (Jillapalli and Wilcox, 2010; Keller, 2007), its conceptualisation, dimensionality and measurement are unclear. Some have argued OBA is unique and differs

from offline brand advocacy and have pushed for further investigation (Graham and Havlena, 2007), while others have suggested there is a need to improve our understanding of how consumers advocate for brands online (Divol *et al.*, 2012; Urban, 2005).

This manuscript is based on a study designed to provide initial insights into OBA's characteristics by looking at OBA posts in two different online communities. It suggests how QSR NVivo and Leximancer can be used in an exploratory study in which a 'visual-first' analysis is used to assist researchers make visual sense of the data and guide subsequent enquiry (Angus *et al.*, 2013). Both programs were used to explore 200 discussion threads containing 1,796 posts in an Online Open Community (OOC) and in an Online Brand Community (OBC). The strengths and weaknesses of both programs are outlined through their application in this exploratory study. Examples of some of the types of analyses each program can undertake, the visual output available and an insight into how each program contributed to the exploration of a new construct are provided. The paper provides practical recommendations to guide researchers and practitioners. Before discussing the study and the applicability of the programs, the next section briefly outlines the literature that informed the research.

Background

Brand advocacy is seen by some as the extent to which consumers are willing to spend time and effort to actively recommend, and to support a brand because of a connection to the brand (Jillapalli and Wilcox, 2010; Anderson, 1998). Brand advocacy is also defined as social advocacy, by way of a recommendation of a brand to others, the defence of a brand when it is attacked or as the recruitment of potential customers (Bhattacharya and Sen, 2003; Stokburger-Sauer *et al.*, 2012). To date, little attention has been devoted to understanding brand advocacy in different communication platforms, especially online; although a recent study highlighted the need for a further exploration of the message characteristics in posts advocating brands (Parrott *et al.*, 2015).

The online space has created prosuming users or 'prosumers' who are active online, who produce and consume content at the same time, and who are noticeable in online discussion forums (O'Reilly, 2005). Research has shown such discussions influence sales, regardless of whether the community is company-owned or independently-owned (McAlexander *et al.*, 2002; Muniz and O'Guinn, 2001). Porter (2004), for example, differentiated commercial and non-commercial online communities, while Yahia (2005) distinguished between non-commercial brand-based and product-based communities, and those based on brand-related themes or topics. Here, we differentiated between two types of communities, namely:

- Online Brand Communities that are owned, managed and sponsored by a brand; although discussion forum interactions are driven by members. The community's aim is to engage customers with the owner's brand without restricting the discussions, which can be brand or non-brand related, and which focus on topics of common interest.
- Online Open Communities that are independent of any brand affiliation, and which are owned and managed by consumers; although they may be financially supported by advertising revenue. Such online communities bring together consumers with a common product interest, and provide forums for information and support on topics of common interest, including brand-related discussion.

OBA can be found in various online platforms, such as social networking sites (SNS) (e.g. Facebook or Twitter), online opinion platforms (e.g. tripadvisor.com) and discussion forums in online communities (e.g. epicski.com). OBA has been described as viral or connected marketing activities, and is sometimes defined as WOM arising from Facebook 'Likes' and online recommendation to 'friends' (Wallace *et al.*, 2012), customer brand engagement on Facebook (Hausman *et al.*, 2014), 'following' a brand on Twitter (Bulearca and Bulearca, 2010), discussing brands on their blogs (Chu and Kamal, 2008) or online reviews (Karakaya and Barnes, 2010). Online conversations about brands can be proxies for offline conversations

and seem to influence offline and online purchasing decisions (Godes and Mayzlin, 2004; Fagerstrøm and Ghinea, 2011).

Consumers advocate for brands online through brand-related User-Generated Content (UGC) (Smith *et al.*, 2012) that permeates social media channels. Online UGC is different to content found in offline communication (e.g. communicators can be anonymous, as givers and receivers of information may be identified only by usernames) and information can be acted on quickly, is easily accessible for an indefinite period of time and has global reach. OBA is undertaken in a unique setting and, just as eWOM has been differentiated from offline WOM (Chu and Kim, 2011; Hennig-Thurau *et al.*, 2004), OBA deserves to be explored and assessed in its own right. However, which approach (QSR NVivo or Leximancer) is most useful in such an exploration?

The study

Sample

Two hundred active C2C discussion threads (1,796 posts) in two different online communities were examined. One hundred discussion threads (1,060 posts from 437 unique usernames) were from an OOC, while 100 discussion threads (736 posts from 430 unique usernames) were from an OBC. Both communities were Australian-based and designed to provide online support for parents with young children. Data were collected between November 2014 and February 2015. Brand advocacy in the threads included discussions about local and international brands, and ranged from high-involvement products, such as prams and family car brands, to low-involvement products, such as baby formula and hygiene products.

The number of discussion threads (100 discussion threads from each of the two online community forums) was deemed sufficient, as this was the point at which no new insights were being generated. This decision was based on the 'thematic, data saturation' principle that underpins qualitative research (Corbin and Strauss 2007, Green and Thorogood 2004,

Gaskell 2000) and adheres to the general netnographic rule that “*data collection should continue as long as new insights on important topical areas are still being generated*” (Kozinets, 2002, p. 64).

Procedure

The netnography procedure suggested by Kozinets (2010) was undertaken here, with the QSR NVivo and Leximancer programs being used to examine the 1,796 online posts (Jones and Diment, 2010; Sotiriadou *et al.*, 2014). Their combined use enabled an elaborate exploration of the data and showcased how each program contributed towards understanding OBA, as is outlined in subsequent sections.

QSR NVivo

The online discussion threads were imported into QSR NVivo as MS Word documents and classified according to the type of online community from which they originated. In the concept identification stage, distinct events in the data were identified, intensively scrutinised and meaning labels were attached to the identified segments (Hutchison *et al.*, 2010). By creating nodes (codes) and storing relevant text relating to the concept represented by each node, a researcher-driven coding was obtained that provided an understanding of what consumers were saying about brands and, more specifically, how consumers were advocating for brands in online discussions. While time consuming, the researcher-driven coding process enabled the inclusion of researcher’s insight and an interpretation of meanings to occur at the coding stage, rather than at the analysis stage, as was the case with Leximancer.

To obtain an initial impression of the data, a Word Frequency Query was used to identify the most frequently occurring words across all posts. This approach gave a good indication as to which codes should be considered. The Coding Stripes Analysis (Figure 1) helped in the study’s conceptual development by comparing nodes (emergent concepts) and by visually depicting how they related to one another. This enabled a search for intersecting codes to

identify text coded to more than one node; suggesting connections between emerging concepts. For example, the most commonly referenced node and one of specific interest, was 'positive brand mentions', which included all positive mentions of a brand name in the posts. The Coding Stripes Analysis enabled the 'positive brand mentions' node to be depicted alongside nodes with which it most frequently co-occurred; highlighting important OBA characteristics.

A Matrix Coding Query enabled an examination of the data at a community level (i.e. the OBC and OOC datasets), and identified some community-specific OBA characteristics. The resulting Coding Stripes Analysis provided a visual representation of associations and connections between nodes, according to the type of online community. Although the QSR NVivo analysis is influenced and, to some degree, limited by researchers' analytical decisions and epistemological positions, it helped the iterative concept exploration process by suggesting subsequent lines of enquiry.

FIGURE 1 HERE

Leximancer

Leximancer analysis is program-driven, and uses blocks of text to identify concepts and themes that are identified through an iterative process of seeding word definitions from frequencies and co-occurrences (Sotiriadou *et al.*, 2014; Angus *et al.*, 2013). Leximancer does not automatically present a definition for each 'concept'. Words are 'concepts' that form clusters called 'themes'. Concept grouping identifies concepts that have contextual similarity and appear close to each other in a Concept Map, as such related concepts represent a theme.

The most frequently co-occurring concepts are clustered together and grouped by theme circles that represent the main ideas (Cretchley *et al.*, 2010). Leximancer-driven themes are named after the most prominent concept in the cluster (i.e. the concept with the largest dot in

that theme). Here, the theme names were revised so as to better reflect the concepts within them. The size of the themes is not representative of the importance of the themes; rather it is indicative of the concepts' co-occurrence with other concepts. The theme colours represent the importance of each theme, with themes heat-mapped from hottest to coolest (i.e. red is the 'hottest' or most prominent theme and purple is the 'coolest' or least connected theme). The Concept Map further illustrates how the concepts (keywords) are connected by lines between those concepts which share the strongest conceptual similarity. A Two-in-One Analysis was obtained in the Concept Map (Figure 2) in which tags identify common themes in each of the two communities.

The Leximancer-produced Insight Dashboard Report provides a quantitative overview of the Concept Map, and is designed to provide an understanding of project results (Leximancer, 2017). The Dashboard is best used for comparison, or difference analysis, and researchers must create tags as part of this process (e.g. source document, speaker or folder). Here, two separate Insight Dashboard Reports were created:

1. Where there was only the one category for comparing the emergent concepts, namely 'Brand Mention', our key theme; and
2. Where the categories of comparison were our tags for each of the two online communities studied (OBC and OOC).

The first report illustrated how consumers mentioned brands in online posts advocating for a brand, whereas the second report allowed us to determine the way in which consumers advocated for brands in the two online communities. All of the concepts were assessed for their 'prominence' (represented by their respective Prominence Scores) in relation to a 'Brand Mention' and in relation to the two different community types being studied. This report can be used to investigate the concepts or attributes associated with relevant tags or categories in the data (Leximancer, 2017). Further, the report showcases the relative frequencies for concept combinations evident in the Concept Map, and, using Bayesian algebra, calculates a

Prominence Score (PS) for each concept and for each compound concept (pairs of concepts co-occurring together). A score greater than 1.0 suggests the co-occurrence between a concept or compound concept and a category or tag, happens more often than by chance (Leximancer, 2017). Here, such a score was considered sufficient to identify unique OBA characteristics and, for compound concepts, a score of 3 or more was deemed satisfactory.

FIGURE 2 HERE

Key differences highlighted through this analysis were explored further in a One-in-One Analysis for each online community separately, with the results shown in Figure 3 and Figure 4. This approach provided an overview of OBA across both communities and enabled a comparison of OBA in each of the online communities. With a connectivity of 100%, 'Brand Mention' emerged as the key theme linking the other themes in the concept maps. The 'Positive Communication' theme was most closely related (i.e. had the highest connectivity) to the 'Brand Mention' theme in the three concept maps produced, suggesting that, whenever a brand name was mentioned, it was usually mentioned positively. Two compound concepts ('Positive brand mentions' and 'Negative brand mentions') were seeded to explore emerging relationships of interest. This manual seeding process is akin to setting up of two queries ('Brand mention' AND 'Positive communication' as 'Positive brand mention'; and 'Brand mention' AND 'Negative communication' as 'Negative brand mention'), which enabled us to pinpoint instances of positive and negative brand mentions.

FIGURE 3 HERE

FIGURE 4 HERE

Findings

Both programs contributed to our understanding of the OBA concept being explored. Their strengths and weaknesses are outlined in Table 2, and although these are self-explanatory, some deserve further discussion.

TABLE 2 HERE

Some key strengths of QSR NVivo and Leximancer

A key QSR NVivo strength is its ability to allow researchers to assign meaning to the data during the coding stage rather than after lexical analysis, as is the case in Leximancer. This ensured:

1. Key concepts of interest were identified.
2. There was congruity between the researcher-identified nodes (codes) and the data classified to those nodes.
3. Nodes (codes/concepts/themes) were identified that could not have been identified by Leximancer.
4. Meaning was assigned from a human-perspective that required human intellect, and judgement, rather than by an automated, computer-driven perspective.

QSR NVivo, enabled us to recognise “Reactive OBA” and “Proactive OBA” as two different types of OBA. Reactive OBA included all OBA posts that were responses to specific questions or queries about an advocated brand, while proactive OBA included all OBA posts and discussion thread starters that initiated or re-ignited discussion about an advocated brand. The identification of such concepts of interest requires foresight and human intellect at the data coding stage, which is facilitated by QSR NVivo. OBA posts could only be classified as reactive or proactive through a researcher deducing meaning based on the totality of the message (the post’s whole wording) and the post’s position in the overall discussion thread. This process allowed us to see that OBA can be unprompted or prompted, improving our understanding of the nature of OBA.

QSR NVivo also enabled a mapping onto existing theory, as parent and child nodes were created to better reflect categories that were indicative of prior brand advocacy definitions (e.g. recommendation, defence, promotion, positive word of mouth). We then visually represented

how these categories included some aspects of OBA. By assessing the node structure, and through the coding stripes analysis, it was evident new aspects of OBA had emerged (e.g. positivity, knowledge sharing, virtual positive expression). In Leximancer, attempts were also made to manually seed concepts of interest that were automatically mapped onto the Concept Map (e.g. to identify brand defence, a concept was seeded for words inclusive of “‘talk up’ and ‘brand’”, and “‘stand up’ and ‘brand’”). However, due to aspects of linguistics underpinning online communication (i.e. the ways in which consumers advocated for brands online varied and deviated from the standard brand advocacy definitions), this process did not identify existing concepts of interest in the online posts. For example, consumers did not use words such as “I am talking up brand X here”; rather they defended a brand by using various expressions such as “I have never had problems with brand X” or “Brand X is better than other brands I have tried”. As a result, we were not able to produce a Concept Map that mapped existing brand advocacy definitions accurately. It is possible, however, to feed manuscripts which a researcher is considering as part of a literature review informing a study, to uncover themes in prior research and to compare these to results obtained in a study itself.

Leximancer’s strength is its expedient identification of emergent ‘concepts’ and ‘themes’ without a researcher’s active intervention. Its results are neatly displayed in a Concept Map, which is supported by information about the strengths of the relationships between the ‘concepts’ and the ‘themes’ that is provided in an Insight Dashboard Report. The Leximancer-labelled ‘concepts’ are words that most frequently and strongly co-occur with other words in the dataset. ‘Themes’ are the clusters of these key words, and each ‘theme’ is assigned a name based on the most prominent concept in that cluster. We found the ‘themes’ to be key to understanding OBA. The impartiality of the Leximancer process is very useful in an exploratory study in which key concepts may not be clear, which is likely to be an issue when using big data. For example, without Leximancer, we would not have found differences in OBA posts in the OBC and OOC communities (Figure 2).

A key difference in the OBA posts was in the types of products more prominently (although not exclusively) advocated on each of the two online communities studied. For example, the Leximancer-discovered 'High Involvement Products (HIP)' theme was clearly 'pulled' by the OOC tag, suggesting OBA posts on the OOC site were advocating for products in this category more than they did on the OBC site. On the other hand, the 'Low Involvement Products (LIP): Feeding' and 'Low Involvement Products: Hygiene' themes were more closely associated with the OBC tag. This suggested LIP were advocated on the OBC more than on the OOC, further highlighting that OBA posts on the OBC were mostly about the community owner's brand, its immediate competitors and closely related but non-competing product categories. However, on the OOC forum, OBA was provided for a wider variety of products and significantly more OBA posts seem to be about HIP. This Leximancer finding presented insights into the nature of OBA posts and how OBA differed on the two online community forums. Such insights would be difficult to obtain when using QSR NVivo, where the groupings of the different products forming the HIP and LIP product categories would not have been as obvious.

Leximancer allows researchers to seed concepts of interest (actual words) in the form of a query that asks the program to map instances of the queried concept onto the Concept Map. Two compound concepts ('Positive brand mentions' and 'Negative brand mentions') were seeded to further explore emerging relationships of interest. This manual seeding process is similar to setting up of two queries ('Brand mention' AND 'Positive communication' as 'Positive brand mention'; and 'Brand mention' AND 'Negative communication' as 'Negative brand mention'), which enabled us to pinpoint instances of positive and negative brand mentions (Figures 2, 3 and 4).

Instances of brand names being mentioned in a positive way (for example: 'Brand name' and 'great'; or 'Brand name' and 'love') and instances of brand names being mentioned in a negative way (for example: 'Brand name' and 'bad'; or 'Brand name' and 'awful') were highlighted on the resulting Concept Maps. Figures 2, 3 and 4 show the close proximity of the seeded compound concepts of 'Positive brand mention' and 'Negative brand mention'. A

closer inspection of the dataset, found that OBA posts frequently included positive and negative aspects of the advocated brand, or of brands to which the advocated brand was compared. This insight resulted in the identification of three different ways through which OBA is given:

1. A positive-negative brand comparison within the advocated brand, where the good and not so good points of the advocated brand are discussed (we labelled this as 'advocacy despite some shortcoming').
2. A positive-negative brand comparison between brands, where the positive points of the advocated brand and the negative aspects of the competing, compared to, non-advocated brand were discussed.
3. A positive-negative comparison within and between brands, where both (1) and (2) occurred within an OBA post. This finding would have been difficult to identify had we only used QSR NVivo.

Leximancer also enables a quantitative analysis of the Prominence Scores calculated in the Insights Dashboard Report, as illustrated in Table 3 and Table 4. The scores represent the relationship between concepts and categories of interest visually depicted in the Concept Map. Table 3 highlights the most prominent or most important concepts used by consumers when referring to a brand (Brand Mention) in the online post advocating a brand and advocating a brand on the two different online communities. We were able to interpret these results to better understand the concept being studied (i.e. OBA). Thus, when a brand was being advocated online, consumers:

- Had 'tried' (1.7) and used (1.6) the brand and so communicate online from their own experiences.
- 'Love' (1.4) the brand and felt the brand was 'better' (1.4) than other brands.
- Encouraged others to 'buy' (1.3) the brand.

Table 4 suggests the most prominent compound concepts used by consumers when referring to a brand (Brand Mention) in an online post advocating a brand and advocating a brand on the two online communities. These compound concepts offered additional insights into how consumers advocate for brands online, as these words paired most frequently.

Key weaknesses of QSR NVivo and Leximancer

The analysis highlighted some key weaknesses of both programs (Table 2). QSR NVivo's key shortcomings stem from its key strength, which is the program's reliance on the researcher driving key aspects of the analysis. In QSR NVivo, researcher(s) identify the nodes (codes) and, therefore, the key themes and concepts of interest; the researcher(s) drive the coding of the data to relevant researcher-judged nodes; and determine the type of analysis that is used. This can be a subjective, time-consuming and elaborate process, particularly when using big data. Such processes are automated in Leximancer. In QSR NVivo the identification of nodes (codes) can be primed and assisted through word frequency queries, which show the most frequently occurring words and provide insights into the key concepts that might be identified as nodes in the coding stage. The coding stage is usually followed by a decision as to which analysis to use. These steps may be limited by a researcher's epistemological position and the time and resources available, which may impact on the reliability of the process and, hence, on the reliability of the results.

Leximancer's key weakness is its inability to capture the online posts' communication style and implied tone of voice, which was important in understanding OBA. Some affective and virtual visual OBA characteristics identified in QSR NVivo would have been unnoticed in the Leximancer analysis. These included key aspects of online communication, such as acronyms particular to the online community, the implied tone of voice (often marked with exclamation marks (!!!), or with CAPITALS and/or **bold lettering**), which enabled advocates to better portray their intended feelings in their OBA posts. Manually coding this in QSR NVivo allowed the researchers to capture this important aspect of OBA posts.

Another observed Leximancer weakness that may be overcome with training and practice, is the way Leximancer names each 'theme' after its most prominent 'concept'. A first Concept Map often produces unexpected or unusual themes, and a researcher's first thought maybe "*This does not tell me anything!*". By gradually adjusting the resolution of the Concept Map, its theme sizes, and by rotating and re-clustering, researchers can produce a Map with more meaningful themes.

Leximancer's user-friendly and intuitive interface (a "click and drag", or just "one click" functionality) allows a researcher to easily and gradually adjust the Concept Map to produce visual outputs that represent meaningful themes. For example, a researcher can adjust the resolution of the Concept Map by sliding the "% Visible Concepts" bar; its theme sizes by sliding the "% Theme Size" bar; rotate the map by sliding the "Degree of Rotation" bar; and to re-cluster by selecting the "Recluster Map" button. The thematic and conceptual meaningfulness of the visual output can also be improved by manually renaming the themes in the Concept Map, enabling the Map to better reflect the themes' composition and their overall thematic essence. This was the case here, as the themes in Figures 2, 3 and 4, were renamed to reflect their concepts; thus helping in the identification of key OBA characteristics and in seeing how OBA differed from other relevant constructs. This process was simpler than that offered in QSR NVivo. Programs such as Inkscape enable researchers to improve the visual appearance of a Leximancer-produced Map (e.g. by improving the spacing around concept names that may overlap on the original map).

QSR NVivo and Leximancer programs are complements

The analysis suggested QSR NVivo and Leximancer programs complement each other and that weaknesses in one program can be addressed by strengths in the other. We found each program contributed a different visual and evidence-based perspective and added to our understanding of OBA. Had we only used one program, we would have only had results from one side of the analysis. The QSR NVivo Coding Stripes Analysis (Figure 1) enabled us to

determine which of the nodes (characteristics of OBA) were common across both online communities, and which were particular to each. This allowed us to determine common OBA characteristics and, therefore, those that made OBA unique in an online C2C communication setting. This process also allowed us to pinpoint some OBA characteristics that were unique to each of the online communities. However, the QSR NVivo Coding Stripes Analysis was not sufficient to explain the magnitude of those differences and the reason why these differences occurred (i.e. why some characteristics of OBA were more prominent on the OOC and others were more prominent on the OBC). The Leximancer analysis (Figure 2, 3 and 4), provided further insights through the emergent 'High Involvement Products' and 'Low Involvement Products' themes.

The themes which emerged in the Leximancer analysis helped us to explain why there were differences in the way people advocated for brands in each of the two communities. That is, the OBA posts on the OBC were about the brand that owned the OBC and about competing brands, as well as brands closely related to the product category of the brand that owned the OBC. We found these brands clearly in the 'Low Involvement Products: Hygiene' and 'Low Involvement Products: Feeding' themes (Figure 2), where both themes were 'pulled' by the OBC tag, meaning they were most prominent on the OBC. This is consistent with OBA evident in the OBC posts, which were mostly about the brands in these two product categories. On the other hand, the 'High Involvement Products' theme was 'pulled' by the OOC tag, which suggests there were more OBA posts about these products in the OOC forum.

These findings helped explain why some OBA characteristics occurred more on the OBC than on the OOC and vice versa. For example, on the OBC where OBA was mostly about low involvement products, advocates demonstrated 'product category involvement', explicitly stating their 'brand commitment', provided 'brand advice or problem support' and 'recommendations based on brand comparisons' and elaborated on 'brand distinctiveness', as highlighted in the QSR NVivo analysis (Figure 1). Whereas, on the OOC, where the OBA posts were mostly about high involvement products (Figure 2), OBA post advocates provided

'recommendations based on criteria or requirements', displayed 'brand warmth', used 'brand language which was technical', and provided 'extra brand information' such as websites, photos, and prices (Figure 1). This further highlighted that both, QSR NVivo and Leximancer, complement each other, thus had we used only one program we would have understood only a certain aspect of the OBA characteristics displayed in C2C communication online.

Discussion

There seem to be benefits to using both QSR NVivo and Leximancer programs in exploratory social media research involving big, text-based data analysis. This study showed that the two programs complemented each other and that the weaknesses of one were addressed by the strengths of the other (Table 2). This finding addresses the need to further understand how the research issues and data analysis of one CAQDAS program (in this case, QSR NVivo) can be enriched by the use of another CAQDAS program (Leximancer) (Crofts and Bisman, 2010; Davies *et al.*, 2006). In this study, Leximancer was a useful interpretative tool that enabled a better understanding of the results obtained through the QSR NVivo analysis. Each program contributed a different visual and evidence-based perspective to the data analysis that, overall, provided a more comprehensive and insightful view of OBA.

Leximancer analysed a very large amount of data (1,796 online posts) in an expedient way, providing an automated, impartial analysis that highlighted the key concepts, themes and their connectivity (Figures 2, 3 and 4). This study showed that when applied to large quantities of text, such as big data, Leximancer enables efficient 'text mining' by transforming lexical co-occurrence information from natural language into semantic patterns (Smith and Humphreys, 2006). Here, Leximancer identified themes that would have been missed or overlooked had we only used QSR NVivo. This is consistent with other researchers noting that the Leximancer program "*(makes) the analyst aware of the global context and significance of concepts and (helps) to avoid fixation on particular anecdotal evidence, which may be atypical or erroneous*" (Smith and Humphreys, 2006, p. 262). QSR NVivo, on the other hand, enabled this research

to precisely and rigorously identify concepts and themes of interest, with the researchers' insights driving the processes (Figure 1), and to identify OBA types that would not have been found in a Leximancer analysis.

This study found both programs to be flexible and both assisted the researchers to work with unstructured qualitative data, to generate textual relationships, identify key areas that emerged from the data and to visually represent this output. However, the task of interpreting such visual output remained with the researchers. After undertaking QSR NVivo and Leximancer analysis, the researchers went back to engaging directly with the data to further explore and interpret textual meanings, in line with the suggestion that *"the application of CAQDAS should not operate as a substitute for the researcher's immersion in, or interpretation of the data but rather as a means for enriching the research process"* (Crofts and Bisman, 2010, p. 197). This follow-through enabled the researchers to draw meaningful conclusions based on the 'visual first' approach provided by the two programs, and to guide future OBA studies.

Conclusions and Implications

This study contributed to our understanding of how qualitative text-based data analysis programs can be used to explore big data obtained from social media, answering a call for further insight into such programs' functionality (Sotiriadou *et al.*, 2014; Angus *et al.*, 2013). This paper illustrates how such programs can be used as powerful tools when undertaking big data, exploratory analysis; presenting valuable visual analysis beyond just an 'end-stage output' for readers. The 'visual-first' analysis used, illustrates how such analysis can be integrated with critical reasoning and decision-making about the data, enabling researchers to use such integration to guide subsequent enquiry (Angus *et al.*, 2013).

Each of the two programs showcased in this paper has its strengths and limitations that should be assessed prior to their use. QSR NVivo analysis is researcher-driven and is, therefore, influenced by and, to some degree, limited by researchers' analytical decisions and

epistemological positions. The coding process is manual and time consuming. However, QSR NVivo analysis facilitates an iterative concept exploration process at the time of coding (Hutchison *et al.*, 2010). The Leximancer analysis is more automated and relies on the researchers assigning meaning, interpreting and working with the results obtained and represented in a Concept Map and Insight Dashboard Report. Leximancer requires a close analysis and refinement of the initial output, a process underpinned by the researchers' understanding of the data. This study shows that Leximancer should not be expected to 'do the work' for you, rather, it should do the work with you (Penn-Edwards, 2010).

CAQDAS applications provide new ways to develop visual output that can help researchers make visual sense of their big data. Such sense-making requires intellectual rigour and researchers' full involvement; highlighting the importance of human intervention in analysing and interpreting big, qualitative data. These tools assist researchers, but they are not replacements for human analysts (Angus *et al.*, 2013). It is imperative for researchers working with these tools to be intimately and comprehensively familiar with the data set and with the programs being used. Researchers must prepare the data according to the requirements of each program. In other words, the quality of the analysis reflects the quality of the data and of the researchers' involvement with the tools, as well as their understanding of the data and of the prior research that guides their study. As illustrated in this paper, researchers should also consider using more than one CAQDAS program when analysing large text-based datasets, because such programs complement one another, providing a more comprehensive insight into the phenomenon being studied.

We used the qualitative findings from both CAQDAS analyses to guide a subsequent OBA scale development process. The intricate qualitative insights achieved through the use of QSR NVivo and Leximancer suggested OBA has some unique characteristics that need to be included in any scale. The findings also suggested some potential OBA scale items that should be considered if any OBA scale is to reflect OBA's true nature.

References

- Adjei, M. T., Noble, S. M., and Noble, C. H. (2010), "The influence of C2C communications in online brand communities on customer purchase behavior", *Journal of the Academy of Marketing Science*, Vol. 38 No. 5, pp. 634-653.
- Anderson, E. W. (1998), "Customer satisfaction and word of mouth", *Journal of Service Research*, Vol. 1 No. 1, pp. 5-17.
- Angus, D., Rintel, S., and Wiles, J. (2013), "Making sense of big text: a visual-first approach for analysing text data using Leximancer and Discursis", *International Journal of Social Research Methodology*, Vol. 16, pp. 261-267.
- Bhattacharya, C. B., and Sen, S. (2003), "Consumer-company identification: a framework for understanding consumers' relationships with companies", *Journal of Marketing*, Vol. 67 No. 2, pp. 76-88.
- Brodie, R. J., Ilic, A., Juric, B., and Hollebeek, L. (2013), "Consumer engagement in a virtual brand community: An exploratory analysis", *Journal of Business Research*, Vol. 66 No. 1, pp. 105-114.
- Bulearca, M., and Bulearca, S. (2010), "Twitter: a viable marketing tool for SMEs?", *Global Business and Management Research*, Vol. 2, pp. 296-309.
- Chaudhuri, A. (2000), "A macro analysis of the relationship of product involvement and information search: The role of risk", *Journal of Marketing Theory and Practice*, Vol. 8 No. 1, pp. 1-14.
- Chu S. C., and Kamal S. (2008), "The effect of perceived blogger credibility and argument quality on message elaboration and brand attitudes: An exploratory study", *Journal of Interactive Advertising*, Vol. 8 No. 2, pp. 26-37.
- Chu, S. C., and Kim, Y. (2011), "Determinants of consumer engagement in electronic word-of-mouth (eWOM) in social networking sites", *International Journal of Advertising*, Vol. 30 No. 1, pp. 47-75.
- Corbin, J., and Strauss, A. (2007), *Basics of Qualitative Research*, 3rd edition, Thousand Oaks, CA: Sage.
- Cretchley, J., Rooney, D., and Gallois, C. (2010), "Mapping a 40-year history with Leximancer: Themes and concepts in the Journal of Cross-Cultural Psychology", *Journal of Cross-Cultural Psychology*, Vol. 41 No. 3, pp. 318-328.
- Crofts, K., and Bisman, J. (2010), "Interrogating accountability: An illustration of the use of Leximancer software for qualitative data analysis", *Qualitative Research in Accounting & Management*, Vol. 7, pp. 180-207.
- Davies, I., Green, P., Rosemann, M., Indulska, M., and Gallo, S. (2006), "How do practitioners use conceptual modeling in practice?", *Data & Knowledge Engineering*, Vol. 58 No. 3, pp. 358-380.
- Divol, R., Edelman, D., and Sarrazin, H. (2012), "Demystifying social media", *McKinsey Quarterly*, Vol. 2, pp. 66-77.

Fagerstrøm, A., and Ghinea, G. (2011), "On the motivating impact of price and online recommendations at the point of online purchase", *International Journal of Information Management*, Vol. 31 No. 2, pp. 103-110.

Gaskell, G. (2000), "Individual and group interviewing" in Bauer, M. and Gaskell, G. (eds), *Qualitative Researching with Text, Image and Sound*, London: Sage, pp. 38-56.

Godes, D., and Mayzlin, D. (2004), "Using online conversations to study word-of-mouth communication", *Marketing Science*, Vol. 23 No. 4, pp. 545-560.

Graham, J., and Havlena, W. (2007), "Finding the "missing link": Advertising's impact on word of mouth, web searches, and site visits", *Journal of Advertising Research*, Vol. 47, pp. 427-435.

Green, J., and Thorogood, N. (2004), "Observational methods", *Qualitative Methods for Health Research*, Sage Publications Ltd, pp. 131-134.

Hausman, A. D., Kabadayi, S., and Price, K. (2014), "Consumer-brand engagement on Facebook: liking and commenting behaviors", *Journal of Research in Interactive Marketing*, Vol. 8, pp. 203-223.

Hennig-Thurau, T., Gwinner, K. P., Walwsh, G., and 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*, Vol. 18 No. 1, pp. 38-52.

Hutchison, A. J., Johnston, L. H., and Breckon, J. D. (2010), "Using QSR-NVivo to facilitate the development of a grounded theory project: An account of a worked example", *International Journal of Social Research Methodology*, Vol. 13 No. 4, pp. 283-302.

Jillapalli, R. K., and Wilcox, J. B. (2010), "Professor Brand Advocacy: Do Brand Relationships Matter?", *Journal of Marketing Education*, Vol. 32 No. 3, pp. 328-340.

Jones, M., and Diment, K. (2010), "The CAQDA paradox: A divergence between research method and analytical tool", *The International workshop on Computer-Aided Qualitative Research Asia (CAQRA2010)*, The Netherlands: Merlien Institute, pp. 82-86.

Karakaya, F., and Barnes, N. G. (2010), "Impact of online reviews of customer care experience on brand or company selection", *Journal of Consumer Marketing*, Vol. 27, pp. 447-457.

Keller, E. (2007), "Unleashing the power of word of mouth: Creating brand advocacy to drive growth", *Journal of Advertising Research*, Vol. 47 No. 4, pp. 448-452.

Kozinets, R. V. (2002), "The field behind the screen: Using netnography for marketing research in online communities", *Journal of Marketing Research*, Vol. 39 No. 1, pp. 61-72.

Kozinets, R. V. (2010), *Netnography: Doing ethnographic research online*, Sage Publications.

Lawer, C., and Knox, S. (2006), "Customer advocacy and brand development", *Journal of Product and Brand Management*, Vol. 15 No. 2, pp. 121-129.

Leventhal, R. C., Wallace, E., Buil, I., and de Chernatony, L. (2014), "Consumer engagement with self-expressive brands: brand love and WOM outcomes", *Journal of Product and Brand Management*, Vol. 23 No. 1, pp. 33-42.

Leximancer Pty Ltd. (2017), *Leximancer User Guide: Release 4.5*, Retrieved from <http://doc.leximancer.com/doc/LeximancerManual.pdf>

Marketing Science Institute. (2016), "MSI Research Priorities 2016-2018", Retrieved from: http://www.msi.org/uploads/articles/MSI_RP16-18.pdf

McAlexander, J. H., Schouten, J. W., and Koenig, H. F. (2002), "Building brand community", *Journal of Marketing*, Vol. 66 No. 1, pp. 38-54.

McAfee, A. and Brynjolfsson, E. (2012), "Big Data: The Management Revolution", *Harvard Business Review*, October, pp. 61-68.

Moghaddam, A. (2006), "Coding issues in grounded theory", *Issues in Educational Research*, Vol. 16 No. 1, pp. 52-66.

Muniz Jr, A. M., and O'Guinn, T. C. (2001), "Brand community", *Journal of Consumer Research*, Vol. 27 No. 4, pp. 412-432.

O'Reilly, T. (2005), "Web 2.0: Compact definition", *Message posted to* http://radar.oreilly.com/archives/2005/10/web_20_compact_definition.html.

Parrott, G., Danbury, A., and Kanthavanich, P. (2015), "Online behaviour of luxury fashion brand advocates", *Journal of Fashion Marketing and Management*, Vol. 19 No. 4, pp. 360-383.

Penn-Edwards, S. (2010), "Computer aided phenomenography: The role of Leximancer computer software in phenomenographic investigation", *The Qualitative Report*, Vol. 15 No. 2, pp. 252-267.

Porter, C. E. (2004), "A typology of virtual communities: A multi-disciplinary foundation for future research", *Journal of Computer-Mediated Communication*, Vol. 10, pp. 00-00.

Risch, J., Kao, A., Poteet, S. R. and Wu Y. J. (2008), "Visual data mining", Springer-Verlag, Berlin Heidelberg.

Smith, A. E., and Humphreys, M. S. (2006), "Evaluation of unsupervised semantic mapping of natural language with Leximancer concept mapping", *Behavior Research Methods*, Vol. 38 No. 2, pp. 262-279.

Smith, A. N., Fischer, E., and Yongjian, C. (2012), "How does brand-related user-generated content differ across YouTube, Facebook, and Twitter?", *Journal of Interactive Marketing*, Vol. 26 No. 2, pp. 102-113.

Sotiriadou, P., Brouwers, J., and Le, T. A. (2014), "Choosing a qualitative data analysis tool: A comparison of NVivo and Leximancer", *Annals of Leisure Research*, Vol. 17 No. 2, pp. 218-234.

Stokburger-Sauer, N., Ratneshwar, S., and Sen, S. (2012), "Drivers of consumer-brand identification", *International Journal of Research in Marketing*, Vol. 29 No. 4, pp. 406-418.

Urban, G. L. (2005), "Customer advocacy: a new era in marketing?", *Journal of Public Policy & Marketing*, Vol. 24, pp. 155-159.

Wallace, E., Buil, I., and De Chernatony, L. (2012), "Facebook 'friendship' and brand advocacy", *Journal of Brand Management*, Vol. 20 No. 2, pp. 128-146.

Yahia, I. B. (2005), "Non commercial B2C virtual communities: definition and classification an exploratory qualitative study", *IADIS International Journal on WWW/Internet*, Vol. 5, pp. 129-144.

Table 1: OBA Characteristics and Analysis: An excerpt from the complete table.

Note: To illustrate the true nature of brand advocacy occurring online, the OBA examples featured in the table below have been transcribed as they appeared within the discussion forums of the online communities studied in this research, and include the following: spelling mistakes, lack of punctuation and the direct nature of the written form. Words in [] are explanations added in by the researcher to clarify words used in the OBA post.

Cognitive OBA Characteristic	Leximancer Analysis & Findings	QSR NVivo Analysis & Findings	Example
<p>1. Positive-negative brand comparison:</p> <ol style="list-style-type: none"> within brand (advocacy despite shortcoming) between two or more brands within brand and between brands simultaneously 	<p>OBC and OOC Concept Maps:</p> <ul style="list-style-type: none"> 'positive brand mentions' co-occurring with 'negative brand mentions'; shown overlapping on both community-specific maps On OBC "positive community owner's brand mention" & "negative community owner's brand mention"; and "positive community owner's brand mention" & "negative competitor's brand mention" overlapping, suggesting frequency and importance of co-occurrence <p>Insight Dashboard:</p> <ul style="list-style-type: none"> 'positive brand mentions' & negative brand mentions' high ranking compound concept on both online communities: OOC PS = 23.3; OBC PS = 13.8 OBC PS for 'positive community owner's brand mention & negative community owner's brand mention (advocacy despite shortcoming)' = 42.8 	<p>Coding Stripes Analysis based on Matrix Coding Query:</p> <ul style="list-style-type: none"> 'recommendation given based on brand comparison' co-occurs with 'positive brand mentions' <p>Text Search Query:</p> <ul style="list-style-type: none"> 'price', 'quality' and product attributes ('light', 'space', 'comfortable') common to brand comparison through positive-negative brand mentions 	<p>1 a. "These <brand name> bottles are expensive but they are the best bottles on the market in my opinion anyway!!! My daughter is great on these bottles but she wasn't very good on any other bottles."</p> <p>1 b. "I have 3 little ones and have tried pretty much all the brands and was a bit turned off on <brand name A> nappies but thought I would try them and have never turned back they are the best ones they are as good as <brand name B> and so much cheaper."</p> <p>1 c. "I used to use <brand name A> for a bit but <brand name B> are the best trust me especially during teething it is worth it you don't want your baby anymore miserable! all other nappies don't compare and you will find the nappy rash might get that bad it bleeds which I don't like to put baby through definitely worth <brand name B> buy in bulk and it adds up to the same as the cheap nasty ones!"</p>
<p>2. Superiority of product attributes.</p>	<p>Two-in-One Concept Map:</p> <ul style="list-style-type: none"> connectivity and positioning of 'recommendations', 'high involvement products' and 'brand suitability' themes illustrates that OBA within OOC discussions stems from brand recommendation seeking based on requirements and brand suitability 'Brand issues support' and 'Brand mention' themes connectivity within OBC suggests OBA is often instigated and results from discussion about some brand-related issue about 'Low Involvement Products' 'High Involvement Products' theme on OOC includes technical and feature-related language such as 'fold', 'light', 'easy' 'better' is highly related to 'positive communication' about brands on both communities; OOC 'better' PS = 1.7; OBC PS = 1.5 	<p>Coding Stripes Analysis based on Matrix Coding Query:</p> <ul style="list-style-type: none"> 'technical brand language', 'recommendations based on requirements', 'reasons for advocating' and 'recommendations based on brand comparison' are key features of OBA 'brand distinctiveness' particular to OBC OBA posts 'technical brand language' and 'recommendations based on requirements' are more noticeable within OOC OBA posts 'recommendation based on brand comparison' more prominent within OBC OBA posts <p>Word Frequency Query:</p> <ul style="list-style-type: none"> 'best', 'better', 'easy', 'great' most frequently used words <p>Text Search Query:</p> <ul style="list-style-type: none"> enabled to identify how frequently used words descriptive of superiority of products attributes (eg 'better', 'easy' etc) had been used within OBA posts 	<p>"<Brand name> has the BEST maternity wear I've ever tried and I have bought stuff from there and would buy again. It's easy to work out their sizing and the material is so comfy. I personally couldn't find any maternity shops around our area."</p>

Table 2: Strengths and Weaknesses of QSR NVivo and Leximancer.

QSR NVIVO	LEXIMANCER
Strengths	
<ul style="list-style-type: none"> • Researcher-driven, at researcher's discretion which nodes to identify for data classification. This may be perceived as specific and efficient, in identifying only those concepts, themes or keywords, which the study is interested in exploring. • Code and analyse data to specific concepts. As above. • Suitable for interpretative approach, in studies where a specific conceptual model is of interest to be investigated and the concepts/ constructs are known. • Researcher assigns meaning to the data at coding stage. • Akin to manual handling of data. A manual way of coding with the aide of a computer program. • Content analysis, data linking and data display based on nodes (codes). • Various analyses and visual output produced (e.g. Word Frequency Query, Coding Stripes Analysis, Matrix Coding Query). • Linking function allowing access from nodes to the original data. 	<ul style="list-style-type: none"> • Program-driven, automated analysis which may be perceived as more objective. • Automatic identification of key words (concepts) and clusters (themes). • Seeding based on frequencies and co-occurrences of words (concepts). • Suitable for exploratory study as "themes" emerge via automated lexical analysis. • Content analysis, data linking and data display based on emergent themes and concepts. • Efficient for large volumes of data. Quick, automated analysis. • Researcher able to manually seed (define) concepts required for the program to identify. Akin to setting up queries. • Program develops Concept Map and Insight Dashboard with Prominence Scores, to highlight key "themes" and "concepts" within them. • Linking function allowing access from the Concept Map to the original data.
Weaknesses	
<ul style="list-style-type: none"> • Subjective and researcher bias possible. Limited by researcher's epistemological position. • Time consuming in identifying what the concepts could be, thus what the nodes should be, and in the coding of data. • Questionable reliability. Due to the researcher's heavy involvement through the whole process, it is arguable to what extent the results are reliable. • Auto-Coding, should be used with caution. Albeit efficient, did not prove to be effective at capturing the correct information required for the purposes of this study, resulting in manual coding of data. 	<ul style="list-style-type: none"> • Lack of human insight during lexical analysis which is driven solely by the program. • Input data needs specific formatting and spelling checking prior to input into the program, which may be time consuming for large quantities of data. The program will only recognise correctly spelt words, and in the right format. • Lexical analysis occurs in 2 sentence blocks, which may be adjusted up or down. This is problematic in particular for data sourced online, where, unlike any other written form, the form of online expression can be short or long winded. • Researcher assigns meaning after program-analysis (i.e. at Concept Map configuration stage). • Sentiment lens is only suitable for at best compound concept (two 'affective' words) type analysis but it is not suitable for in-depth affective-type analysis. • Unable to capture the online communication style (e.g. acronyms) or implied tone of voice (e.g.!!!), common to online written form. • "Theme" names after the most prominent concept but do not necessarily represent the essence of the other "concepts" within the theme. • Unexpected or unexplained emergent concepts and relationships. • Misleading terminology, i.e. "concepts" = keywords and "themes" = concepts. • Somewhat awkward and problematic researcher-driven identification of the themes' size, the number of clustering attempts and rotation of the Concept Map.

Table 3: Top ranking concepts and their Prominence Scores (PS) against three categories of interest: 1. Brand Mention; 2. Online Brand Community; and 3. Online Open Community.

Brand Mention		Online Brand Community		Online Open Community	
Concept	PS	Concept	PS	Concept	PS
Tried	1.7	OBC Brand Name	1.7	Love	1.4
Use	1.6	Read	1.7	Price	1.3
Love	1.4	Tried	1.7	Looking	1.3
Better	1.4	Problem	1.6	Bought	1.1
Buy	1.3	Best	1.4	Great	1.1

Table 4: Top ranking compound concepts and their Prominence Scores (PS) against three categories of interest: 1. Brand Mention; 2. Online Brand Community; and 3. Online Open Community.

Brand Mention		Online Brand Community		Online Open Community	
Compound Concept	PS	Compound Concept	PS	Compound Concept	PS
Tried & brands	17.4	Read & understand	22.0	Easy & fold (product functionality)	39.3
Positive brand mention & negative brand mention	16.8	Tried & brands	12.1	Price & range	11.5
Better & cheaper	11.6	Best & brands	8.4	Looking & reviews	8.5
Positive brand mention & reviews	10.0	OBC Brand Name & brands	8.1	Issues & pay	8.2
Problem & never	9.3	Positive brand mention & negative brand mention	7.9	Recommend & compact (product feature)	7.6

Matrix Coding Query - All Node

OBC OBA post example

I noticed that I was having to buy nappies more frequently.. So I did my own little test. I bought the cheaper nappies, and each day I wrote down how many nappies I'd been through. I did this for 2 weeks, and then I bought <brand> and wrote down how many per day for another 2 weeks. Anyway... The result ended up being that I changed the cheaper ones much more frequently because otherwise they'd leak. Some brands I even used twice as many as I did with <brand> ... Which meant it saved me nothing buying cheaper, and in some cases even cost more as well as caused more work for me with so many changes and leakages. So when ds was born I didn't bother with any other brands. I'm a loyal <brand> buyer now!

Section 1 of 5

- Brand distinctiveness
- Recommendation given (brand comparison)
- Emotion (icons, exclamations)
- Brand advisor problem support
- Brand commitment (explicit)
- Product category involvement
- Reasons for advocating
- Re-active OBA
- Brand ownership (own use)
- Brand experience
- Brand mentions (positive)

Matrix Coding Query - All Node

OOC OBA post example

I've got the <brand name> . It's got a quad blade plus lots of attachments, two bowls, wide chute etc. It's got a storage container for the attachments so they all pack away neatly. I love it. 25yr warranty on the motor. I got it for \$375 tho I think rrp is \$500+

When I was researching, I read An article about the development of the <brand name> . A team went out and bought every fp they could find and wrote up everything they could find wrong with them. Then they came up with a dream list of everything a FP should do, and the <brand> was born. I love mine!

I have this one too, it's brilliant!! I think I got it for about \$420. Worth every dollar!

Section 2 of 5

- Emotion (icons, exclamations)
- Extra brand info (links, photos)
- Brand language (technical)
- Brand warmth (feelings)
- Recommendation given (requirements)
- Reasons for advocating
- Re-active OBA
- Brand experience
- Brand ownership (own use)
- Brand mentions (positive)

Figure 1: QSR NVivo Coding Stripes Analysis.

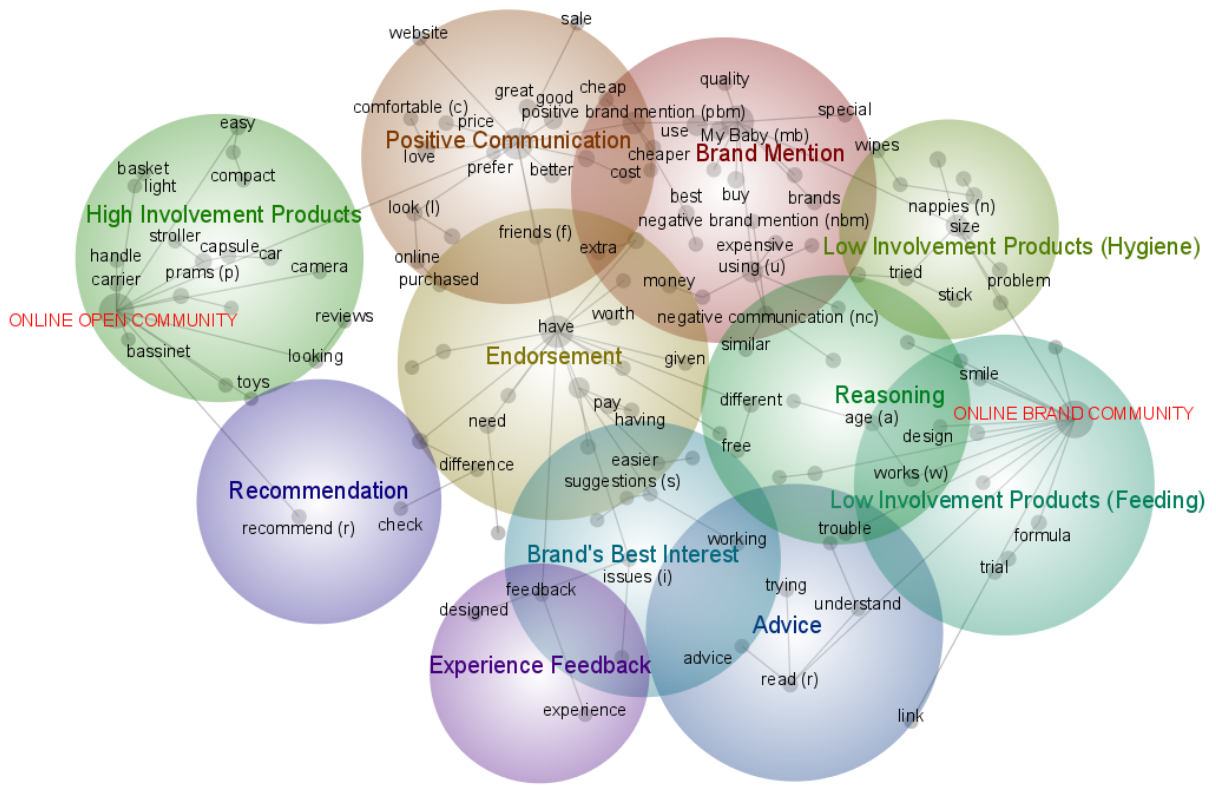


Figure 2: Leximancer Two-in-One OBA Concept Map.

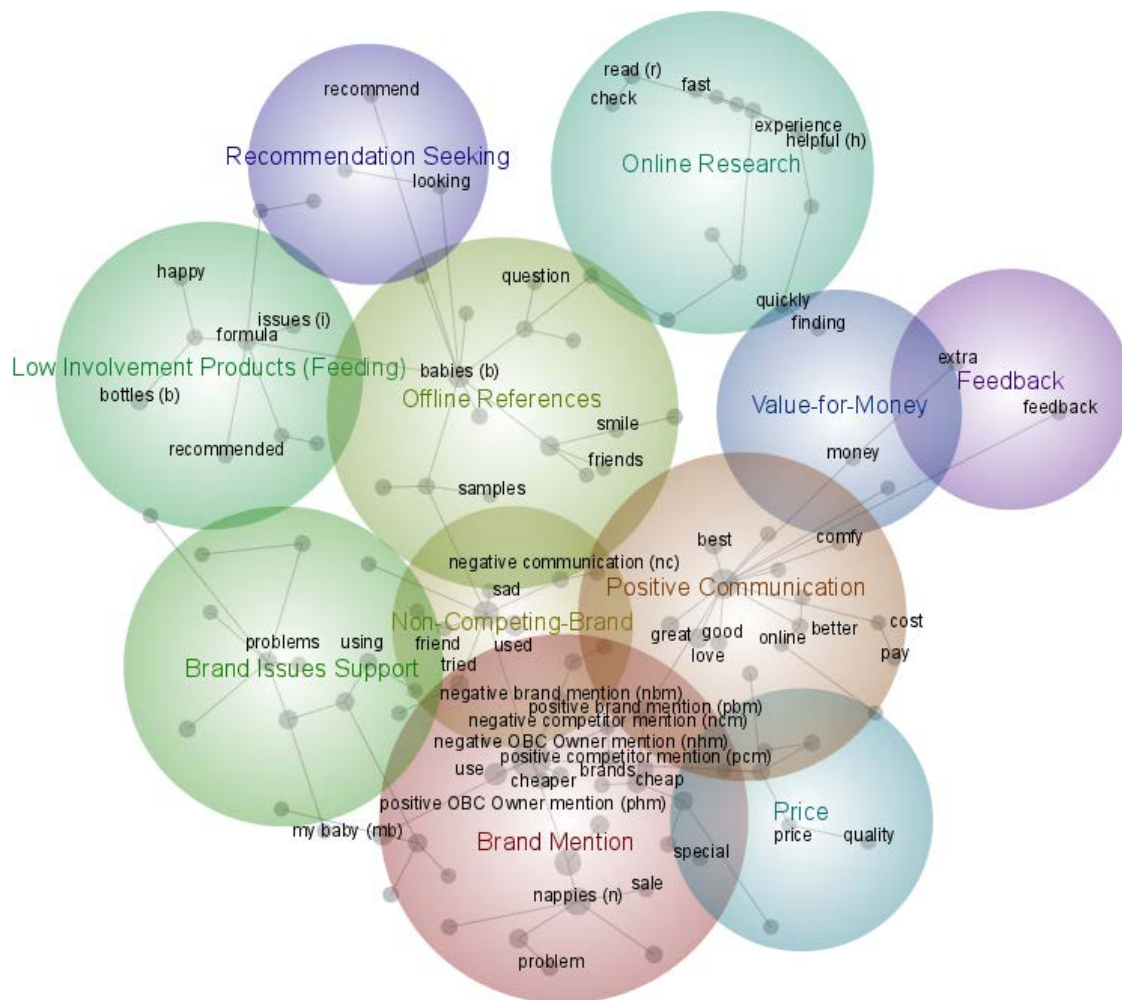


Figure 3: Leximancer OBC OBA Concept Map.

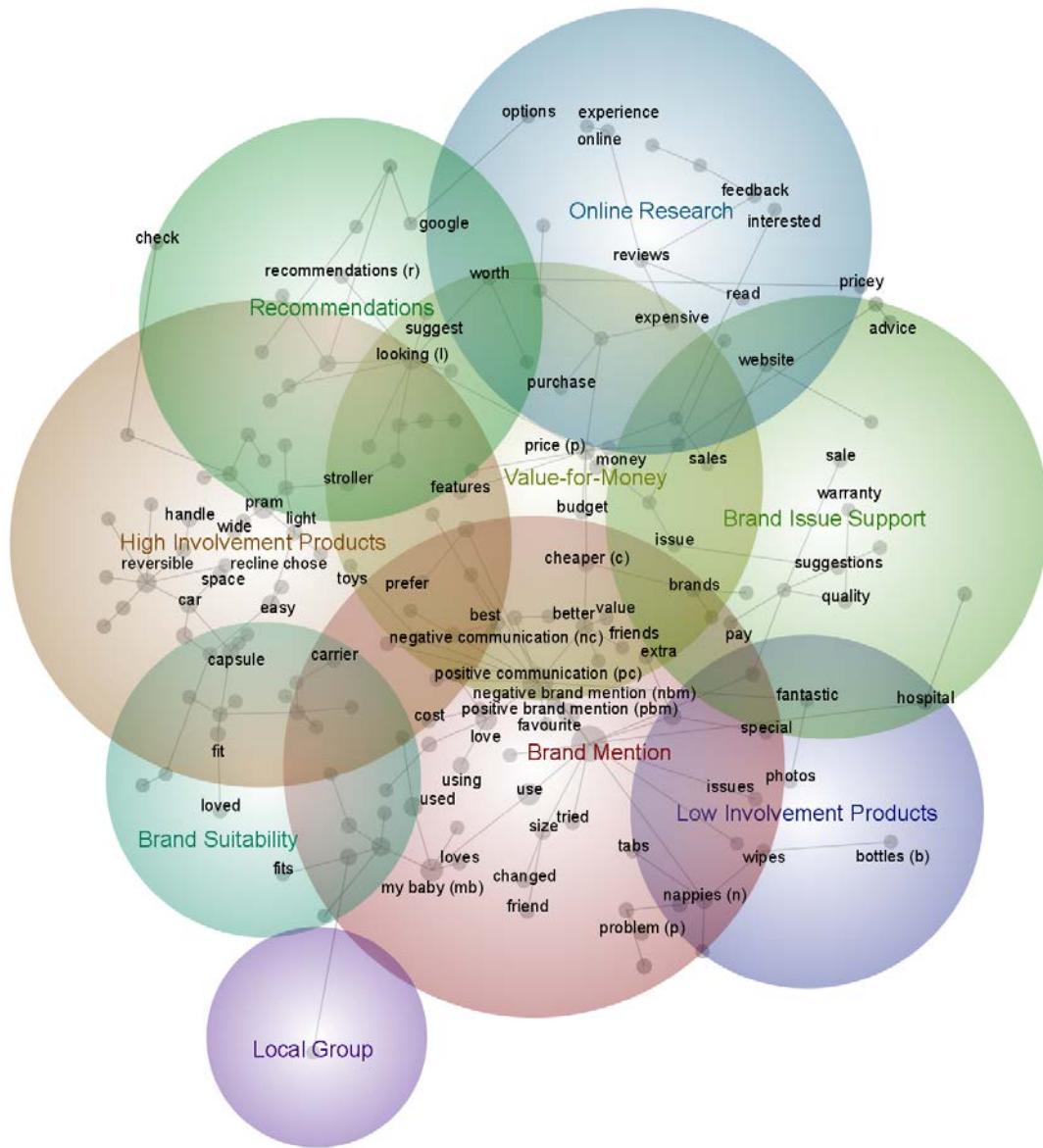


Figure 4: Leximancer OOC OBA Concept Map.