SocialBrands: Visual Analysis of Public Perceptions of Brands on Social Media

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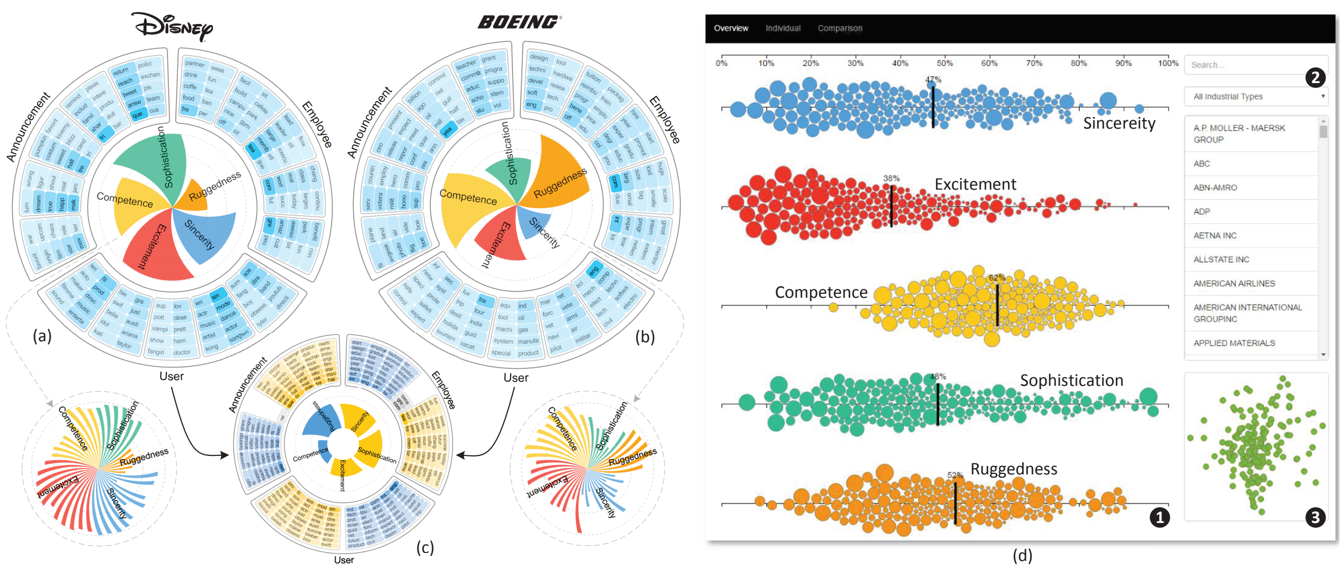

Figure 1: SocialBrands illustrates brand perceptions on social media with our designed visualizations. (a,b) The BrandWheels of two brands "Disney" and "Boeing", each illustrates a brand's perceived personality (in 5 broad traits or 42 subtraits) with visual evidence and related details from three social media factors. (c) The Comparative BrandWheel highlights the similarities and differences of two brands in their perceived personalities and topic discussions on social media. (d) The Overview of brand perceptions: (1) BrandSediments visually summarize the distribution of brands over personality traits and the clusters of brands; (2) search and filtering widgets; (3) MDS embedding of brand perceptions.

Abstract

Public perceptions of a brand is critical to its performance. While social media has demonstrated a huge potential to shape public perceptions of brands, existing tools are not intuitive and explanatory for domain users to use as they fail to provide a comprehensive analysis framework for perceptions of brands. In this paper, we present SocialBrands, a novel visual analysis tool for brand managers to understand public perceptions of brands on social media. SocialBrands leverages brand personality framework in marketing literature and social computing approaches to compute the personality of brands from three driving factors (user imagery, employee imagery, and official announcement) on social media, and construct an evidence network explaining the association between brand personality and driving factors. These computational results are then integrated with new interactive visualizations to help brand managers understand personality traits and their driving factors. We demonstrate the usefulness and effectiveness of SocialBrands through a series of user studies with brand managers in an enterprise context. Design lessons are also derived from our studies.

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1 Introduction

Public perceptions of a brand is critical in determining its performance, as these perceptions influence people's brand preferences and purchase intentions. Social media allows people to share opinions and experiences freely, and offers a great opportunity for companies to assess and construct brand perceptions. As a result, many analytics tools have been designed to assess public perceptions through analyzing trending topics [38], sentiments [22] and emotions [42] on social media. However, existing tools lack a comprehensive framework to assess public perceptions, and many analytics results related to sentiments and emotions can rarely be applied to the daily tasks of domain users (i.e., brand managers) for understanding and managing people's perceptions on brands.

When developing and managing brand perceptions, brand managers often use *brand personality* [1, 23], the most well-established framework to measure brand perceptions in marketing literature. The framework includes a comprehensive set of human characteristics associated with brands. For example, IBM is considered to be *old* and *competent*, while Apple is considered to be *young* and *cool*. In marketing practice, brand managers carefully define the *intended* *brand personality* that they would like customers to perceive, and invest extensive resources into brand-related marketing activities to reinforce such perceptions. Nevertheless, it is profoundly challenging to develop and maintain the intended brand personality, as there often exist gaps between the intended brand personality and consumers' actual *perceived brand personality*. Thus, one important task for brand managers is to assess the perceived brand personality in their daily practice. So far brand managers mostly rely on surveys to collect descriptive ratings on multiple brand personality scales to assess brand personality. Unfortunately, conducting surveys is time-consuming and labor-intensive, which makes it difficult to assess brand personality frequently. This problem becomes even more challenging when assessing brand perceptions from multiple perspectives, as perceptions of a brand can be influenced by multiple factors such as typical users and employees of the brand as well as its official marketing messages [26]. More importantly, with survey ratings, brand managers are often incapable of understanding and explaining the reason behind the perceived brand personality traits as well as their relations to multiple driving factors.

To address these challenges, we present *SocialBrands*, a novel visual analytic tool for brand managers to assess and analyze public perceptions of brands on social media. The key contributions of SocialBrands are three-fold.

- A computational approach that is designed to assess brand personality from three driving factors of user imagery, employee imagery and official announcement on social media, and construct an evidence data explaining the association between brand personality and its driving factors.

- A visualization design that conveys an integrated sense of multi-dimensional brand personality with visual evidence and related details. It enables visual explanation of how the perceived brand personality can be derived from the driving factors in social media, and visually highlights varying contributions of social media factors on different personality traits.

- A visualization design that enables a contextual understanding of the marketplace of many brands. It facilitates perception-based market segmentation through visual summarization of the distribution of brands over different personality dimensions and the clusters of brands.

We evaluated the usefulness and usability of SocialBrands through interviews and surveys with brand managers in an enterprise context. The evaluation shows that SocialBrands enabled brand managers to assess and analyze brand perceptions on social media, identify gaps between the intended and the perceived brand personality, understand multiple factors that drive brand personality, gain insights from successful brands through visual comparison, and discover perception-based market segments. Based on our studies, we discussed the design lessons for developing future brand analysis systems.

2 Related Work

Social media has transformed the way people market their businesses. Considerable research efforts have been made to support visual analysis of social media data. Dork et al. [6] introduced visual back-channel as a way of following and exploring online conversations about large-scale events. Cuvelier and Aufaure [5] proposed topographic networks of tags, representing a tag cloud with a topographic metaphor to highlight the most important concepts found for a given search on Twitter. Hansen et al. [9] presented a process model to analyze and visualize social media data. Whisper [4] traced and visualized the process of information diffusion in social media using a sunflower metaphor. Liu et al. [18] created a monitoring tool that preserved the user's mental map of streaming tweet clusters. Kraft et al. [15] extracted structured representations of Twitter events and visualized key event indicators from Twitter stream. Google+ Ripples [35] showed social media interactions on Google+ with a mix of node-and-link and circular Treemap metaphors. Xu et al. [38] analyzed topic computation on social media by integrating ThemeRiver with storyline style visualization. Liu et al. [19] developed a visualization system to analyze Twitter users' influence and passivity conditioned on specific themes. Mahmud et al. [20] supported visual analysis of Twitter users' attitudes towards brands. In contrast with the above tools, we propose a computational approach that derives perceived brand personality from social media data, and present intuitive designs for brand managers to assess perceptions of brands.

With recent advances in human personality and emotion analysis, researchers have developed new visualization tools for exploring analysis results. TwitInfo [22] employed a timeline-based display to highlight peaks of high tweet activity with the associated text sentiment. WeFeelFine [12] collected emotion-related keywords from social media texts for visual search and exploration. PEARL [42] supported multi-dimensional emotion analysis with a timeline-based visualization. FluxFlow [41] combined anomaly detection with thread glyphs and timelines for exploring anomalous information spreading on social media. KnowMe and ShareMe [8] studied the effectiveness of deriving personality traits from social media data and how users shared their personality traits using a multi-view visualization. VeilMe [36] employed a genome representation to visualize personality portraits for privacy configuration. However, existing tools are not designed to understand and assess public perceptions of brands, and many tools related to sentiments and emotions can rarely support the daily tasks of brand managers to analyze and manage people's perceptions on brands. In this work, we applied marketing theories to develop a new visual analytic system for brand personality analytics.

3 Background and Motivation

This section introduces the background knowledge on brand personality, and summarizes the domain tasks for system design.

3.1 Brand Personality

A company can significantly enhance its performance and consumer loyalty by building a strong and differentiated brand. A brand is essentially an aggregation of the name, design, symbol and all experiences that distinguishes one company's product from those of others [13]. Brand perceptions are consumers' interpretations of a brand, which can be shaped by functional experiences (e.g., quality and reliability) as well as emotional experiences (e.g., making one feel better or making one's life easier). Brand managers need to comprehensively understand how customers perceive their brand in specific market segments, particularly compared with other competitive companies. In marketing practice, the most well established framework for assessing brand perceptions is ***brand personality***, which is reflected by human-like features that are strongly associated with a brand [23].

Brand personality can be characterized by traits that uniquely identify a brand [13]. *Brand personality scales* [1] serve as a reliable, valid and generalizable measure for assessing brand personality in marketing literature. They consist of 5 broad personality traits: *Sincerity*, *Excitement*, *Competence*, *Sophistication* and *Ruggedness*, which are characterized by 42 subtraits [1].These personality scales measure how descriptive a trait is of a brand: 0% means not at all descriptive, and 100% means extremely descriptive (e.g., "20% sincerity" means sincerity is slightly descriptive on a 0 – 100% scale).

Brand personality analytics has received considerable attention in brand management and marketing. Brand managers carefully define the *intended brand personality* that they would like consumers to perceive, and invest extensive resources into brand-related marketing activities to reinforce such perceptions. However, successful formulation and implementation of brand personality is often a difficult challenge, as there often exist gaps between the intended brand personality and consumers' actual *perceived brand personality*. Thus, one important task for brand managers is to assess the perceived brand personality in their daily practice. Public perceptions of brand personality can be possibly influenced by at least three driving factors: *User Imagery*, *Employee Imagery*, and *Official Announcement* [10]. *User Imagery* are human characteristics associated with a brand's typical users. *Employee Imagery* are human characteristics associated with the employees of a company. *Official Announcement* refers to marketing messages that are designed specifically to engage consumers for brand loyalty and brand awareness.

Social media has demonstrated a huge potential to shape public perceptions of brands. One major category of marketing research on social media relies on linguistic models to understand consumer behavior as consumers' beliefs, feelings and emotions can be inferred from what they say. The multi-faceted nature of social media and rich data sets create a good opportunity to understand public perceptions of brand personality. We base our work on branding theory and social computing research to help brand managers understand the association between social media factors and public perceptions of brand personality.

3.2 Domain Problem Characterization

To distill the domain problems and typical tasks for brand management, we worked closely with domain experts such as brand managers from multiple marketing departments in a large international information service corporation. We conducted a series of interviews with the domain experts, and summarized a list of analysis tasks to characterize the domain problem and identify the challenges faced by the target users.

T1. *How to efficiently assess perceived brand personality on social media?* Prior to our work, brand managers mostly used surveys to collect descriptive ratings on brand personality scales to assess brand personality. However, conducting surveys is time-consuming and labor-intensive. It is significantly difficult to assess brand personality frequently. A computational approach that derives perceived brand personality from social media data is urgently needed by the domain experts.

T2. *How to relate a brand's perceived personality with multiple social media factors? Which is the driving factor that contributes most to the perceptions of a certain personality trait?* Brand managers are interested in analyzing the association between social media factors and perceived brand personality. The identification and analysis of varying effects of factors on different personality traits are crucial for them to make corresponding strategic decisions on a specific social media platform.

T3. *What are the reasons that a brand is strong on a certain trait? How to interpret and explain the formation of a certain perception from linguistic footprints on social media?* Brand managers want to determine the reasons behind the perceived brand personality traits. They are concerned with the popular opinions and discussions on social media that have influenced brand perceptions. Linguistic evidence should be provided to facilitate experts' analytical reasoning in understanding and explaining the trait modeling results.

T4. *What are the differences in perceived brand personality of related brands?* Brand managers want to analyze the differences between multiple brands to identify the strengths and weaknesses of a company based on their winning and losing personality traits. This task is critical to evaluating their daily practice as good marketing strategies should differentiate a company from its major competitors in the marketplace. It can also help them identify a set of successful exemplars to improve their existing marketing strategies for achieving better perceptions.

T5. *How to identify market segments within a set of brands from the perspective of perceived brand personality?* Brand managers are encountering with hundreds of brands including their competitors and collaborators in their daily practice. Groups of brands with similar perceived personality are of particular interest for their analysis. Identifying such personality-based market segments can facilitate the domain experts in designing and implementing marketing plans to address specific demands of the target segment.

4 System Design

In this section, we discuss the design rationales for our system, SocialBrands, and provide an overview of the system architecture.

4.1 Design Rationale

The domain tasks suggest that a visual analytics system is urgently needed to enable brand managers to understand and analyze public perceptions of brand personality. We identified a set of design goals as follows to address these analysis tasks based on our initial investigation with the domain experts.

G1. **Computational Brand Personality Analytics.** To save the time and efforts of our domain users in repeatedly conducting surveys for assessing perceived brand personality, it is crucial to provide a computational workflow that automatically derives personality scales from public social media data (T1). More importantly, this design could effectively improve their daily work performance in other analysis tasks (T2-T5).

G2. **Intuitive Self-Explanatory Metaphor.** Brand personality is intrinsically complex and multi-faceted. A visual metaphor capable of intuitively conveying an integrated sense of multi-dimensional brand personality is preferred by our domain users for the analysis tasks (T2-T4). To facilitate analytical reasoning and accountable explanation, the visual metaphor should be able to show how the perceived brand personality can be derived from the driving factors in social media with the support of visual evidence and related details. Varying contributions of social media factors on different personality traits should be visually highlighted to enhance the understanding of association between social media factors and brand perceptions.

G3. **Visual Analysis of Brand Comparison.** To support the analysis tasks (T2-T5), a visualization system should offer comparative analysis of two brands in terms of how similar or different their brand personality is and what the driving factors are to lead such similarity or difference. Since our domain users are concerned with examining and comparing personality profiles of related brands, the desired visual metaphor should help them easily distinguish one from another for comparative analysis.

G4. **Visual Aggregation and Summarization.** In marketing and brand analysis, brand managers often classify brands into different market segments that share common needs and interests in the marketplace. The domain experts are concerned with identifying and analyzing different market segments (T5). A visual overview of perceived personalities of a set of brands is desired by our domain users. The overview should present a contextual understanding of the marketplace of many brands by providing summarization information such as the distribution of brands over different trait dimensions and the clusters of brands.

G5. **Interactive Visual Exploration.** A visualization system that enables brand managers to interact with the data directly and see the perception results immediately is always preferred by the domain experts to complete the described tasks (T2-T5). A visual analytical workflow with rich interactions should be provided to allow brand managers to gain insights into a brand's personality profile and its association with multi-faceted social media factors, and view related topics and discussions to completely understand public perceptions of brands on social media. They should also be allowed to flexibly explore perceived personalities of different brands in a collection.

4.2 System Overview

With these design goals in mind, we developed the SocialBrands system. Figure 2 illustrates the system architecture and the analytical workflow. The system consists of three modules: (1) the data collection and preprocessing module, (2) the brand personality modeling module, and (3) the interactive visualization module. The data collection and preprocessing module collects and stores the online social media text documents such as tweets, online reviews, and user profiles to account for three facets of linguistic footprints that drive perceptions of brand personality on social media. Tokenization and stemming are performed to preprocess the social media text documents into words as the basic linguistic evidence. The brand personality modeling module extracts topics from the words as representative semantic features, which are used to predict brand personality. Furthermore, given the multi-dimensional hierarchical personality profiles produced by the brand personality model, the interactive visualization module transforms them into multiple interactive views to represent brand personality at various finer granularities for different analysis tasks. For example, an individual view and a comparative view are designed to illustrate the association between brand perceptions and social media driving factors with linguistic evidence. An overview is designed to illustrate the visual aggregation and summarization of perceived personality of all the user-provided brands.

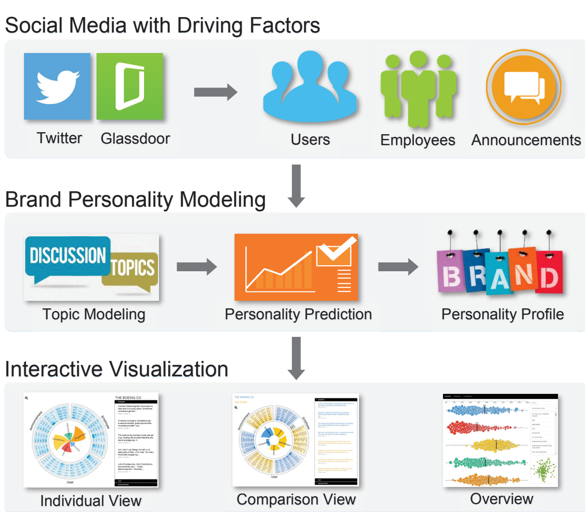

Figure 2: Overview of the SocialBrands system.

5 A Computational Approach for Brand Perception Analytics in SocialBrands

This section presents a computational approach that derives brand personality traits from social media data (G1). We first introduce a multi-level model for computational brand personality analytics, and then describe how to derive a brand's personality traits from linguistic footprints on social media [37].

5.1 A Multi-Level Model for Brand Personality Analytics

We base our approach on social computing studies [30, 39, 40] to assess perceived brand personality on social media. Computationally, a trait of a brand's personality can be modeled as a linear combination of relevant semantic features:

$$T_i = g_i(F_j(W_k)), \tag{1}$$

where g_i is a linear function mapping semantic features to a personality trait, F_j is a function mapping words to semantic features, and W_k is a word that is correlated with trait T_i and appears in the text footprints. To represent the multi-level relationships between personality traits, semantic features, words, and texts, we use a compound graph defined as:

$$TKG = (T, K, g). \tag{2}$$

The personality traits of a brand's personality profile are represented as a *personality tree*, $T = (V_T, E_T)$, where a set of nodes V_T denotes the traits, and a set of edges E_T denotes the relationships between the basic traits and their subtraits. The linguistic evidence used to derive a trait, including related semantic features, words, whole texts, and weighted links among them, is represented as an *evidence network*. The evidence network is essentially a k-partite graph, $K = (V_K, E_K), V_K = K_1, K_2, ..., K_k$, where K_l is a set of nodes representing a set of evidence at a particular level l (e.g., word level), and E_K is a set of edges representing the relationships between the nodes. A mapping function, g, links the linguistic evidence to the derived personality traits, $g(n_K) \to n_T$, where $n_K \in V_K, n_T \in V_T$.

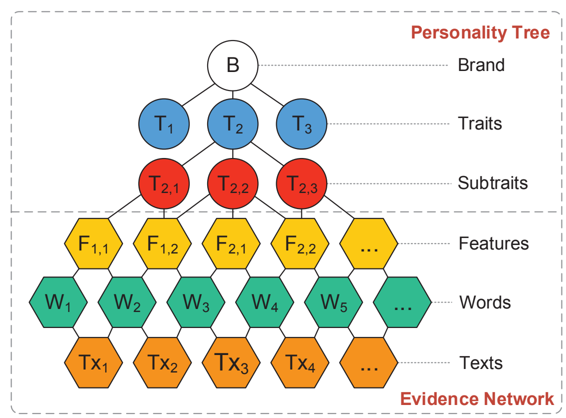

Figure 3: The multi-level model of a brand's personality traits (represented as a personality tree) with associated linguistic evidence (represented as an evidence network). This model is used to design a computational workflow to derive brand personality from social media linguistic footprints.

The compound graph view of this multi-level data model is illustrated in Figure 3. Given a brand B, its personality tree has several broad traits T_i, which are characterized by subtraits $T_{i,j}$ (the j-th subtrait of the i-th trait). The subtraits are linked with a set of linguistic features $F_{i,j}$ (the j-th feature of the i-th social media factor) in the evidence network. These features are linked with a set of representative words W_i, which are extracted from a set of text documents Tx_i. The key property of this model is that the nodes at one level are derived and linked from the nodes at the level below. This multi-level property motivates us to design a computational workflow to derive brand personality from social media linguistic footprints by (1) collecting multi-faceted linguistic footprints on social media, (2) extracting semantic features from linguistic texts and words, and (3) mapping semantic features to personality traits. Next we describe the key steps of this computational workflow.

5.2 Multi-faceted Social Media Data Collection

User Imagery A brand's followers on social media are very likely to use and like the particular brand. We considered a set of brand followers as *User Imagery* represented on social media. For each brand, we collected its followers' self-description on Twitter [33], which is a short description in a follower's public profile. Overall, we obtained 1,996,214 brand follower descriptions.

Employee Imagery Glassdoor [7] is an online social media where employees and former employees anonymously review companies and their management. The reviews often contain statements about working conditions, company culture and management styles, which are used to describe *Employee Imagery*. We collected 312,400 Glassdoor employee reviews in total.

Official Announcement Companies can create their own Twitter accounts and publish marketing information to the public. We considered the tweets from a brand's Twitter account as its *Official Announcements*, and collected 680,056 tweets all together.

5.3 Brand Personality Computation

As described in Section 5.1, a personality trait can be modeled as a linear combination of semantic features. To extract semantic features from the text corpus, we employed Latent Dirichlet Allocation (LDA) [3], a topic modeling technique that analyzes topics in text documents. In total, 200 topics were extracted as representative semantic features in the documents for each social media factor. Each topic is summarized by a set of representative words, which are associated with relevant texts.

To map semantic features to personality traits, we built a regression model for brand personality prediction based on observed personality scales. The observation data was obtained from a survey of 10,950 valid responses on the 219 brands, where 3,060 participants rated how descriptive the personality traits were of a brand using a 7-point scale. Each brand was treated as one observation and each personality trait was regarded as a dependent variable, so that 219 observations and 42 dependent variables were included. Seven feature descriptors from the distribution of documents over each feature were used as predictors: mean, 5th to 95th percentile, variance, skew, kurtosis, minimum, and maximum. Therefore, the input of the prediction model has totally 4,200 predictors (200 features $\times$ 7 descriptors $\times$ 3 factors). Since the number of predictors exceeds the number of observations with a high collinearity between predictors, we used Lasso regularized regression [32]:

$$L(\gamma_1, ..., \gamma_P) = \arg\min \|\mathbf{y} - \sum_{j=1}^{P} \gamma_j \mathbf{x}_j\|^2, \text{subject to} \sum_{j=1}^{P} |\gamma_j| \leq t, \quad (3)$$

with P the number of predictors, $\mathbf{x}_j$ the predictors, $\mathbf{y}$ the dependent variables, γ_j the regression coefficients, and t the Lasso parameter. Lasso is able to seek for a sparse solution by constraining the coefficients of weak and correlated predictor variables to zero [32].

The relative importance of the three social media factors is evaluated based on the associated coefficients after the Lasso regression fits the observation data. The weight of a factor with respect to a trait is calculated by summing the standardized coefficients of the predictors used to predict the corresponding dependent variable:

$$W(P_k) = \sum_{j=1}^{P_k} \gamma_j \frac{SD(\mathbf{x}_j)}{SD(\mathbf{y})}, P_k \subset P, \quad (4)$$

where P_k is the set of predictors that belong to the k-th social media factor. The average weight of a factor on a broad trait is calculated by averaging the weights over all its subtraits.

The prediction model was evaluated with the observation data being ground truth. 10-fold cross validation was used to assess the model accuracy. The evaluation showed our model achieved predicted R^2 as high as 0.67, and the mean absolute error as low as 0.01 on a $0-1$ scale. A comprehensive report of the evaluation can be found in [37].

After predicting the 42 personality traits, the values of the five broad traits were aggregated accordingly based on the trait hierarchy. Thus, for each brand, our computational approach generates a comprehensive multi-level model (as described in Section 5.1) that consists of the derived personality traits linked with the linguistic evidence from social media data. From now on, we denote the output of brand personality computation as *personality profiles* for further visual analytics.

6 Visualizing Brand Perceptions with SocialBrands

Following the design goals (G2-G5), we develop an interactive visualization module for SocialBrands, which consists of three major views: an Individual View, a Comparative View and an Overview. Both the **Individual View** and the **Comparative View** include a *BrandWheel* visualization (Figure 1(a,b,c)) with an additional document panel that shows related social media documents regarding each driving factor. The **Overview** (Figure 1(d)) consists of (1) multiple *BrandSediments* for visual aggregation of multidimensional brand personalities, (2) a list view of brands with search and filter widgets, and (3) a multidimensional scaling (MDS) view that embeds brands based on their overall personalities [16].

6.1 BrandWheels: Visual Summarization and Explanation of Brand Personality

To convey an integrated and organic sense of multi-dimensional brand personality with accountable visual explanation from linguistic perspective (G2), we design the *BrandWheel* visualization to illustrate a brand's personality profile and its association with social media factors (Figure 4(c)). The wheel metaphor, inspired by both classic Radial Space Filling (RSF) technique [28] and the beauty of Goethe's color wheel [17], has several benefits compared with a traditional bar chart: the wheel metaphor with radial sectors conveys a representative sense of a brand's personality, and lower memory cost with the metaphor from real life [2]; it is also aesthetically more appealing and engaging than a bar chart. We describe each of these components below.

Personality Sectors Personality sectors form the inner component of a BrandWheel. In analogy to the Goethe's color wheel (Figure 4(a)), each personality sector represents one personality trait, and multiple sectors in an RSF layout illustrate a brand's personality profile with a set of personality traits (Figure 4(b)). Following the design of Goethe's color wheel, the *trait type* is mapped to the color of a personality sector and the radius R_t of a personality sector encodes the *trait value*: the higher a trait value is, the farther a sector spreads out (Figure 5(a)). Concentric circles are drawn in a dashed and grey manner to show the value range of traits, and serve as reference scales for visual alignment (Figure 5(a)); meanwhile, a Tooltip will pop up to show the exact trait value when the mouse is hovering on a sector. To balance aesthetics and functionality, curved wheel sectors are used to achieve the visual appearance of Goethe's color wheel. We note that the perception of a trait's value does not significantly depend on whether the sector is curved or not as a trait's value is encoded by a sector's radius.

Factor Bands Surrounding the personality sectors, factor bands are shown in the outer component of a BrandWheel in an RSF layout. To support visual explanation of the influence of each driving social media factor on different personality traits, the closeness C_f of a factor band with respect to the view center (shown in Figure 5(b)) indicates the weight of the corresponding driving factor (defined in equation (4)): the closer a factor band is to the center, the more contribution it has to predict a certain trait. As three factor bands are initially aligned in an RSF layout, changes of the factors' weights when focusing on a specific trait are prominent due to the effectiveness of the visual channel *aligned spatial position* [24], as

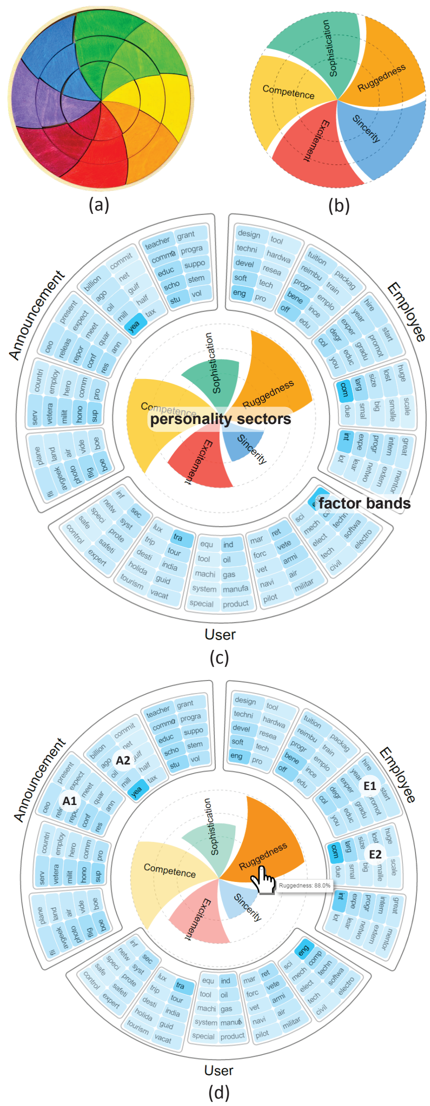

Figure 4: The visualization design of BrandWheel. (a) A jigsaw of Goethe's color wheel [17]. (b) A visual metaphor of personality wheel inspired from (a). (c) The visual metaphor of BrandWheel, composed of personality sectors (illustrating personality traits) and factor bands (showing linguistic evidence from social media factors). (d) The BrandWheel visualization with a focus on the *Ruggedness* trait: the User-factor-band gets closer to the view center than the other two, indicating a higher contribution in perceiving Ruggedness; the closeness of topic blocks (e.g., A1, A2, E1, E2) towards the center also indicates their specific relevance to Ruggedness.

illustrated in Figure 4(d). To help users understand and verify the perceived personality traits, factor bands include the linguistic evidence used to derived the traits from the social media factors in our data model (Figure 3). The most popular topics (i.e., salient semantic features in the evidence network) are visualized in *topic blocks*, which are tiled by *word bricks* of the representative words in an RSF layout (Figure 5(b)). Similar to the impact of factors on different traits, the extracted topics may also have various contributions to predict different traits (i.e., the regression coefficient γ_j of a topic in equation (3) can vary in different regressions regarding different dependent variables). To encode such impact of topics in the visualization, the closeness C_t of a topic block (with respect to

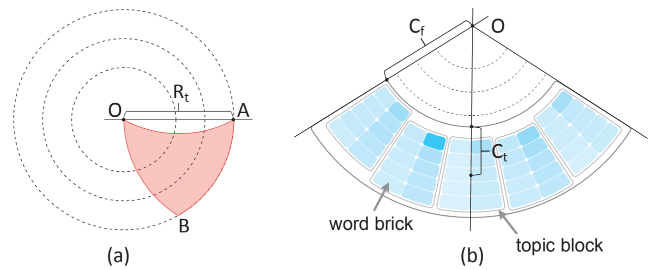

Figure 5: The visual encodings of BrandWheel. (a) The radius R_t of a personality sector shows a trait value. (b) The closeness C_f of a factor band (with respect to the view center) depicts the weight of the corresponding social media factor; the closeness C_t of a topic block (with respect to the inner boundary of the belonging factor band) depicts the weight of the corresponding topic regarding a particular trait; the color intensity I_w of a word brick encodes the frequency of the word in the underlying linguistic documents.

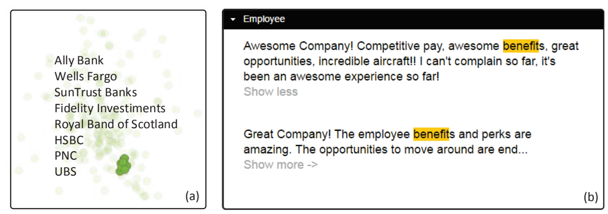

Figure 6: Visualization components. (a) A group of related brands identified as financial firms in the MDS view. (b) A text panel along with the BrandWheel visualization, showing relevant text documents with highlighted topic words (e.g., "benefit") for each social media factor that contribute to a trait of interest.

the inner boundary of the associated factor band) is used to show the weight of the corresponding topic with respect to a trait of interest, as shown in Figure 5(b). To show the popularity of words in the related topics, the color intensity I_w of a word brick encodes the frequency of the word in the underlying linguistic documents. When selecting a word brick of interest, a text panel along with the BrandWheel visualization shows relevant texts with highlighted topic words to help users further understand the linguistic footprints (Figure 6(b)).

Comparative BrandWheels To support visual comparison of two brand personality profiles (G3), we extend the BrandWheel design and create *Comparative BrandWheel* by highlighting the similarities and differences of two brands' personality profiles with representative topical words (Figure 7). In this comparison view, personality sectors explicitly encode the absolute value differences of the traits of two brands (the center is made hollow to differentiate such comparison sectors from the individual sectors in a standard BrandWheel). The sectors are radially reordered by their actual value differences for visual classification of the personality traits into winning and losing traits when comparing a brand to another. Two distinct colors are mapped to the two underlying brands. In particular, the color of a personality sector is mapped to the brand that has a higher value in the corresponding personality trait, which supports easy identification of the winning and losing traits of a brand. To visualize the similarities and differences of the topical words of two brands (denoted as A and B), the word bricks of two brands in each factor band are grouped into three topic blocks based on their logical relations: words only related to A, words shared by A and B, and words only related to B. In this way, the visualization of topic blocks in a factor band is reminiscent of a *Venn diagram* [34] that shows logical relations of two sets, as shown in Figure 7. To support interactive exploration, the individual personality sectors of a brand can be retrieved when hovering on a brand, and the topic blocks associated with the focus brand will be highlighted.

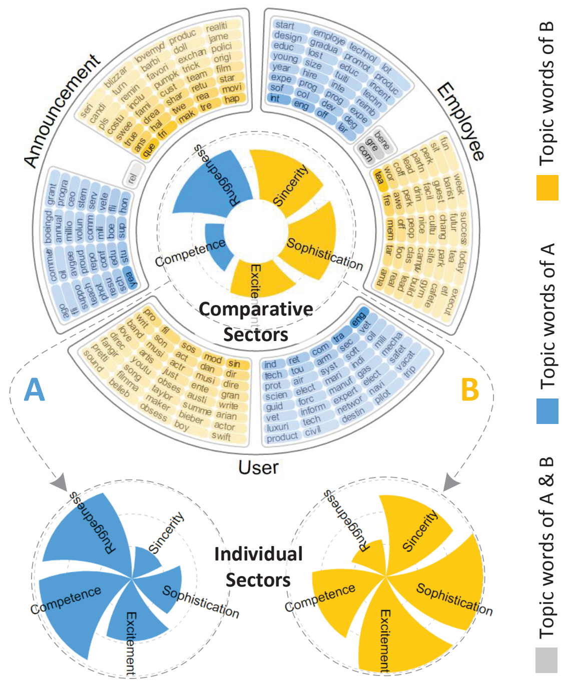

Figure 7: The visualization design of Comparative BrandWheel. Personality sectors explicitly encode the absolute value differences of traits of two brands. The color of a personality sector is mapped to the brand that has a higher value in the corresponding personality trait (personality sectors of a brand can be retrieved when hovering on a brand). The word bricks of two brands in each factor band are grouped into three topic blocks based on their logical relations.

6.2 BrandSediments: Visual Aggregation of Perceived Brand Personality

To provide a context of the marketplace where a collection of brands stand over the multiple trait dimensions (G4), we design the *BrandSediments* visualization using a sedimentation metaphor [11]. This metaphor is inspired by real-world sedimentation processes where objects aggregate into strata over time. In contrast to the conventional sedimentation designs for temporal data streams [11, 41], in our BrandSediments design, brands aggregate into strata over a brand personality scale. Multiple BrandSediments are drawn side by side simultaneously to illustrate visual aggregation of brands over the scales of different personality traits. Figure 8 shows an example of BrandSediments aggregating brand perceptions of two personality traits *Sincerity* and *Competence*.

Visual Encoding Each bubble in BrandSediments represents a brand. The colors of bubbles reflect their personality traits, which are consistent with the colors used in the BrandWheel visualization. The size of a bubble encodes *brand singularity*, which measures the degree of focus and single-mindedness of a brand's overall personality scales (brands of high singularity tend to leave an enduring impression among consumers [21]). As the BrandSediments metaphor

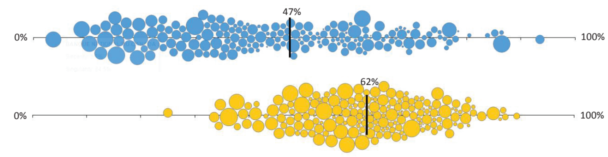

Figure 8: BrandSediments of the overall perceptions of brands on *Sincerity* (top) and *Competence* (bottom) in a brand collection. From an aggregated perspective, these brands are mostly perceived as competitors while sharing a varying degree of perceptions regarding sincerity .

is designed for visual aggregation of brands over a personality scale, the horizontal position of a bubble depicts the trait value of the corresponding brand, and brands of similar trait values are aggregated vertically to form a personality-based market segment within a trait value interval. To achieve such visual sedimentation, we employ a force-directed method with a horizontal constraint and collision detection to densely pack bubbles while reducing overlaps along the vertical direction. A vertical bar highlights the median value of the overall trait value distribution as a visual reference point.

6.3 Interactions

Semantic zooming allows users to drill down into a broad trait to view its subtraits in both the BrandWheel and the BrandSediments visualization. By default, five broad traits were shown to emphasize an aggregated sense of perceived personality.

Highlighting, searching and filtering allows users to interact with brands of interest for exploratory analysis. For instance, hovering over a bubble in BrandSediments (or a brand in the list view) automatically highlights all the bubbles representing the selected brand. Users can also look for a particular brand in the search box (Figure 1(d-2)), or select a group of brands that fall into a specific industrial category; the other brands will be filtered out in the BrandSediments.

Brushing and linking enables users to interactively specify a region in one BrandSediment (or in the MDS view) to select a group of brands that have similar personality trait(s), and view how they are aggregated in other BrandSediments. The list view is also linked with the other views for showing the brands in a brushed region.

6.4 Usage Scenario

To illustrate the capability of *SocialBrands*, we describe a scenario of investigating the perceived brand personalities using our system. Suppose Emma is a brand manager whose job is to assess brand perceptions on social media. She used SocialBrands for this purpose. Her data have been processed and analyzed by the SocialBrands system for a collection of brands of her interest.

To start with, Emma viewed the aggregation of brand perceptions in the SocialBrands Overview (Figure 1(d)). She observed a cluster of brands that share similar overall brand personalities in the MDS view (Figure 6(a)), which were identified as financial companies such as Ally Bank, Wells Fargo and HSBC. She then focused on the *Competence* trait in the BrandSediments visualization. After selecting a small subset of highly competent brands by brushing the BrandSediments, she found that they represent high-tech companies such as Boeing, Apple, and Cisco. She then drilled down into the *Competence* trait to see the underlying personality traits, and observed that most brands are extremely *corporate*.

To investigate why people perceived a particular brand to be competent, Emma selected the brand "Boeing" to view its BrandWheel in the Individual View (Figure 4(c)). She found that Boeing's employees frequently mentioned words such as "benefits", "offer" and "products", as revealed by the topic blocks in the Employee-factor-band. For instance, one relevant employee review on Glassdoor said that "Awesome Company! Competitive pay, awesome benefits, great opportunities, incredible aircraft!" (Figure 6(b)). To gain further understanding of the perceived personality of Boeing, Emma selected the *Ruggedness* trait. From the displacement of factor brands (from Figure 4(c) to Figure 4(d)), she learned that the *User Imagery* factor affects more on perceiving Boeing as *rugged* as the User-factor-band moved closer to the view center. Furthermore, from the displacement of topic blocks, she observed that the topic popularity remains roughly the same in the User-factor-band, while those in the other two showed prominent changes. For instance, topic A2 (with words "million", "tax", etc.) becomes more relevant to *Ruggedness* than A1 (with words "result", "report", etc.) in the Announcement-factor-band, while the topic E2 (with words "company", ""large", etc.) is more related to *Ruggedness* than E1 (with words "cool", "you", etc.) in the Employee-factor-band.

As a follow-up study, Emma selected another brand "Disney" to compare its perceived personality with "Boeing" in the Comparative View. As shown in Figure 7, Boeing (A) and Disney (B) have distinct perceptions in the *Ruggedness* and *Sincerity* traits — Boeing is perceived as much more rugged than Disney, while Disney is perceived as far more sincere than Boeing. To explain such differences, she resorted to the data evidence in the factor bands. She learned that the social media discussions about these two brands are very different, as they share few common topic words. For example, Disney's employees frequently mentioned words such as "free", "amazing", and "member", while Boeing's employees preferred to discuss "intern", "engineering", and "offer".

7 Evaluation

SocialBrands is the very first visual analytic system for brand personality analysis. Thus, we adopted an exploratory study with a think-aloud protocol that helps us understand how domain users naturally use such a new system, and collects rich information when users freely express their own thoughts during exploration. We evaluated SocialBrands through in-depth interviews and surveys with marketing brand managers. The interviews and surveys helped us obtain detailed qualitative feedback from the domain users.

7.1 Participants and Procedure

Participants for both the interviews and the surveys were 12 brand managers from different marketing departments such as sales, consumer research, and advertising in a large international IT company. Their management positions ranged from managers and directors to vice president, and their experiences ranged from 4-24 years. A majority of them ($n = 10$) have worked at multiple companies for brand management. We denote the participating managers as M1-M12. The data set used for interviews contains 181 brands of leading companies in various industrial sectors including electronics, banking, entertainment, health care and so on.

Interviews lasted one hour and were audio recorded and transcribed respectively. Interviews were split into three stages: a pre-interview (10 minutes), a system walkthrough (40 minutes) and a post-interview (10 minutes). In the pre-interview, we asked the participants about their experience and training in marketing and branding. Then we asked the participants how familiar they were with the concept of brand personality, and what they thought of the personality of their company and their clients. In the system walkthrough, participants were introduced to the system and requested to explore it openly with a think-aloud protocol. In the post-interview, we asked the participants what they learned about the brands, and how this system worked to meet their expectations. Then we asked the participants when and how they might use this type of system in their marketing or branding work. Finally, we asked the participants what parts of the interface were particularly useful to them, and what parts were confusing or otherwise need improvement. Afterwards, participants took a post-interview survey, which contains 12 seven-point Likert-scale questions about the usefulness and usability of SocialBrands (Table 1).

Table 1: Usefulness and usability of SocialBrands. The average ratings (μ) with standard deviations (σ) from brand managers. 7 means "strongly agree" with a statement, 1 means "strongly disagree" with it, and 4 indicates "neutral".

	Question	μ	σ
Q1.	Overall, assessed the personality of brands	6.4	0.52
Q2.	Assessed a brand's personality profile	6.6	0.52
Q3.	Identified gaps between the inferred and the intended personality of a brand	5.4	1.06
Q4.	Understood relationships between a brand's personality and contributing factors	5.3	1.28
Q5.	Identified gaps between brands	6.5	0.53
Q6.	Identified patterns of brands based on personality	5.9	0.99
Q7.	Easy to learn and use SocialBrands	6.0	0.93
Q8.	The *Personality Sectors* design conveyed an integrated sense of brand personality	6.1	0.64
Q9.	The *Factor Bands* design was helpful for connecting the personality to contributing factors	5.1	1.36
Q10.	Easy to identify winning/losing traits of a brand in the Comparative View	6.0	0.76
Q11.	Easy to find relevant brands in the Overview	6.6	0.52
Q12.	Willing to use a system similar to SocialBrands for brand management in the future	6.1	0.64

7.2 Results

Our evaluation captured a continuous exploration process of using such a new system. Overall the brand managers responded positively to our SocialBrands system and found it useful for exploring, assessing and interpreting perceived brand personality on social media (see survey results in Table 1). Below we report the study results of the SocialBrands system in several key aspects.

Assessing Brand Perceptions All participants found the SocialBrands system highly useful in assessing brand personality both in general (Q1, μ=6.4, σ=0.52) and individually (Q2, μ=6.6, σ=0.52), which are among the most helpful features based on the ratings. Before using the system, participants thought perceptions of a brand were very difficult to describe in an comprehensive and accurate manner. For example, M1 stated that *"there are probably a lot of instances that people may have an idea of a company, but they cannot put fingers on what exactly that is"*. In contrast, after using SocialBrands, participants were able to have a quick grasp of the overall personality pattern for a brand, as the personality sectors of BrandWheel conveyed a compact and organic sense of brand personality (Q8, μ=6.1, σ=0.64). M1 commented that *"the circular layout [of BrandWheel] is intuitive in terms of quickly identifying the best and the worst traits of a brand"*.

Visual Explanation of Brand Perceptions A majority of the participants highly appreciated the idea of providing linguistic evidence for visual explanation of brand perceptions. They were interested to see the actual data that behind the perceptions of a brand,

and were excited to discuss different topics emerging in the BrandWheel. For instance, M3 said *"this [BrandWheel] is really useful, powerful and believable — as a marketer, it certainly helps me to explore how my brand is represented across these key social media platforms; otherwise, I just have to believe whatever the personality is"*. Furthermore, many participants confirmed the effectiveness of the interactive movements of factor bands in revealing the changes of contributions of social media factors when focusing on different traits. M9 remarked that he was *"able to see which factor is most associated with [a trait], and what are the differences of the associations among factors"*. Nevertheless, a few participants mentioned that it was still difficult to reason a factor's effects based on linguistic footprints. The variance of survey ratings on Q9 is relatively high (σ=1.36), though the average rating is still positive (μ=5.1).

Identification of Perception Gaps Many participants expressed that our system assisted them in identifying personality gaps between perceived and intended personality of a brand (Q3, μ=5.4, σ=1.06). Specifically, participants were able to validate their marketing strategies by examining dominate traits that they wanted to emphasize, and identifying weakly-perceived traits that need to be targeted or improved further. M2 said that *"we are doing better on several key personality attributes; maybe a little worse on sincerity than I thought, but higher on competence"*.

Comparative Analysis of Brand Perceptions The Comparative BrandWheel visualization helped participants effectively compare personalities of selected brands, and identify gaps between them (Q5, μ=6.5, σ=0.53). Many participants reported that comparing brands with similar personalities can help them discover potential collaborators. M1 said that *"[Comparative BrandWheel] is really great to compare two brands; focusing on 'accomplished', 'cool' and 'innovated' can leverage what you know about similar brands to find complementary clients"*. Furthermore, Comparative BrandWheels supported participants to learn from winning brands (Q10, μ=6.0, σ=0.76). M3 commented that *"[Comparative BrandWheel] tells who may be strong or weak on particular personality traits, helping me understand what our brand needs to do"*.

Perception-based Market Segmentation Most participants enjoyed the BrandSediments visualization (Q11, μ=6.6, σ=0.52), enabling a contextual understanding of the marketplace by showing where a brand stands with regard to other representative companies. This contextual understanding facilitated participants to gain insights into the distribution of brands over personality traits. M4 commented that *"exploring the brands around us gives me a better idea of what was meant by 'original'; these brands help me figure out how to interpret that trait"*. Moreover, participants used our system to easily and systematically identify market segments that share similar personality patterns (Q6, μ=5.9, σ=0.99).

Generalizability of Visual Design Participants were very much impressed with the design of BrandWheels and BrandSediments, and believed that they were generalizable for various marketing purposes. In particular, one participant suggested that interfaces like BrandWheels and BrandSediments can be used by chief marketing officers (CMOs) and chief financial officers (CFO): *"if we come up with five market segments that we think are important to CMOs and CFOs, this [BrandWheel] could be the way to visualize, communicate, and explore segments"*.

Overall System Usability We learned that many participants thought SocialBrands was intuitive, easy to learn and use (Q7, μ=6.0, σ=0.93). The metaphors of BrandWheels and BrandSediments were considered intuitive, explanatory and engaging. They reported that the majority of features in the system were useful and practical. M6 stated that *"we need more such social tools to help us understand what social conversations are around us and other brands and how we compare in personality"*.

8 Discussion and Future Work

Our evaluation of SocialBrands demonstrated the usefulness and usability of this very first visual analytic system in the hands of brand managers. We discuss the implications for developing such visual analytic tools in marketing industry.

First of all, SocialBrands is a successful example of applying marketing theories (e.g., brand personality) in developing a domain-specific application. Future system designers are encouraged to make use of domain literature and theoretical frameworks that are powerful to explain and guide the practices in the domain for users. This also suggests that the design of visual analytics tools is desirable to root in a theoretical foundation, amplify human's understanding of the domain tasks with interactive visualization, and also loop human's knowledge into the theoretical framework [31].

Second, SocialBrands encodes multi-level data evidence in the visualization for domain users to interpret and explain the analytics results. Future visualization researchers are advocated to design intuitive metaphors that enable domain users to easily relate analytics results to their evidence at multiple levels and facilitate their analytical reasoning. The domain experts can collect and synthesize such evidence to either confirm or discard the hypotheses in their minds, and the intuitive visual metaphors of evidence serve as an important resort to build the loop in the visual analytics process [14].

Third, SocialBrands exposes the transparency of the computational model to the domain users for them to understand how the model works. The most challenging task in our system design was to help users understand how perceived personality was derived from different social media factors. While we implicitly encodes the contributions of factors through interaction (i.e., displacements of factor bands), alternative designs such as explicit encoding through visual links [29] may also be considered to address this open problem. Furthermore, with a deeper understanding of how the model works, the domain users can interact with the analysis results and give the feedback to the system. Such feedback from domain users can be further fed into the model to refine the analysis results and close the human-in-loop visual analytics.

There are several interesting directions for generalizing and extending our current system. First, our system can be easily integrated with existing social marketing tools [25, 27] to bring a new perspective about brand performance. Second, our system can be used to analyze perceptions of sub-brands to help brand managers understand the roles of sub-brands in a brand's architecture. Third, we plan to conduct graphical perception studies to investigate the functionality and engagement of curved charts against bar charts by measuring interpretation accuracy and long-term recall. Finally, we would like to supplement SocialBrands with historical marketing abilities to analyze brand perceptions over time.

9 Conclusion

We present SocialBrands, a novel visual analysis tool for brand managers to understand public perceptions of brands on social media. Based on branding theories and advanced social computing approaches, we compute the perceived brand personality with linguistic features extracted from driving factors of user imagery, employee imagery and official announcement, and quantify the associations between brand perceptions and social media factors. The computational results are integrated with new visualization designs for visual aggregation, summarization and explanation of brand perceptions. Through in-depth interviews and surveys with brand managers, we find that brand managers can gain new insights into brand perceptions in five ways: (a) assessing and analyzing brand perceptions on social media, (b) identifying gaps between the intended and the perceived brand personality, (c) understanding multiple factors that drive brand personality on social media, (d) learning from successful brands through visual comparison, and (e) discovering new perception-based market segments.

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