Postprint *in European Journal of Marketing*, 48(5/6), 2014, 1092-1112.

https://doi.org/10.1108/EJM-12-2011-0770

Exploring brand associations: an innovative methodological approach

Belinda Crawford Camiciottoli – University of Pisa

Silvia Ranfagni – University of Florence

Simone Guercini – University of Florence

Structured Abstract

Purpose

The objective of this exploratory study is to propose a new methodological approach to investigate brand associations. More specifically, the study aims to show how brand associations can be identified and analysed in an online community of international consumers of fashion in order to determine the degree of matching with company-defined brand associations.

Design/methodology/approach

The methodology is two-pronged, integrating qualitative market research techniques with quantitative text mining. It was applied to determine types and perceptions of brand associations among fashion bloggers with reference to three leading Italian fashion houses. These were then compared to brand associations found in company-generated texts to measure the degree of matching.

Findings

The results showed consistent brand associations across the three brands, as well as substantial matching with company-defined brand associations. In addition, the analysis revealed the presence of distinctive brand association themes that shed further light on how brand attributes were perceived by blog participants.

Practical implications

The methods described can be used by managers to identify and reinforce favourable brand associations among consumers. This knowledge can then be applied towards developing and implementing effective brand strategies.

Originality/Value

The authors propose an interdisciplinary approach to investigate brand associations in online communities. It incorporates text mining and computer-assisted textual analysis as techniques borrowed from the field of linguistics which have thus far seen little application in marketing studies, but can nonetheless provide important insights for strategic brand management.

Keywords: Brand associations, online communities, fashion industry, text mining, textual analysis, qualitative-quantitative approach

Introduction

It is important for companies to have a clear understanding of consumer brand knowledge in order to develop marketing activities that will improve brand equity (Keller, 2003a). Brand knowledge consists of the personal meanings linked to a brand that are stored in consumers' memories (Keller, 2003a; Supphellen, 2000; Aaker, 2003). It is thus a strategic resource to be analysed, controlled and managed over time (Romaniuk and Gaillard, 2007). Brand knowledge can be further conceptualized as a set of associations related to a brand (Anderson, 1983), or more specifically, a node in consumer memory to which a variety of associative links are connected. According to Biel (1991), the meanings that consumers assign to a brand are synthesized into brand associations formed by the components perceived to underlie the brand's image. Keller (1993) classifies brand associations as attributes of the product itself (product-related), or attributes linked to the purchase and consumption of the product, such as price information, product appearance, usage and user imagery (non-product related). However, brand associations may also be related to perceived benefits and product experiences, including the feelings, thoughts, and attitudes that consumers have towards a brand (Broniarczyk and Alba, 1994; Keller, 2003a). These may be expressed by means of descriptive adjectives such as *elegant*, *strong*, *chic*, thus forming a distinct brand personality (Maehle and Supphellen, 2011; Plummer, 1985).

Strong, positive and unique associations reinforce a brand and increase its equity. Brand equity creates market leverage and is affected by the types of associations that a brand has (Bridges *et al*., 2000; Broniarczyk and Gershoff, 2003). According to Keller (2003b), brand associations are a source of brand equity and can be drivers of the brand strategy a company decides to implement. For example, a brand "reinforcement strategy" (Keller, 2003b, p. 634) strengthens a brand's attributes in order to increase brand awareness and brand loyalty, while fortifying product associations. A "revitalization strategy" (Keller, 2003b, p. 651) can instead refresh existing brand attributes or identify new ones, thereby generating changes in competitive positioning which have an effect on the perceived quality of the product. The development of strong and distinctive brand associations thus reflects a brand strategy that can have a positive influence on consumer choices (Carpenter *et al.*, 1994) and forms the basis of brand differentiation (Pechmann and Ratneshwar, 1991).

The differentiating power of a brand and its influence on consumer attitude are closely connected to the phenomenon of *congruence*, whereby the associative links that distinguish brands in consumer memory share content and meaning (Keller, 1993). The absence of such congruence has been discussed in terms of *brand image incongruity*, i.e., a discrepancy or "mismatch between brand communication and existing brand associations" (Sjödin and Törn, 2006, p. 34). Some research has focused on *fit* between brand attitude and information conveyed through brand extension (Grime *et al*., 2002), as well as *match* or *congruity* between existing brand associations and marketing policies relating to, for example, sponsorship (Gwinner and Eaton, 1999), advertising (Dahlen *et al*., 2005) and country of origin (Häubl and Elrod, 1999). Though using different terms, these studies have highlighted the importance of brand association matching, which implies the broader issue of the degree of match/mismatch between brand associations from the perspective of the company vs. the consumer. More specifically, here the determination of match vs. mismatch involves a comparison between brand associations as defined by the company (brand identity) and those actually perceived by consumers (brand image), which may be further articulated into the degree of match among brand associations, and between brand associations and marketing decisions. For the purposes of the present study, the authors adopt the term “matching” and define brand association matching as a situation in which company and consumer brand associations are aligned. The issue of intended vs. actual perceptions of brands was recently addressed in a study by Ross and Harradine (2011) who found substantial misalignment between how a supermarket clothing brand is intended to be perceived by its owners and how it is actually perceived by consumers. Similarly, the present study investigates the phenomenon of match/mismatch, but focuses specifically on brand associations as defined by companies vs. those perceived by online consumers, while also seeking to identify highly articulated brand attributes that may (or may not) be shared by companies and their consumers. It is important to acquire a better understanding of brand association match/mismatch as conditions that impact brand equity, but also influence brand differentiation and drive the definition of brand strategies. In particular, brand equity requires significant internal brand identity efforts, which should create a corresponding brand image through integration in overall marketing programs (Keller, 2003a). While brand association matching may be difficult to achieve due to the complexity of communications needed to transfer brand identity (Madhavaram *et al*., 2005), companies that are able to do so can achieve greater alignment with consumer brand knowledge and better reshape the network of brand associations in the consumer’s mind in comparison to competitors (Brandt *et al.*, 2011). Therefore, determining the degree of brand association matching has implications for positioning, image, communication, brand equity management and perceptual competition analysis (Till *et al.*, 2011).

In the preceding paragraphs, we have discussed the concepts of brand knowledge (Keller, 2003a; Supphellen, 2000; Aaker, 2003) and brand associations (Anderson, 1983; Keller, 1993; Keller, 2003a), and how they contribute to generating brand equity (Keller, 2003b) and, consequently, to driving brand strategy (Keller, 2003b; Carpenter *et al.*, 1994; Pechmann and Ratneshwar, 1991). In addition, the discussion has traced the interrelatedness of these key concepts from the scholarly literature on brands, thus constituting the theoretical underpinning upon which we propose a new methodological approach to investigate brand associations.

Context of analysis and research questions

This study of brand associations is contextualized in an online community as a social setting that is considered to be a new type of market (Muniz and O'Guinn, 2001). More specifically, this is a market where consumers and users interact in digital environments to produce and mutually exchange information (Szmigin *et al*., 2005). These virtual settings can generate a rich source of data, reflecting a convergence of actors who may assume a variety of roles, e.g., consumers, current or potential customers, enthusiasts, experts (Cova, 1997). It is thus possible to study the complex interactions of consumers with the market and, in particular, with brands and companies (De Valck, 2005).

Drawing on the research context described above, brand associations will be investigated according to the following research questions:

1. How can consumer brand associations be identified in online communities?
2. How can the degree of brand association matching be determined and measured?
3. What kind of themes emerge from brand association matching and what are the implications for brand strategy?

The next section presents an innovative methodological approach which integrates quantitative text mining techniques and qualitative analytical methods to analyse brand associations that emerge from an online community of consumers and those found in the communications of the companies that own the brand. This is followed by a detailed description of an exploratory implementation in a small-scale study focusing on three fashion brands. The paper continues with a discussion of the findings and concludes with managerial implications.

Analysing brand associations: an integrated approach

Brand associations have been studied using conventional techniques, such as focus groups, in-depth personal or group interviews and ethnography (cf. Henderson *et al*., 1998; Roedder John *et al*., 2006, Till *et al.*, 2011). This study instead investigates brand associations through the observation of consumer interactions in an online community (a qualitative method) and text mining to analyse the language used to discuss brands during these interactions (a quantitative method). The advantages of this two-pronged approach will be discussed in the following paragraphs.

The qualitative component of this study is broadly inspired by a research method known as netnography, developed by Kozinets (2002) to understand the interactive processes of a community of consumers through their computer-mediated discourses, rather than data collected from live encounters. With respect to the traditional approaches to brand association research mentioned above, netnography is less obtrusive and allows researchers to access and collect data from larger numbers of participants in a relatively easy manner. It can also be an effective way to analyse brand associations in communities of consumers where conventional forms of access may be difficult (cf. Langer and Beckman, 2005). For example, consumers of fashion interact extensively by means of digital platforms (cf. Thomas *et al.*, 2007; Rickman and Cosenza, 2007). These interactions provide textual resources that often contain well-articulated expressions of brand-related perceptions among fashion consumers. As a consequence, fashion marketers have begun to recognize that trend watching and word-of-mouth monitoring of the online community are important tools for keeping up with today's fashion-conscious and fickle consumers (Kim and Jin, 2006). Indeed, the analysis of an online fashion community can promote the development of the relational and distinctive power of a brand that represents a strong point of convergence between consumer and market (Fournier, 1998). In internationalization processes, fashion companies consider consumer knowledge as a strategic resource to discover market diversities and enhance brand identity. Given the important role of consumer brand knowledge and perceptions in the fashion industry, an online fashion community has been selected as the context of research for the present study.

As a quantitative method, text mining refers to the extraction of information from relatively large amounts of electronically-stored textual data by means of computer applications (Witten, 2005). Its distinguishing feature is the capacity to derive new types of information from textual data sources (e.g., overviews of thematic content across texts, graphical visualizations of news cycles), thus going beyond simple information access and retrieval (Hearst, 1999). This is accomplished by inserting metadata (i.e., data about data) into text files, often in the form of descriptive tags that label items according to specific criteria, such as part-of-speech category or semantic domain. In this way, it is possible to discover important trends and patterning across textual data that could not otherwise be detected. Empirical data that emerge from text mining procedures can also serve as a launching pad for follow-up in-depth qualitative analysis that provides additional insights into language usage. Clearly, text mining can provide a wealth of information about how language is used in communicative situations of interest to researchers.

The potential of text mining to offer new insights into consumer perceptions has begun to be tapped in some recent marketing research. In a practice-oriented article, Rickman and Cosenza (2007) briefly illustrate how a text mining tool can be applied to trend forecasting by tracking ‘buzz’ (i.e. key words and phrases) in fashion weblogs. Reyneke (2011) applied the content analysis software Leximancer to produce simple visual concept maps of consumer conversations about luxury brand advertisements that had been posted on YouTube. Using customer reviews of electronic products on Amazon.com, Archak *et al*., (2007, p. 56) combined text mining and econometrics to “extract actionable business intelligence from the data and better understand the consumer preferences and actions”. Lee and Bradlow (2011) implemented text mining to automatically generate and examine product attributes for purposes of market structure analysis. Text mining was proposed as a way to complement existing methods and also reveal new product attributes that cannot be identified with traditional approaches.

While the studies described above have used text mining techniques to shed light on consumers' attitudes towards brands, they do not distinguish how perceived attributes may come together to form unique brand associations. To do so requires not only the identification of brand associations in the discourse of consumers, but also a systematic analysis of the language used to describe them. Towards this goal, in the following section we propose an innovative and interdisciplinary methodology that combines techniques from qualitative market research and computer-assisted linguistic analysis.

Methodology

This section provides a step-by-step description of the integrated approach presented above. According to guidelines established for netnographic studies of online communities (Kozinets, 2002), the analysis is articulated into the following phases: identification of data source, data collection and compilation, data analysis and data interpretation.

Identification of data source

The initial step was to find a source of online data that would be appropriate for the fashion brand focus of the research. After careful consideration, the authors opted to access a fashion blog rather than a fashion forum. Fashion blogs contain texts written by both experts (opinion leaders) and enthusiasts (consumers), and are therefore often considerably richer than those typically found in fashion consumer forums. At the same time, fashion blogs can be seen as a community or "ecosystem" in which everyone is a "real" consumer (Pettit, 2010, p. 241), and thus representative of fashion consumers in general. Among the myriad of fashion blogs found on the Internet today, Style.com was selected as the most suitable for the research goals for several reasons. First, it consistently ranks highly according to well-established blog rating criteria, including membership, Alex traffic data, number of indexed pages and incoming links. Posts/comments on Style.com are also available for approximately three years which enabled the collection of a sufficient amount of data for an exploratory study. In addition, a preliminary perusal of Style.com posts showed that they dedicate considerable space to well-known fashion brands, unlike other top-ranking fashion blogs that focus more on street fashion, celebrities or gossip. Finally, Style.com is a multi-authored blog written by both staff and guest contributors, thus better reflecting the idea of an online community with respect to some popular single-author fashion blogs.

Data collection and compilation

After identifying Style.com as the data source, the authors decided to focus the analysis on the brand associations of three leading Italian fashion companies: Valentino, Dolce & Gabbana and Giorgio Armani. All three are globally-recognized brands and have well-consolidated processes of internationalization. They also represent brands that are closely identified with iconic personalities and the world of luxury, thus offering the type of rich and articulated comments that have been linked to consumers of fashion (Xun and Reynolds, 2010). Data were then collected from all the blog posts that contained comments about the three brands, i.e., where the brand names appeared at least once. This selection process was facilitated by the tagging and search tools provided on the Style.com website. The data were then compiled into three separate datasets to represent each brand. To identify the degree of brand association matching, the authors collected three parallel datasets based on company communications, including presentational information and brand-related press releases found on websites, non-financial narrative from annual reports and interviews with house designers published in mainstream media sources. In this way, the textual data not only suit the aims of the research, but also follow the principle of *tertium comparationis*. This is a fundamental premise of contrastive discourse studies: texts compared must differ in some respects, but also present some degree of sameness to justify the comparison (Connor and Moreno, 2005). In this case, the blogs and company communications have similar overall content linked to the brand. However, unlike the company-produced texts, blogs are generated by third parties over whom the company has no control (cf. Keller and Lehman, 2006). This key difference can reveal insights into potential match or mismatch in brand associations. Table 1 provides an overview of the data sources.

Table 1 about here

Data analysis

The text mining software *WMatrix* (Rayson, 2008) was first used to identify broad categories of brand associations in the fashion blog datasets by extracting keywords which reveal the 'aboutness' of a text (Scott and Tribble, 2006). The software generated a frequency list of all the words contained in the three combined blog text files (34,529 words total), which was then compared to a larger normative dataset, i.e., the British National Corpus sampler of spoken English (982,712 words). The log-likelihood (LL) statistical measure incorporated in *WMatrix* identified words that appeared with significantly higher frequencies in the fashion blogs in comparison to the normative dataset (i.e., keywords). The log-likelihood value takes into account the word frequencies of the two datasets (observed values) and calculates expected values (see Appendix A for details). This procedure enabled the identification of three brand association categories: *product-related attributes*, *non-product related attributes* and *designer identity*. The keyword analysis will be thoroughly illustrated in the Results section.

The authors then carefully read the three fashion blog datasets to locate each mention of the brand in question and, on the basis of contextual cues, label it according to three brand association categories that emerged from global keyword analysis described above. Although this process was rather straightforward, to avoid possible mislabelling, the procedure was carried out separately by the authors, who then compared their results in order to determine the reliability of the labelling process. Inter-rater reliability was 88.6%, i.e., the percentage of brand associations that were labelled in the same way by the authors out of the total number identified in the corpus. Consensus was reached for the remaining percentage. This procedure served not only to confirm the categories that had emerged in the automated global keyword analysis, but also to compare brand association categories across the three brands.

The authors then conducted a systematic analysis of the adjectives used by fashion bloggers to characterize brand associations. This was possible thanks to *WMatrix* which automatically tags each word according to its part-of-speech, thus enabling the extraction of complete adjective lists for each dataset. Following Lyons (1995), we assume that there is an intrinsic link between language and meaning: the words that we use encode our perceptions, attitudes and emotions. The extracted adjectives were then examined qualitatively in their context of usage to verify their reference to the three brands in question. Because each of the datasets contained several hundred adjectives (average of 677), this was limited only to items with a minimum frequency of five, which is also the default cut-off frequency utilized by *WMatrix* for keyword analysis as described previously.

To tease out even more adjectives, separate searches were performed on some words that had emerged as statistically significant in the keyword analysis and were conceptually linked to brand associations (e.g. *collection*, *designer*, *fashion*). This process was manageable due to their relatively low frequencies. In this way, it was possible to identify additional adjectives that had been used in concomitance with these words, even if their frequencies were lower than five. This two-pronged procedure resulted in three composite lists of adjectives used to characterize brand associations for each fashion blog dataset. These lists were then cross-checked with adjective lists extracted from the three parallel datasets of company communications in order to distinguish common items. Appendix C shows samples of adjectives extracted by *WMatrix* for all the datasets. A percentage of match was calculated in terms of overlapping adjectives, or the ratio between the total number of adjectives found in the blog datasets and the number of adjectives in common with the company communications datasets, i.e., the texts collected from the three companies' websites, annual reports and published interviews. The adjectives of all the datasets were then manually examined to identify potential themes reflected in semantically-related sets of adjectives as a way to gain further insights useful for shaping and refining brand strategy.

Data interpretation

Each of the above phases of analysis led to progressively fine-tuned results which combined specific competencies associated with market research and linguistic analysis. The findings were then interpreted in relation to their implications for brand strategy. In particular, companies may exploit this knowledge to make and implement decisions involving the reinforcement or the revitalization of brand associations as sources of brand equity (Keller, 2003b).

Results and discussion

Keyword analysis

The keyword analysis is illustrated in the *WMatrix* screenshot reproduced in Figure 1. The software generated a word cloud for the three combined fashion blog datasets showing items having statistically higher frequencies when compared to a normative dataset of general spoken English (see Methodology section).

Figure 1 about here

To be statistically significant at the .01 level, the items must have an LL (log-likelihood) value above 6.63, which is the cut-off level for 99% level of confidence (Rayson, 2008). Although all the words in the cloud have LL values higher than 6.63, those in larger fonts have particularly high frequencies across the datasets. The higher the frequency, the higher the LL value, or keyness score (Rayson, 2008). For example *designer*, *collection* and *dresses* have respective LL values of 185.70, 77.64 and 73.73, and are thus more 'key' than items such as *Italian*, *celebrity* and *classic* with respective LL values of 58.21, 43.04 and 36.22 (see Appendix B for details of the LL analysis results).

The word cloud in the figure shows that many keywords denote products, designers, events and personalities linked to the fashion world, representing three major categories of brand associations: product-related attributes, non-product related attributes, and designer identity. While the first two categories clearly reflect Keller's (1993) framework, the strong presence of designers' proper names suggested the need for a specific category, corroborating Thomas *et al.*'s (2007) work which also found references to individual designers in their analysis of an online fashion forum. In the case of Valentino, designer identity comprehends not only the founder of the fashion house, but also other house designers who are well-known among fashion enthusiasts. Table 2 provides a description of the categories, along with illustrative textual samples from the blog text files.

Table 2 about here

Comparative analysis

The comparative analysis of brand association categories across the three datasets is shown in Table 3. The data are presented in both raw frequency counts of categories manually labelled in the blog files and the normalized value of instances per 1000 words (PTW). This parameter provides a more accurate profile of variation since the three datasets have different lengths (i.e., total word counts), as shown in Table 1.

Table 3 about here

On a general level, Table 3 shows substantial homogeneity in terms of the frequency of brand associations that emerge from the three fashion blogs, ranging from 9.18 to 10.17 PTW. This can be an indicator of a relatively high level of competition among the three brands (Punj and Moon, 2002). However, at the level of individual brands, there are some interesting differences shown by the wider range of PTW values across the three categories. The Valentino brand has a higher level of brand associations linked to designer identity (5.31 PTW), with Valentino himself contributing 3.84 PTW to this total. This is somewhat surprising considering the fact that the company has made a strong effort to distinguish the brand identity from the person of Valentino after he relinquished ownership (Burresi and Ranfagni, 2011). Apparently, fashion bloggers still tend to associate the brand with its founding designer. Dolce & Gabbana instead has relatively high levels of product-related attributes (5.79 PTW). Product-related attributes similarly characterize Armani brand associations (4.20 PTW), although we also find a relatively strong designer identity (3.11 PTW). Moreover, considering that Armani also has the highest level of non-product related attributes (2.27 PTW), it would seem that consumers perceive its network of brand associations in a more balanced way in comparison with the other two brands (Broniarczyk and Gershoff, 2003).

Adjective analysis

As anticipated in the methodology section, it was necessary to verify which adjectives extracted from the three fashion blog datasets actually referred to the brands in question. Therefore, the output had to be extensively edited to remove those adjectives that qualified other brands or non-brand related entities. This was accomplished by carefully examining the adjectives within their context of usage to identify such unwanted items. A case in point is the adjective *new* frequently found in name of the city *New York*. This labour-intensive process was facilitated by using a concordancer, i.e., a text analysis tool that generates vertical lists of each instance of the adjective along with some co-text to the right and left. In some cases, concordances did not present sufficient text to determine the referents of adjectives, so it was necessary to return to the complete text file for more extensive analysis of context. Figure 2 illustrates a sample of edited concordances for the adjective *new*.

Figure 2 about here

From the combined text mining procedures and follow-up qualitative analysis, composite lists of adjectives for the fashion blog datasets were produced. Table 4 shows the adjectives used to characterize brand associations for each fashion brand, common adjectives detected through cross-checks with adjective lists extracted from company communications (see Appendix B), and the percentage of match in terms of overlapping items.

Table 4 about here

As can be seen, the percentage of match (i.e., alignment between brand associations defined by the companies and those perceived by the bloggers) across the pairs of datasets for each of the three luxury fashion brands is roughly similar, ranging from 46.9% to 52.9%. The authors interpret these values as substantial brand association matching since the adjectives used by the multiple participants within the online community converged with those found in texts produced by the company as a single entity. This result contrasts with Ross and Harradine’s (2011) study where substantial misalignment was found between intended brand identity and perceived brand image for supermarket clothing brands, suggesting that brand association matching in high-end vs. low-end products would warrant further investigation.

In several cases, in the blog datasets it was possible to identify other adjectives that are semantically linked to common items (see Table 4). For example, in the adjective list for the Valentino blog dataset, in addition to *light* and *airy*, we also find *lacy*, *gossamer-light*, *paper-thin*, *peep-toe*. In the context of fashion, these can be interpreted as semantically related to *light* and *airy*, thus forming what the authors define as a 'brand association theme'. This and other theme-based adjective sets that emerged from the lists in Table 4 are illustrated in Figure 3.

Figure 3 about here

The above results indicate that the three brands have largely succeeded in aligning brand associations defined by the company with those perceived by consumers. Moreover, the presence of semantically-related sets of adjectives that suggest key themes also reflects strong internal brand cohesiveness (Keller, 1993). It was interesting to see that in some cases the fashion bloggers introduced creative alternatives such as *gossamer-light*, *curve-enhancing*, *razor-sharp* and *bejewelled* that reinforced and revitalized the company-defined brand associations. This type of knowledge can allow the companies to determine which shared brand associations are particularly strong in the consumer's mind, thus providing important indications for brand strategy. For example, the awareness of highly nuanced brand associations can be exploited to improve competitive positioning and marketing communications.

The analysis of brand association themes was also undertaken from the perspective of the three companies. In this case, some themes that were identified among the adjectives extracted from the company communications dataset (see Appendix C), were instead largely absent from the corresponding blog datasets. For example, in Valentino company communications we find the theme of modernity in the adjectives *modern, contemporary,* and *young*. In Dolce & Gabbana, colour is a key theme, seen in *black, white, blue, grey, red, brown* and *golden*. Armani communications contain adjectives that evoke the theme of sophistication (*sophisticated, glossy, exclusive* and *aesthetic*). However, these themes that were promoted by the companies in their communications did not emerge in the adjectives used by bloggers to characterize the brands, and therefore may not be components of their brand knowledge (Esch *et al*., 2006). If instead they represent brand associations that companies wish to reinforce, then they should engage in strategies to transfer these components of brand identity (Keller, 2003b).

To summarize the results of this multi-faceted analysis, three types of brand associations linked to product attributes, non product-related attributes and designer identity were consistently present across the three fashion brands investigated. This suggests that they form a core of consumer brand knowledge of luxury fashion brands. There was also a relatively high level of brand association matching, calculated by the percentage of overlap between adjectives used by consumers to characterize the brand associations and those used by the fashion companies in their brand-related communications. In addition, some distinct brand association themes emerged from a qualitative analysis of semantically-related sets of adjectives. This served to highlight themes that were perceived as particularly strong among the consumers, as well as some that were missing.

Conclusion and managerial implications

This paper has proposed a new methodological approach to identify consumer brand associations and to determine the degree of matching with the company’s definition of the brand. It combined quantitative text mining and qualitative market research methods to systematically analyse texts produced by online consumers. This allowed us to discover highly articulated representations of brand associations in terms of descriptive adjectives and some key themes that emerged from them. With respect to traditional techniques involving focus groups or interviews that have been used to study brand associations (cf. Henderson *et al*., 1998; Roedder John *et al*., 2006, Till *et al.*, 2011), the interdisciplinary methods presented here offer important advantages. First, the analysis of consumer discourse with linguistic software enables the identification of brand associations at a level of detail and refinement that could not be otherwise achieved. Second, the use of online communities greatly increases the number of consumers that can be accessed for market research, while also facilitating the collection of naturalistic data from authentic interactions.

The approach presented in this study has enabled us to respond to the three research questions posited at the outset. The first question asked how consumer brand associations can be identified in online communities. The keyword analysis of the combined fashion blog datasets performed by the software *WMatrix* (Rayson, 2008) revealed three main types of brand associations linked to the fashion brands. In addition, the comparative analysis of the three datasets highlighted broad similarities in terms of the brand association categories that emerged, as well as some interesting differences in terms of which categories were more or less prominent. In this exploratory study, these methods were implemented to analyse brand associations in the online fashion community with reference to three brands. However, they could also be effectively used with larger samples which contain more data for each brand and/or comprise a larger range of brands.

The second research question asked how the degree of matching between consumer and company-defined brand associations can be determined. This was answered though a targeted analysis of adjectives as expressions of brand associations (Maehle and Supphellen, 2011; Plummer, 1985). The degree of match was determined by the percentage of overlapping between the adjectives referring to the three brands in blog datasets and those found in company communications. This quantitative analysis revealed substantial alignment for all three brands, with percentages of exact match of roughly 50%.

The third research question asked what themes emerge in brand association matching and what are the implications for brand strategy. Through a qualitative analysis of the adjectives found in the datasets, it was possible to identify sets of semantically-linked adjectives that reflected highly nuanced themes unique to the brands in question. The presence of these theme-based sets served to reinforce and extend the quantitative measure of single matching adjectives described above. In addition, the themes that emerged from company adjective lists, which were instead missing in the fashion blogs, enabled the identification of brand associations considered important to the company, but apparently not perceived by consumers. On a practical level, this method would enable managers to identify the 'dark side' of consumer perceptions, i.e. those perceptions that may exist, but which consumers may be reticent to express using traditional and more intrusive market research tools. This type of knowledge can enable managers to acquire a deeper understanding of consumer perceptions which may be utilized to shape or re-define brand identity and thus drive brand strategy.

While our exploratory study has yielded insights into consumer vs. company-defined brand associations, it is not without limitations. As previously mentioned, it would be useful to enlarge and extend the datasets to render findings more generalizable. In addition, this type of contrastive analysis could be further strengthened if companies could provide specific information regarding the key brand associations that they intend for consumers to perceive, perhaps in the context of personal interviews with brand managers.

The integrated approach implemented in this study has important managerial implications. It represents a structured process that investigates brand association matching by exploiting information from an online community, without directly involving the consumer or using complex mathematical and statistical techniques (cf. Roedder John *et al*., 2006). In other words, it provides managers with a more accessible way to analyse brand associations as perceived by online consumers. Although the application of this method clearly requires a strong integration between language skills and managerial skills, the quantitative and qualitative dimensions of the approach can be articulated into different levels of complexity. This allows managers to choose the desired degree of depth for analysing brand association matching.

The study provides insights into the differentiating power of a brand. In particular, its analytical tools are able to: a) determine whether the unique brand associations in the mind of the consumer correspond to the attributes that define competitive positioning, b) reveal possible new themes of brand associations represented by adjective sets generated by online communities, and c) analyse ex-post the impact of new brand associations as expressed in specific marketing actions (e.g., new communications, distribution, sponsorship) on existing brand representations. An in-depth understanding of brand associations would also be useful for strategies of brand extension, when a company has to decide how to transfer specific attributes from an existing brand to a new product category (Aaker and Keller, 1990; Day *et al*., 1979; Hatch and Shultz, 2001; Tauber, 1981).

The methods utilized in this study also have the advantage of allowing managers to analyse brand associations with reference to competitors. This process would be facilitated by using information that is easily accessible at relatively low costs, which can then be analysed with targeted research methods. In other words, managers can analyse levels of matching with competitors through cross-brand comparisons between adjectives used by consumers and by competitors to characterize brand associations. The methodology therefore constitutes a valuable tool for an intelligent analysis of competition.

Companies could also benefit from integrating these methods with other more traditional qualitative and quantitative research methodologies (e.g., focus groups, in-depth personal interviews). This would be useful for a more refined analysis of the relationship between fashion brands and consumption behaviour, particularly to investigate in greater depth the specific reasons underlying consumption and the relationship with the brand.

The methodological approach applied in this study can be easily transferred to other research domains. Beyond the fashion community, it can be used to examine any marketing context where a brand is characterized by a strong identity and therefore high potential for interaction. The approach can also be utilized to explore perceptions of brand associations among consumers in markets that differ in terms of culture, traditions and relationships with the consumer. More specifically, it can be useful for enterprises that are consolidating their processes of internationalization in different foreign markets, especially when deciding whether to adapt or propose the same brand identity for different markets.

An interesting topic for future research would be an in-depth analysis of brand associations in relation to other attributes, such as country of origin. This would entail the creation of datasets of consumer blogs related to companies that make country of origin one of their distinctive attributes. In this case, an analysis of brand associations would lead to a better understanding of the cultural dimension of consumer brand knowledge. Another area of research focus could be synergies between brand association matching, consumer attitude and indicators of brand performance, e.g., price, market share and sales. This could be achieved by integrating additional secondary data and performing further refined linguistic analysis to reveal positive or negative attitudes in brand associations. A system of interactions between these indicators and brand associations could be delineated as a way to orient brand strategy. The new approach proposed in this study could thus be developed to a fuller potential.

References

Aaker, D. A., and Keller, K. L. (1990), "Consumer evaluations of brand extensions", *Journal of Marketing*, Vol. 54, No. 1, pp. 27-41.

Aaker, D. A. (2003), "The power of the branded differentiator", *MIT Sloan Management Review*, Fall, pp. 83-87.

Anderson, J. R. (1983), *The Architecture of Cognition*, Harvard University Press, Cambridge, MA.

Biel, A. L. (1991), "*The Brandscape. Converting Image into Equity"*, ADMAP, Vol. 26, October, pp. 41-46.

Archak, N., Ghose, A. and Ipeirotis, P. G. (2007), "Show me the money!: deriving the pricing power of product features by mining consumer reviews", in *Proceedings of the 13th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, San Jose, CA, 2007, ACM, San Jose, CA, pp. 56-65.

Brandt, C., De Mortanges, C. P., Bluemelhuber, C. and Van Riel, A. C. R. (2011), "Associative networks. A new approach to market segmentation", *International Journal of Market Research* Vol. 53, No. 2, pp. 187-208.

Bridges, S., Keller, K. L. and Sood, S. (2000), "Communication strategies for brand extensions: enhancing perceived fit by establishing explanatory links", *Journal of Advertising*, Vol. 29, Winter, pp. 1-11.

Broniarczyk, S. M. and Gershoff, A. D. (2003), "The reciprocal effect on brand equity and trivial attributes", *Journal of Marketing Research*, Vol. XL, May, pp. 161-175.

Broniarczyk, S. M. and Alba, J. W.(1994), "The importance of brand in brand extension", *Journal of Marketing Research*, Vol. 23, May, pp. 214-228.

Burresi, A. and Ranfagni, S. (2011), "Congruity brand image and multichannel distribution in fashion companies", in Andreani, J. C. and Collesei, U. (Eds.), *Proceedings of 10th International Marketing Trends Conference, Paris, 2011*, Marketing Trends Association, Paris-Venice, pp. 1-35.

Carpenter, G. S., Glazer, R. and Nakamoto, K. (1994), “Meaningful brands from meaningless differentiation: the dependence on irrelevant attributes”, *Journal of Marketing Research*, Vol. 3, August, pp. 339-350.

Connor, U. M. and Moreno, A. I. (2005), “Tertium comparationis: a vital component in contrastive rhetoric research”, In Bruthiaux, P., Atkinson, D., Eggington, W. G., Grabe, W and Ramanathan, V. (Eds.), *Directions in Applied Linguistics Essays in Honor of Robert B. Kaplan*, Multilingual Matters, Clevedon, UK, pp. 155-164.

Cova, B. (1997), “Community and consumption: towards a definition of the linking value of product or services”. *European Journal of Marketing*, Vol. 31, No. 3/4, pp. 297-316.

Dahlen, L. M., Sjödin, H. and Törn, F. (2005), “Effect of ad-brand incongruency”, *Journal of Current Issues & Research in Advertising*, Vol. 27, No. 2, pp. 1-12.

Day, G. S., Shocker, A. D. and Srivastava, R. K. (1979), “Customer-oriented approaches to identifying product-markets”, *Journal of Marketing*, Vol. 43, No. 4, pp. 8-19.

De Valck, K. (2005), “*Virtual Communities of Consumption: Networks of Consumer Knowledge and Companionship”,* ERIM PhD, Series: Research in Management.

Esch, F. R., Langner, T., Schmitt, B. H. and Geus, P. (2006), “Are brands forever? How brand knowledge and relationships affect current and future purchases”, *Journal of Product & Brand Management*, Vol. 15, No. 2, pp. 98-105.

Fournier, S. (1998), “Consumers and their brands: developing relationship theory in consumer research”, *Journal of Consumer Research*, Vol. 24, March, pp. 343-373.

Grime, I., Diamantopoulos, A. and Smith, G. (2002), “Consumer evaluations of extensions and their effects on the core brand: key issues and research propositions”, *European Journal of Marketing*, Vol. 36, No. 11/12, pp. 1415-1438.

Gwinner, K. P. and Eaton, J. (1999), “Building brand image through event sponsorship. The role of image transfer”, *Journal of Advertising*, Vol. 28, No. 4, pp. 47-57.

Hatch, M. J. and Schultz, M. (2001), “Are the strategic stars aligned for your corporate brand”, *Harvard Business Review*, Vol. 79, February, pp. 129-134.

Häubl, G. and Elrod, T. (1999), “The impact of congruity between brand name and country of production on consumers’ product quality judgments”, *International Journal of Research in Marketing*, Vol. 16, No. 3, pp 199-215.

Hearst, M. A. (1999), “Untangling text data mining”, paper presented at the 37th Annual Meeting of the Association for Computational Linguistics, University of Maryland, June 20-26, available at: http://people.ischool.berkeley.edu/~hearst/papers/acl99.pdf. (accessed on July 9, 2011).

Henderson, G. R., Iacobucci, D. and Calder, B.J. (1998), “Brand diagnostics: mapping branding effect using consumer associative networks”, *European Journal of Operational Research*, Vol. 111, December, pp. 306-327.

Keller, K. L. (1993), “Conceptualizing, measuring and managing customer-based brand equity”, *Journal of Marketing*, Vol. 57, January, pp. 1-22.

Keller, K. L. (2003a), “Brand synthesis: the multidimensionality of brand knowledge”, *The Journal of Consumer Research*, Vol. 29, March, pp. 595-600.

Keller, K. L. (2003b), *Strategic Brand Management: Building, Measuring, and Managing Brand Equity. 2nd Edition*, Pearson, Upper Saddle River, NJ.

Keller, K. L. and Lehmann, D. R. (2006), “Brands and branding: research findings and future priorities”, *Marketing Science*, Vol. 25, No. 6, pp. 740-759.

Kim, H. S. and Jin, B. (2006), “Exploratory study of virtual communities of apparel retailers”, *Journal of Fashion Marketing and Management*, Vol. 10, No. 1, pp. 41-55.

Kozinets, R. V. (2002), “The field behind the screen: using netnography for marketing research in online communities”, *Journal of Marketing Research*, Vol. XXXIX, February, pp. 61-72.

Langer, R. and Beckman, S. C. (2005), “Sensitive research topics: netnography revisited”, *Qualitative Market Research*, Vol. 8, No. 2, 189-203.

Lee, T. Y. and Bradlow, E. T. (2011), “Automated marketing research using online customer reviews”, *Journal of Marketing Research*, Vol. 48, No. 5, pp. 881-894.

Lyons, J. (1995), *Linguistic Semantics. An Introduction*, Cambridge University Press, Cambridge, UK.

Madhavaram, S., Badrinarayanan, V. and McDonald, R. E. (2005), “Integrated marketing communication (IMC) and brand identity as critical components of brand equity strategy”, *Journal of Advertising*, Vol. 34, No. 4, pp. 69-80.

Maehle, N. and Supphellen, M. (2011), “In search of the sources of brand personality”, *International Journal of Market Research*, Vol. 53, No. 1, pp. 95-114.

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

Pechmann, C., and Ratneshwar, S. (1991), “The use of comparative advertising for brand positioning: association versus differentiation”, *Journal of Consumer Research*, Vol. 18, No. 9, pp. 145-160.

Pettit, R. (2010), “Digital anthropology: how ethnography can improve online research”, *Journal of Advertising Research*, Vol. 50, No. 3, pp. 240-242.

Plummer, J. T. (1985), “How personality makes a difference”, *Journal of Advertising Research*, Vol. 24, No. 6, pp. 27-31.

Punj, G. and Moon, J. (2002), Positioning options for achieving brand association: a psychological categorization framework, *Journal of Business Research*, Vol. 55, No. 4, pp. 275-283.

Rayson, P. (2008), “From key words to key semantic domains”, *International Journal of Corpus Linguistics*, Vol. 13, No. 4, pp. 519-549.

Reyneke, M. (2011), “In the lap of luxury: consumer conversation concerning online advertisements of luxury brands”, *South African Journal of Business Management*, Vol. 42, No. 2, pp. 27-34.

Rickman, T. A. and Cosenza, R. M. (2007), “The changing digital dynamics of multichannel marketing. The feasibility for the weblog: text mining approach for fast fashion trending”, *Journal of Fashion Marketing and Management*, Vol. 11, No. 4, pp. 606-621.

Roedder John, D., Loken, B., Kim, K. and Monga, A. B. (2006), “Brand concept maps: a methodology for identifying brand association networks”, *Journal of Marketing Research*, Vol. XLIII, November, pp. 549-563.

Romaniuk, J. and Gaillard, E. (2007), “The relationship between unique brand associations, brand usage and brand performance: analysis across eight categories”, *Journal of Marketing Management*, Vol. 23, No. 4, pp. 267-284.

Ross, J. and Harradine, R. (2011), “Fashion value brands: the relationship between identity and image”, *Journal of Fashion Marketing and Management*, Vol. 15, No. 3, pp. 306-325.

Scott, M. (2010), *Wordsmith Tools Version 5.0,* Oxford University Press, Oxford.

Scott, M. and Tribble, C. (2006), *Textual Patterns: Key Words and Corpus Analysis in Language Education*, John Benjamins, Philadelphia.

Sjödin, H. and Törn, F. (2006), “When communication challenges brand associations: a framework for understanding consumer responses to brand image incongruity”, *Journal of Consumer Behaviour*, Vol. 5, No. 1, pp. 32-42.

Supphellen, S. (2000), “Understanding core brand equity: guidelines for in depth elicitation of brand associations”, *International Journal of Market Research*, Vol. 3, No. 3, pp. 319-338.

Szmigin, I., Canning, L. and Reppel, A. E. (2005), “Online community: enhancing the relationship marketing concept through customer bonding”, *International Journal of Service Industry Management*, Vol. 16, No. 5, pp. 480-496.

Tauber, E. M. (1981), “Brand franchise extension: new product benefits from existing brand names”, *Business Horizons*, Vol. 24, No. 2, pp. 36-41.

Till, B. D., Baack, D. and Waterman B. (2011), "Strategic brand association maps: developing brand insight", *Journal of Product & Brand Management*, Vol. 20, No. 2, pp. 92- 100.

Thomas, J. B., Peters, C. O. and Tolson, H. (2007), "An exploratory investigation of the virtual community MySpace.Com. What are consumers saying about fashion?", *Journal of Fashion Marketing and Management*, Vol. 11, No. 4, pp. 587-603.

Witten, I. H. (2005), "Text mining," In Singh, M. P. (Ed.), *Practical Handbook of Internet Computing*, Boca Raton, Florida, Chapman & Hall/CRC Press, pp. 14-1 - 14.22.

Xun, J. and Reynolds, J. (2010), "Applying netnography to market research: the case of the online forum", *Journal of Targeting, Measurement and Analysis for Marketing*, Vol. 18, No. 1, pp. 17-31.

Table 1. Fashion brand data sources

Brand	N. blog posts	N. user comments	Blog timeframe	Blog dataset word count	Company text dataset word count
Valentino	36	38	Aug 2008 – July 2011	8836	6322
Dolce & Gabbana	48	103	Sept 2008 – July 2011	13,809	6765
Giorgio Armani	41	60	Aug 2008 – July 2011	11,884	9749

Table 2. Brand association categories

Categories	Description	Examples
Product-related attributes	Comments relating to the distinctive characteristics of the brand, products campaigns and collections	- Dolce & Gabbana is a classic brand with beautiful timeless pieces. - In a perfect world, we'd be dancing the night away in these bow-embellished Valentino pumps. - I love the Giorgio Armani Fall 2010 collection. The black beret and glasses give it that uniform look.
Non product-related attributes	Comments relating to celebrities who wear products and social events that involve/promote the fashion house	- Paltrow went hard-edged in a Giorgio Armani tailored blazer and shorts suit with jet black accessories. - Expect plenty of Valentino: label heavy and jewelry designer Carlos de Souza is doing the list this year, and the house is co-sponsoring the event. - Dolce & Gabbana's massive new book, "Diamonds and Pearls," seems like a straightforward celebration of the pair's gran amor for embellishment.
Designer identity	Comments relating to the fashion designers associated with the brand	- Valentino is looking a tad too tan lol. - Alessandra Facchinetti, formerly of Gucci and Valentino, has found new life working on Tom Ford's womenswear. - The Gabbana half of Dolce & Gabbana hates strawberries in winter and buying fur coats in July. - The famously controlling Mr. Armani is letting go just a little.

Table 3. Distribution of brand association categories across fashion blog datasets

	Product-related attributes		Non product-related attributes		Designer identity		Totals	
	N	PTW	N	PTW	N	PTW	N	PTW
Valentino	32	3.62	11	1.24	34[a] 13[b]	3.84 1.47	90	10.17
Dolce & Gabbana	80	5.79	27	1.95	20	1.44	127	9.18
Armani	50	4.20	27	2.27	37	3.11	114	9.58

a = Valentino Garavani
b = Other house designers

Table 4. Adjectives characterizing brand associations fashion blogs and company communications

	Fashion blogs	Common items in company communications	% match
Valentino	new (8), Italian (7), beautiful (6), creative (3), red (4), old, white, long, lacy, gossamer-light, airy, feminine, light, stylish, paper-thin, indigo, poetic, adorable, cute, elegant, bow-embellished, peep-toe, studded, expressive, cinematic, unique, important, iconic, arrogant, proud, retired, tan	new, Italian, beautiful, creative, red, airy, feminine, white, elegant, light, stylish, iconic, unique, important, retired	46.9%
Dolce & Gabbana	new (8), beautiful (5), sexy (5), classic (5), chic (4), white (4), great (2), Italian, modern (2), simple (2), clean, crisp, razor-sharp, elegant, sophisticated, timeless, cute, sweet, innocent-looking, traditional, old-fashioned, not-so-traditional, feminine, femme-fatale, pink, seductive, curve-enhancing, jewel-toned, dreamy, massive, piped, quilted, masterful, bank-breaking	new, beautiful, sexy, classic, white, great, Italian, modern, simple, elegant, timeless, sweet, traditional, feminine, pink, seductive, massive, quilted	52.9%
Giorgio Armani	new (8), black (8), Italian (2), uniform (2), great (5), favorite (2), good (3), white (3), navy (2), glittering, starry, high-end, silk, backless, gorgeous, metallic, round-shouldered, sequined, bejeweled, undulating, short, tailored, hard-edged, cobalt-beaded, fluid, soft, shawl-collared, velvet-lapelled, controlling, elegant, trendy, wearable, pink, mostly-mesh, luxury, unstructured, chocolaty, textured	new, black, Italian, great, favorite, white, glittering, high-end, silk, metallic, undulating, short, tailored, fluid, soft, elegant, pink, luxury, unstructured	50.0%

(N) = number of occurrences >1

Figure 1. Keyword cloud for the three combined fashion blog datasets

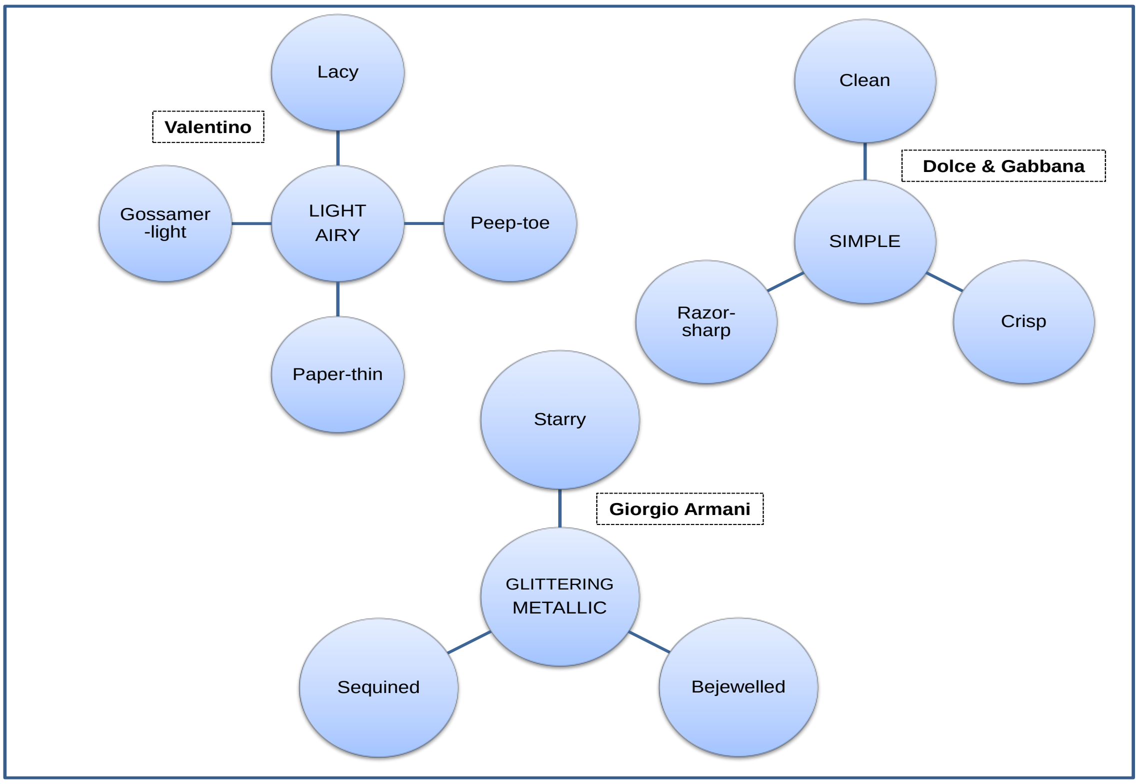
Source: *WMatrix* (Rayson, 2008)

Figure 2. Sample of selected concordances for *new*

N	Concordance
1	a massive handcrafted rose; the New Dentelle, which creates a “new lace” with lasered ponyskin and tulle; and the Cabochon,
2	to purchase when you go to the stores. Sneak Peek: Valentino’s New Ten-Pack Tonight at its Madison Avenue boutique, Valentino
3	the everyday practicality of a tote. The bags go on sale now, with new styles to be released month by month in the year ahead.
4	here); the Pétale, bedecked by a massive handcrafted rose; the New Dentelle, which creates a “new lace” with lasered ponyskin
5	and Stefano Guindani’s book of photographs of the Haiti. Their new, delicately ruffled white tees are also being sold to benefit
6	Facchinetti, formerly of Gucci and Valentino, has found new life working on Tom Ford’s womenswear. As for Ford, he has
7	of their homes.” Above, an exclusive first look at Saner in the new campaign. Send Off 2010, Sealed With A Bow If you haven’t
8	after his father? On Our Radar: Valentino Resort Backpacks The new stewards of Valentino, Maria Grazia Chiuri and Pier Paolo

Source. *Wordsmith Tools* (Scott 2010)

Figure 3. Brand association themes



Appendix A

Log-likelihood is calculated according the following formulae:

$$E_i = \frac{N_i \sum_i O_i}{\sum_i N_i}$$

$$-2\ln\lambda = 2\sum_i O_i \ln\left(\frac{O_i}{E_i}\right)$$

Legend. N: number of words in the datasets, O: the observed values, E: the expected values. Further details about the calculation of log-likelihood by *WMatrix* can be found at:

http://ucrel.lancs.ac.uk/llwizard.html

Appendix B. Log-likelihood (LL) values of top 30 items

Item	O1	%1	O2	%2	LL value
valentino	60	0.77	0	0.00	+581.17
designer	20	0.26	1	0.00	+185.70
fashion	26	0.33	24	0.00	+182.99
Wear	13	0.17	0	0.00	+125.92
Valentinos	13	0.17	0	0.00	+125.92
Paris	14	0.18	5	0.00	+113.78
designers	12	0.15	3	0.00	+101.27
its	28	0.36	228	0.02	+98.08
pier	10	0.13	0	0.00	+96.86
Dolce	9	0.12	0	0.00	+87.18
nt	14	0.18	24	0.00	+85.97
at	76	0.97	2676	0.27	+83.04
collection	11	0.14	10	0.00	+77.64
Paolo_Piccioli	8	0.10	0	0.00	+77.49
his	48	0.61	1243	0.13	+74.39
dresses	9	0.12	3	0.00	+73.73
style	13	0.17	33	0.00	+71.67
her	52	0.67	1515	0.15	+71.21
im	9	0.12	5	0.00	+69.01
theyre	7	0.09	0	0.00	+67.80
emperor	7	0.09	0	0.00	+67.80
cant	7	0.09	0	0.00	+67.80
Mr.	7	0.09	1	0.00	+61.79
season	10	0.13	21	0.00	+58.21
italian	10	0.13	21	0.00	+58.21
theres	6	0.08	0	0.00	+58.12
pictured	6	0.08	0	0.00	+58.12
denim	6	0.08	0	0.00	+58.12
Maria_Grazia_Chiuri	6	0.08	0	0.00	+58.12
Gabbana	6	0.08	0	0.00	+58.12

O1 = observed frequency in the combined three-blog dataset
O2 = observed frequency in BNC normative dataset
%1 and %2 = relative frequencies in the two datasets
+ = positive LL value, i.e., overuse in O1 relative to O2

Appendix C – Top twenty adjectives in fashion brand datasets

Valentino (N)		Dolce & Gabbana (N)		Armani (N)	
Blog	Company text	Blog	Company text	Blog	Company text
new (25)	new (14)	new (27)	printed (22)	new (26)	new (40)
Italian (9)	red (12)	good (12)	black (22)	black (12)	grey (18)
creative (11)	modern (11)	beautiful (11)	white (15)	pictured (9)	black (15)
old 6	international (9)	sexy (10)	tartan (14)	Italian (7)	contemporary (11)
red (6)	contemporary (8)	other (9)	new (14)	uniform (6)	blue (11)
beautiful (6)	young (7)	black (9)	skinny (12)	great (6)	exclusive (10)
long (6)	global (7)	high (9)	blue (12)	favorite (5)	retail (10)
good (6)	fine (6)	hard (8)	different (11)	unexpected (5)	unexpected (10)
left (5)	iconic (5)	great (8)	voluminous (8)	little (5)	glossy (10)
great (5)	classic (5)	only (7)	grey (8)	left (5)	short (10)
other (5)	elegant (5)	real (7)	long (7)	good (5)	slim (10)
young (5)	rich (5)	different (7)	brown (7)	white (5)	important (9)
social (4)	distinctive (5)	little (7)	red (7)	young (4)	precise (9)
red-carpet (4)	white (5)	white (7)	classic (7)	only (4)	formal (9)
white (4)	feminine (5)	Italian (6)	contrasting (7)	real (4)	sophisticated (9)
Chinese (4)	big (5)	big (6)	military (7)	heavy (4)	white (8)
top (4)	creative (4)	left (6)	golden (7)	blue (4)	natural (8)
green (3)	American (4)	classic (5)	chunky (6)	short (3)	single (8)
floral (3)	important (4)	chic (5)	loose (6)	different (3)	long (8)
past (3)	organic (4)	glad (5)	young (6)	shawl-collared (3)	aesthetic (8)