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Using Machine Learning to Compare the Information Needs and Interactions of Facebook: Taking Six Retail Brands as an Example

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Abstract: This study explores the interactive characteristics of the public, referencing existing data mining methods. This research attempts to develop a community data mining and integration technology to investigate the trends of global retail chain brands. Using social media mining and ensemble learning, it examines key image cues to highlight the various reasons motivating participation by fans. Further, it expands the discussion on image and marketing cues to explore how various social brands induce public participation and the evaluation of information efficiency. This study integrates random decision forests, extreme gradient boost, and adaboost for statistical verification. From 1 January 2011 to 31 December 2019, the studied brands published a total of 25,538 posts. The study combines community information and participation in its research framework. The samples are divided into three categories: retail food brand, retail home improvement brand, and retail warehouse club brand. This research draws on brand image and information cue theory to design the theoretical framework, and then uses behavior response factors for the theoretical integration. This study contributes a model that classifies brand community posts and mines related data to analyze public needs and preferences. More specifically, it proposes a framework with supervised and ensemble learning to classify information users′ behavioral characteristics.

Keywords: social media mining; ensemble learning; information cues; behavior trend analyses

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Citation: Chen, Y. Using Machine Learning to Compare the Information Needs and Interactions of Facebook: Taking Six Retail Brands as an Example. *Information* **2021**, *12*, 526. https://doi.org/10.3390/info12120526

Academic Editors: Joanna Paliszkiewicz and Marcin Ratajczak

Received: 15 November 2021
Accepted: 13 December 2021
Published: 17 December 2021

1. Research Background

Social media has become an integral aspect of business strategies [1] and is changing how businesses interact with users [2–4]. Group admins can use social media to increase brand awareness and loyalty by building relationships with potential consumers [5] or by guiding them to participate in promotional events and share information [6]. Social media content to attract consumers has two primary objectives: enhance brand loyalty or affection through improvements in brand image, which is generally image driven, and encourage interactive behaviors through rewards or other marketing techniques. Users participate by liking or commenting on brand posts and by sharing brand content within their network of friends. Such engagement is considered an outcome of marketing simulation [7]. The number of likes and comments is representative of a post′s popularity. However, while more than 80% brands are actively using Facebook, almost 60% group admins reported they are yet to understand how posts and other information can be effectively used to attract consumers [8]. Given the lack of key information analysis, a majority of group admins tend to passively imitate their competitors. Identifying the right solution for various individual brands is not possible.

Although scholars have examined the impact of social media on brands, their research insufficiently discusses the key factors and characteristics of brand messaging in general and the effective communication of social information in particular [9]. Therefore, this study analyzes social media content on the fan pages of global brands and compares the number of likes, comments, and shares for posts by popular brands. The objective is to examine the characteristics of posts that demonstrate exceptional business interaction efficiency, observe correlations between content and user behavior, and suggest effective strategies to manage social media content [10]. Brands must adopt convincing approaches when using online communities to interact with the public [11]. Understanding participation patterns is a critical aspect of brand strategy. However, key information analyses on the topic are lacking. Studies have explored crowd intention [12] and conducted interactive strength tests [11]. By contrast, this research focuses on cues prediction, analyzes users' interaction intensity and participation response to image and marketing cues, and explores message functions and satisfaction provided by a brand from an information perspective [13]. The findings will serve as a reference for future commercial communities pursuing content improvements and increased public interactions.

The rise of e-commerce in recent years has significantly impacted the sales ecology of the physical retail industry. The Internet has pushed the physical retail industry to re-evaluate its positioning to, for example, attract public attention by building brand communities, thereby actively grasping consumer behaviors and stimulating consumption opportunities. Therefore, this study selects affordable brands listed in the Fortune Global 500 and affordable retail and chain stores that rank among the world′s top 100 to analyze their approach toward building brand trust through social media content. The brands include Home Depot, Lowe's Home Improvement, Starbucks, KFC, Walmart, and Costco. The model measures three major behaviors, likes, comments, and shares, to distinguish between post content such as brand image and marketing promotions. In addition to theoretically supporting social media information [14,15], the model can be used to observe specific brand posts and interaction patterns as well as predict and suggest social media information through an AI analysis.

More specifically, this study explores the interactive characteristics of the public by conducting content and preference analyses. It examines publicly accessible community data and compares competitors' strengths and weaknesses to develop a more detailed community-based strategy [16]. Data mining is a popular tool when brand and enterprise trend analyses involve large amounts of community data. Traditional data mining focuses on textual data obtained from within an organization. However, data analyses that are conducted from the outside [17] and not based on a single brand [18] are becoming increasingly important. Therefore, referencing existing data mining methods, this research attempts to develop a community data mining and integration technology to investigate the trends of globally renowned brands. Artificial intelligence (AI) can help identify the diverse operating characteristics of communities. Existing AI research at the community level mainly performs network analyses and automatic classifications of the predictive behaviors of text types [19]. Considering the abovementioned technical characteristics, this study analyzes brand community content to interactively examine and predict brand content trends by exploring structured community-level datasets, combining structured and unstructured data for web content mining, and using Facebook API functions for data collection and pre-processing.

This study focuses on three levels of community issues: information, interactive, and predictive. First, the research explores the similarities and differences in the operating characteristics of a brand's fan pages. Broadly, it examines information on social media platforms and analyzes the content characteristics of images and texts posted by brands. In doing so, it attempts to understand if different brands have common information characteristics. The findings can help managers develop an effective forecasting system. Second, it examines the interactive relationship between information and public participation, information characteristics that are the most effective in improving content participation, and ways to promote behavioral participation on the basis of cognitive and emotional characteristics. Finally, it analyzes if big data and AI technology can predict content engagement (i.e., high or low) in posts by world-renowned brands and identify operating rules that are generally difficult for humans to judge.

The remainder of this paper is structured as follows. Section 2 discusses the relevant literature and theory on data mining and machine learning, brand image, and information cues. Section 3 presents this study′s hypotheses for fan page content to evaluate the influence of different cues on user behaviors. Section 4 explains the research methods adopted in this study. Section 5 details the results of the analyses. Section 6 highlights the theoretical and practical implications and offers recommendation for future research on the basis of this study′s limitations.

2. Literature Review

2.1. Facebook Data Mining

Facebook allows its users to post text, pictures, videos, and links and express themselves through likes, comments, shares, and reaction emojis [20]. The emotional and behavioral data generated by the posts are an effective basis to examine public behavior [21–23]. This study is conducted in line with Facebook′s terms of service to collect research-related material [24–26]. Engagement data for community posts are a critical metric [27]. The analysis uses Facebook′s Graph API to collect data [28,29] on post period, type, time, likes, shares, comments, and sentiments. Some other common estimation parameters include the number of reactions received. Facebook′s page engagement rate is calculated as the rate of posts, clicks, and comments. The study filters and standardizes data from original posts and then applies a two-step simplification process. The first step is to eliminate missing and false outliers and the second step is to filter and reduce data dimensionality to determine information features and then normalize all input categories [30]. As retweets, likes, shares, and comments represent the attractiveness of posts, this study uses supervised learning to create a decision model [31] and text and interactive data (e.g., sentiment, URL, and hashtags) for data analysis and model prediction. The model is used to identify information characteristics on the basis of community interactions and active participants.

Data mining is an exploration technique that relies on the digital features of texts [32]. The process involves data selection, data cleaning, text parsing, text filtering, and results′ interpretation [33]. Data mining helps determine the potential value of information and translates data into comprehensible and effective execution modes. Simply put, it aims to extract unknown knowledge characteristics from existing information. Common data mining techniques include data mining [34], web mining, and text mining [35]. Text mining entails editing, organizing, and analyzing expansive data and offers in-depth information on, for example, representative indicators [36]. Thus, numerous companies have employed community mining to define various services, interact with the public, analyze competition, and transform data into references for decision-making processes.

Moreover, studies have found that data mining simplifies procedures involving large-scale data [37]. The distributed vertical frequent mode, in particular, applies an array method [38] to process large amounts of data and target variables [39]. This mode can be used to optimize problems in the original groups of a data warehouse [40], and thus is widely applied in social network analyses to mine consistent characteristics from social interaction content [41]. Verifying data from actual chat records can help create a framework for a community interaction model to collect data from a software and calculate the relationship and minimum distance between each node [42]. The three most commonly used exploration techniques are mass data, clickstream, and classification analyses. Exploration processes also include data cleaning and pre-processing. An overthrow feature can be used when datasets are balanced and weighting does not produce noise after data mining; however, this feature does not apply until the dataset is balanced, which requires repeated weighting to eliminate noise. Community enhancement services are another approach to understand the benefits of such services, and thus improve users′ cloud experience. Therefore, this study adjusts the content to a community service enhancement model [43] and references information enhancement models available on various community websites to determine judgment strength. If the process reveals that the target variable (variable to be predicted) is a discrete value, a classification algorithm can be used to redefine the information (e.g., new vs. old or strong vs. weak).

2.2. Brand Image and Information Cues

Brand image considerably affects decision-making processes, which directly impacts consumers' evaluation, behaviors, impressions, and feelings in relation to a brand [44,45]. Studies have further classified this impact into cognitive, knowledge, mental, and emotional dimensions. For example, while Zhang and Zhao (2014) evaluate consumers' cognition, emotions, and intentions, they analyze the role of cognition and emotions in decision making. They draw on brand image theory to propose a framework to evaluate the relationship between cognition and emotions. In the context of brand image, cognition refers to knowledge about a brand including its characteristics or symbols; emotions denote individuals' feelings toward a brand; and intentions are actions, behaviors, and reactions in the form of comments and participation [46]. Researchers use a hierarchical causal model to examine the influence of emotions and intentions on cognition and find that emotions affect the degree of cognition. Emotions have a critical impact irrespective of the type or form of information. Research on brand image and emotional response highlights the importance of perceived brand value and its impact on satisfaction and access intention. Tseng et al. (2015) present three stages of brand image formation. First is the induction and modification of an induced image, which can be classified as basic cognitive construction [47]. Second is the construction phase of cognitive transformation into emotions and intentions, which is a predominantly used image theory framework. The final stage is combining brand image and positioning.

A review of the existing literature on brand information highlights research on the concept of image, image composition, and image influence. In addition, scholars have examined the impact of image on decision-making processes and how image varies by brand and socio-cultural aspects. A further review of online text research on image cues reveals a major focus on the estimation of image cues [48–50], testing of image cue theory, and case analysis of image cues. These studies examine data from social media content and emotion surveys and, accordingly, suggest appropriate technologies and methods (Abrahams, Jiao, Fan, Wang, & Zhang, 2013). When using unstructured data, for example, keywords and high-frequency words serve as effective indicators [51], and the technology adopted to classify various topics is critical. This study examines social media data by performing data cleaning, text mining, and content analysis to extract brand and marketing cues [17].

3. Research Hypotheses

3.1. Image Cues

Social media research shows that the public consumes information according to their personal preferences, which significantly impact their brand preferences. Social media allows consumers to share their brand experiences and brands to form a dynamic network with their consumers [52]. A brand's fan page, for example, provides various interactive services and successfully serves as a communication channel for fans [53]. A brand community has an exclusive information structure [54], and all information represents countless relationships and associations with the brand [55]. Fans' response to information helps brands identify problems [21] and assess the popularity of a post or certain information [56]. Likes, comments, and shares are equivalent to viral marketing and promote consumer interactions with brands and increase the willingness to purchase and brand loyalty [57].

The information cueing effect discussed in this study is based on possible crowd behaviors and interactions in response to text information shared in the community. To conceptualize information cues, the research transforms vague information cues into definite text concepts, a problem emphasized in numerous image studies evaluating the individual attributes of information to obtain specific factors composing an image [58]. Information cues are commonly defined as potential ideal information in the minds of the public [59] that may be transformed into a specific image or concept [46]. The impact of the information differs by the media used such as the television, Internet, books, or magazines.

However, such information may prejudice the public even before they make actual contact with the brand. Exploring community information and analyzing interactive responses to information can help brands improve their recognition and positioning [60]. Therefore, this study uses the information construction characteristics of brands' fan pages [61] to explore responses to image cues in posts. In addition, it examines if public interactions differ by brands′ page content. Accordingly, the following hypotheses are proposed (Figure 1).

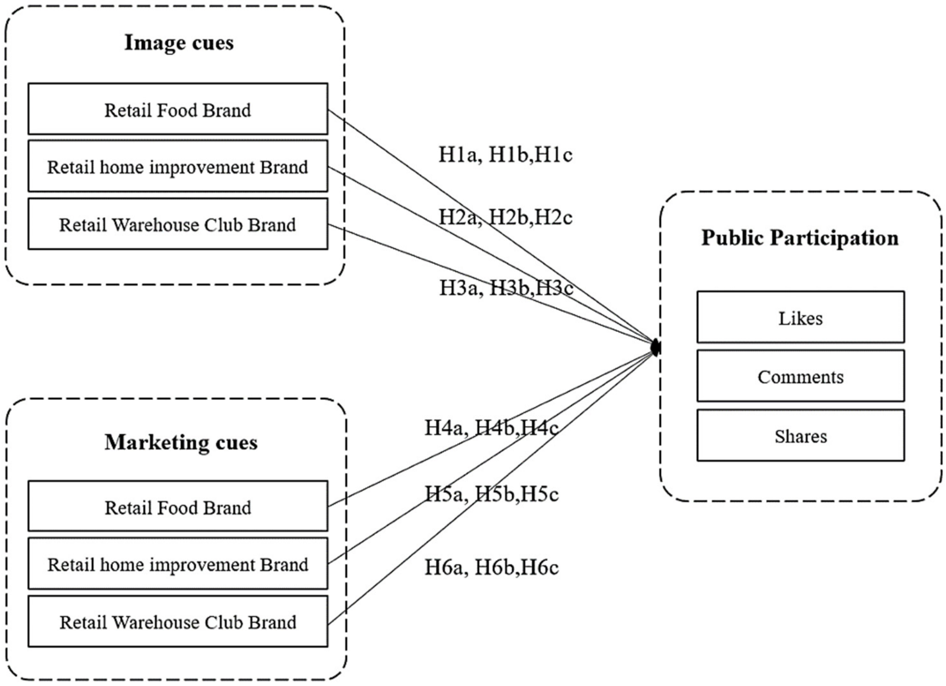

Figure 1. Extended research model.

Hypothesis H1: *Image cues in "retail food brand's posts" encourage public participation through likes, comments, and shares.*

Hypothesis H1a: *Image cues in "retail food brand's posts" encourage public participation through likes.*

Hypothesis H1b: *Image cues in "retail food brand's posts" encourage public participation through comments.*

Hypothesis H1c: *Image cues in "retail food brand's posts" encourage public participation through shares.*

Hypothesis H2: *Image cues in "retail home improvement brand's posts" encourage public participation through likes, comments, and shares.*

Hypothesis H2a: *Image cues in "retail home improvement brand's posts" encourage public participation through likes.*

Hypothesis H2b: *Image cues in "retail home improvement brand's posts" encourage public participation through comments.*

Hypothesis H2c: *Image cues in "retail home improvement brand's posts" encourage public participation through shares.*

Hypothesis H3: *Image cues in "retail warehouse club brand's posts" encourage public participation through likes, comments, and shares.*

Hypothesis H3a: *Image cues in "retail warehouse club brand's posts" encourage public participation through likes.*

Hypothesis H3b: *Image cues in "retail warehouse club brand's posts" encourage public participation through comments.*

Hypothesis H3c: *Image cues in "retail warehouse club brand's posts" encourage public participation through shares.*

3.2. Marketing Cues

Studies suggest that the motivations underpinning information searches include satisfaction [62], participation [63], and the gaining of trust [3]. Consumers read information to understand a brand [64], analyze product characteristics [65], and make purchase decisions. The value of brand fan pages depends on whether the information drives fans toward active participation. Fan pages are considered a reliable source of brand information and can be used to gain consumer trust, making it easier to encourage participation and purchases. Trust is a fundamental factor motivating a community [66] to share and exchange opinions. Many brands encourage communities to actively participate in lotteries and competitive marketing activities aimed at increasing brand interactions through rewards [67]. This marketing operation takes the form of a positive cycle supported by information trust with the public earning rewards as they consume more brand information. Referencing the abovementioned behavioral theories, this study posits that marketing cues impact public participation and, accordingly, makes the following assumptions:

Hypothesis H4: *Marketing cues in "retail food brand's posts" encourage public participation through likes, comments, and shares.*

Hypothesis H4a: *Marketing cues in "retail food brand's posts" encourage public participation through likes.*

Hypothesis H4b: *Marketing cues in "retail food brand's posts" encourage public participation through comments.*

Hypothesis H4c: *Marketing cues in "retail food brand's posts" encourage public participation through shares.*

Hypothesis H5: *Marketing cues in "retail home improvement brand's posts" encourage public participation through likes, comments, and shares.*

Hypothesis H5a: *Marketing cues in "retail home improvement brand's posts" encourage public participation through likes.*

Hypothesis H5b: *Marketing cues in "retail home improvement brand's posts" encourage public participation through comments.*

Hypothesis H5c: *Marketing cues in "retail home improvement brand's posts" encourage public participation through shares.*

Hypothesis H6: *Marketing cues in "retail warehouse club brand's posts" encourage public participation through likes, comments, and shares.*

Hypothesis H6a: *Marketing cues in "retail warehouse club brand's posts" encourage public participation through likes.*

Hypothesis H6b: *Marketing cues in "retail warehouse club brand's posts" encourage public participation through comments.*

Hypothesis H6c: *Marketing cues in "retail warehouse club brand's posts" encourage public participation through shares.*

4. Research Methodology

4.1. Information Sources and Data Collection

The study combines community information and participation in its research framework. The samples are divided into three categories: retail food brand, retail home improvement brand, and retail warehouse club brand. The research definition is adjusted to consider the validity of information cues. This research draws on brand image and information cue theory [1] to design the theoretical framework and then uses behavior response factors for the theoretical integration. Most studies on online text information use single text software to determine the relationship between high-frequency word and image cues, while few use AI to discuss image cues. Given the wide range of information needs today, this study re-evaluates image cues and a community framework while referring to the abovementioned information-related research. Using content exploration and ensemble learning, it examines key image cues to highlight the various reasons motivating participation by fans. Further, it expands the discussion on image and marketing cues to explore how various social brands induce public participation and the evaluation of information efficiency.

The research is conducted in three stages: sample filtering, social data and data collection, and social information analysis and machine learning for element screening. In the first stage of sample filtering, the analysis uses sample home, food, and retail posts by six retail brands listed among the Fortune Global 500, which ranks the world's 500 largest companies on the basis of their turnover. In 2018, the threshold for Fortune Global 500 was USD 242 billion. The list is published in the US *Fortune* magazine and highlights the latest development trends for the world's largest companies. A comparison of industries across the various years gives us an understanding of company characteristics. Following the sample filtering, this study collects data from Facebook posts while adhering to the platform's terms of service [24,26]. It uses Facebook's Graphics API to collect post information [28,29], including post content, type, time, likes, shares, comments, and sentiment during the study period. From 1 January 2011 to 31 December 2019, the studied brands published a total of 25,538 posts, of which 4199 posts were by Home Depot and Lowe's Home Improvement (home brands), 5948 were by Starbucks and KFC (food and beverage brands), and 15,391 were by Walmart and Costco (retail brands). Next, this study integrates random decision forests, extreme gradient boost, and adaboost for statistical verification.

4.2. Data Analysis and Key Clue Extraction

Machine learning focuses on the construction of data exploration and analysis frameworks [68] and analyzes and predicts features hidden in learning data. By teaching machines how to learn, researchers are no longer required to explicitly program computers to accomplish specific tasks. Machine learning is a highly capable and valuable approach used to discover patterns and correct errors. As large-scale data generally have diverse and rapidly changing characteristics, an accurate prediction model derived from adjusting community information can serve as guide for future content output with a better reference basis [69]. Machine learning can be divided into supervised and unsupervised learning. Unsupervised learning lacks categorical variables, whereas supervised learning has clear target or categorical variables and uses these variables to generate association rules [70].

Further, supervised learning continuously improves the minimum value of frequent calculations [40]. Therefore, this study employs supervised learning to develop a prediction model to determine a function that maps labeled training data from input x to output y and to determine the minimum error function that can be predicted using the model. The key characteristic of the model is the attribute training with a classifier and its importance is determined by weights or coefficients ranging between 0 and 1. The feature scores are ranked in order of importance; the higher the score, the more important the analysis characteristics. This study combines supervised learning algorithms with community content and interactions to classify conforming and non-conforming posts [71]. The final value is based on an F-score. If the measurement does not belong to a specific instance, a recall designation is used to re-classify the content according to its corresponding category.

Ensemble learning is a supervised learning algorithm that can be trained and used to make predictions. The integrated model after training represents a single hypothesis, although this hypothesis is not necessarily included in the hypothesis space of the model. Thus, ensemble learning has greater flexibility in its functions. Significant differences between models generally result in the integration producing better results; therefore, various integration methods attempt to promote diversity between the models they combine. Random forests, for example, are mainly used for regression and classification. Bagging generates a decision tree after each bootstrap is returned to sampling and produces as many trees as the sampling. No further intervention is needed while the trees are being generated. Random forests also apply bootstrap sampling, although the approach differs from bagging. That is, when generating a tree, each node variable in a random forest is generated in a small number of randomly selected variables. Therefore, both the sample and the generation of each node variable (features) are random. The combined classifier has a better classification effect than a single classifier. Random forests distinguish and classify data using multiple classification trees. It produces multiple variables while classifying the data (gene) to evaluate the importance of each variable in the classification. The boosting algorithm is used to synthesize weak classifiers into a strong classifier. Boosting associates weights with entities in the dataset and enhances those that are difficult to accurately model. Once a series of models is constructed, the weights are modified after each model and entities that are difficult to classify are assigned greater weight. Machine learning algorithms are computed using a gradient boosting framework. Extreme gradient boost was adopted to quickly and accurately solve numerous data science problems. The same code can be run on the main distributed environment (i.e., Hadoop, SGE, MPI) to solve innumerable problems. Adaboost is an improved boosting classification algorithm derived by increasing the weight of classification error samples linearly combined by previous classifiers. The approach allows us to focus on training samples that are easy to classify every time a new classifier is trained.

5. Data Analyses and Results

5.1. Reliability and Validity

For reliability and validity analysis of the data, principal component factor analysis was performed to test the factor validity of the scale. The factor characteristic value of retail food brands' posts had a total variance of 74.88% and a KMO value of 0.671. The factor characteristic value of retail home improvement brands' posts had a total variance of 64.602% and a KMO value of 0.587. The factor characteristic value of retail brands' posts had a total variance of 66.624% and a KMO value of 0.668. The expected load factor for all items is >0.5, indicating good convergence and discriminant validity. In addition, the reliability test produced a Cronbach's alpha of 0.839 for retail food brands' posts, 0.794 for retail home improvement brand's posts, and 0.748 for retail brands' posts. Each of these results shows good reliability.

5.2. Hypotheses Verification

The extreme gradient boost and random decision forests results show that image cues in retail food brands' posts significantly influenced the prediction of key cues (i.e., likes, comments, and shares). Adaboost, however, reports this impact only for likes and shares (Figure 2). This finding establishes H1a and partially establishes H1b and H1c (Table 1).

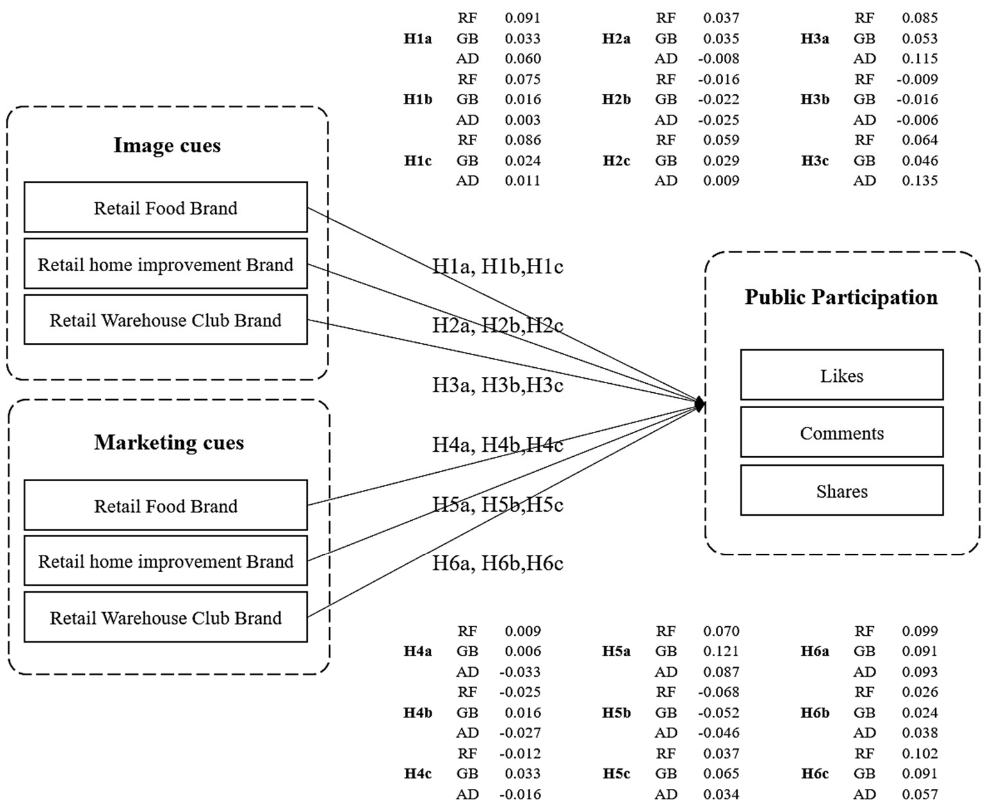

Figure 2. Model results. RF: random decision forests, GB: extreme gradient boost, AD: adaboost.

The extreme gradient boost shows that image cues in retail home improvement brands' posts significantly influenced the prediction of key cues for likes, comments, and shares. Random decision forests results report this impact only for likes and shares. This finding partially establishes H2a, H2b, and H2c.

The extreme gradient boost and random decision forests results show that image cues in retail warehouse club brands' posts significantly influenced the prediction of key cues. Adaboost, however, reports this impact only for likes. This finding establishes H3a and H3c and partially establishes H3b.

For the marketing cues of retail brands' posts, the ensemble learning results were as follows.

The extreme gradient boost and random decision forests results show that marketing cues in retail food brands' posts significantly influenced the prediction of key cues for comments. Adaboost, however, reports this impact only for likes, comments, and shares. This finding establishes H4a and partially establishes H4b and H4c.

The extreme gradient boost, adaboost, and random decision forests results show that image cues in retail home improvement brands' posts and retail warehouse club brands' posts significantly influenced the prediction of key cues for likes, comments, and shares. This finding partially establishes H5a, H5b, H5c, H6a, H6b, and H6c.

Table 1. Summary of hypotheses.

ID	Hypothesis	Verdict
H1.	Image cues in HI the retail food brands' posts encourage public participation through likes, comments, and shares	
H1a.	Image cues in the retail food brands' posts encourage public participation through likes.	Established
H1b.	Image cues in the retail food brands' posts encourage public participation through comments.	Partially established
H1c.	Image cues in the retail food brands' posts encourage public participation through shares.	Partially established
H2.	Image cues in H2 retail home improvement brands' posts encourage public participation through likes, comments, and shares.	
H2a.	Image cues in retail home improvement brands' posts encourage public participation through likes.	Partially established
H2b.	Image cues in retail home improvement brands' posts encourage public participation through comments.	Partially established
H2c.	Image cues in retail home improvement brands' posts encourage public participation through shares.	Partially established
H3.	Image cues in H3 retail warehouse club brands' posts encourage public participation through likes, comments, and shares.	
H3a.	Image cues in retail warehouse club brands' posts encourage public participation through likes.	Established
H3b.	Image cues in retail warehouse club brands' posts encourage public participation through comments.	Partially established
H3c.	Image cues in retail warehouse club brands' posts encourage public participation through shares.	Established
H4.	Marketing cues in H4 retail food brands' posts encourage public participation through likes, comments, and shares.	
H4a.	Marketing cues in retail food brands' posts encourage public participation through likes.	Partially established
H4b.	Marketing cues in retail food brands' posts encourage public participation through comments.	Established
H4c.	Marketing cues in retail food brands' posts encourage public participation through shares.	Partially established
H5.	Marketing cues in H5 retail home improvement brands' posts encourage public participation through likes, comments, and shares.	
H5a.	Marketing cues in retail home improvement brands' posts encourage public participation through likes.	Partially established
H5b.	Marketing cues in retail home improvement brands' posts encourage public participation through comments.	Partially established
H5c.	Marketing cues in retail home improvement brands' posts encourage public participation through shares.	Partially established
H6.	Marketing cues in H6 retail warehouse club brands' posts encourage public participation through likes, comments, and shares.	
H6a.	Marketing cues in retail warehouse club brands' posts encourage public participation through likes.	Partially established
H6b.	Marketing cues in retail warehouse club brands' posts encourage public participation through comments.	Partially established
H6c.	Marketing cues in retail warehouse club brands' posts encourage public participation through shares.	Partially established

5.3. Data Verification

The study results show that content planning for the fan pages significantly affects public participation. The results of the various verification tests are presented below.

First, the influence of the image cues in retail food brands' posts on the behavioral involvement of social media users (H1) was verified. The association between the image cues in retail food brands' posts, the "Likes" (random decision forests: $\beta = 0.091$, $p < 0.000$; extreme gradient boost: $\beta = 0.033$, $p < 0.000$; adaboost: $\beta = 0.060$, $p < 0.000$), the "Comments" (random decision forests: $\beta = 0.075$, $p < 0.000$; extreme gradient boost: $\beta = 0.016$, $p < 0.034$; adaboost: $\beta = 0.003$, $p < 0.653$), and the "Shares" (random decision forests: $\beta = 0.086$, $p < 0.000$; extreme gradient boost: $\beta = 0.024$, $p < 0.002$; adaboost: $\beta = 0.011$, $p < 0.140$) were found to be significant (Table 2).

Second, the influence of the image cues in retail home improvement brands' posts on the behavioral involvement of social media users (H2) was verified. The association between the image cues in retail home improvement brands' posts, the "Likes" (random decision forests: β = 0.037, $p < 0.000$; extreme gradient boost: β = 0.000, $p < 0.000$; adaboost: β = −0.008, $p < 0.341$), the "Comments" (random decision forests: β = −0.016, $p < 0.079$; extreme gradient boost: β = −0.022, $p < 0.013$; adaboost: β = −0.025, $p < 0.004$), and the "Shares" (random decision forests: β = 0.059, $p < 0.000$; extreme gradient boost: β = 0.029, $p < 0.001$; adaboost: β = 0.009, $p < 0.328$) were found to be significant.

Third, the influence of the image cues in retail warehouse club brands' posts on the behavioral involvement of social media users (H3) was verified. The association between the image cues in retail brands' posts, the "Likes" (random decision forests: β = 0.085, $p < 0.000$; extreme gradient boost: β = 0.000, $p < 0.001$; adaboost: β = 0.115, $p < 0.000$), the "Comments" (random decision forests: β = −0.009, $p < 0.046$; extreme gradient boost: β = −0.016, $p < 0.000$; adaboost: β = −0.006, $p < 0.175$), and the "Shares" (random decision forests: β = 0.064, $p < 0.000$; extreme gradient boost: β = 0.046, $p < 0.000$; adaboost: β = 0.135, $p < 0.000$) were found to be significant.

Fourth, the influence of the marketing cues in retail food brands' posts on the behavioral involvement of social media users (H4) was verified. The association between the marketing cues in retail food brands' posts, the "Likes" (random decision forests: β = 0.009, $p < 0.226$; extreme gradient boost: β = 0.006, $p < 0.429$; adaboost: β = −0.033, $p < 0.000$), the "Comments" (random decision forests: β = −0.025, $p < 0.001$; extreme gradient boost: β = 0.016, $p < 0.034$; adaboost: β = −0.027, $p < 0.000$), and the "Shares" (random decision forests: β = −0.012, $p < 0.103$; extreme gradient boost: β = 0.033, $p < 0.000$; adaboost: β = −0.016, $p < 0.031$) were found to be significant (Table 3).

Table 2. Linear regression coefficient of determination and beta (image cues).

Image Cues		B	SE	Beta	T	Sig.	R^2	ΔF	F Change	Durbin–Watson
Retail Food Brands' Posts										
H1a Likes	RF	6509.994	532.234	0.091	12.231	0.000	0.008	149.608	0.000	1.204
	GB	1784.118	404.669	0.033	4.409	0.000	0.001	19.438	0.000	1.193
	AD	5739.455	711.084	0.060	8.071	0.000	0.004	65.148	0.000	1.198
H1b Comments	RF	325.768	32.362	0.075	10.066	0.000	0.006	101.330	0.000	1.529
	GB	52.043	24.583	0.016	2.117	0.034	0.000	4.482	0.034	1.519
	AD	19.459	43.258	0.003	0.450	0.653	0.000	0.202	0.653	1.521
H1c Shares	RF	538.372	46.897	0.086	11.480	0.000	0.007	131.786	0.000	1.576
	GB	112.678	35.649	0.024	3.161	0.002	0.001	9.990	0.002	1.568
	AD	92.578	62.736	0.011	1.476	0.140	0.000	2.178	0.140	1.571
Retail Home Improvement Brands' Posts										
H2a Likes	RF	404.018	97.132	0.037	4.159	0.000	0.001	17.301	0.000	1.586
	GB	377.110	95.525	0.035	3.948	0.000	0.001	15.585	0.000	1.587
	AD	−95.474	100.168	−0.008	−0.953	0.341	0.000	0.908	0.341	1.589
H2b Comments	RF	−15.402	8.766	−0.016	−1.757	0.079	0.000	3.087	0.079	1.691
	GB	−21.459	8.619	−0.022	−2.490	0.013	0.000	6.198	0.013	1.691
	AD	−25.787	9.032	−0.025	−2.855	0.004	0.001	8.151	0.004	1.691
H2c Shares	RF	145.271	22.017	0.059	6.598	0.000	0.003	43.535	0.000	1.709
	GB	69.846	21.680	0.029	3.222	0.001	0.001	10.379	0.001	1.711
	AD	22.251	22.729	0.009	0.979	0.328	0.000	0.958	0.328	1.710
Retail Warehouse Club Brands' Posts										
H3a Likes	RF	185.616	10.137	0.085	18.310	0.000	0.007	335.270	0.000	1.784
	GB	133.190	11.597	0.053	11.485	0.000	0.003	131.894	0.000	1.778
	AD	173.223	6.980	0.115	24.815	0.000	0.013	615.807	0.000	1.794
H3b Comments	RF	−1.405	0.703	−0.009	−1.998	0.046	0.000	3.992	0.046	1.851
	GB	−2.795	0.802	−0.016	−3.484	0.000	0.000	12.136	0.000	1.851
	AD	−0.659	0.486	−0.006	−1.357	0.175	0.000	1.842	0.175	1.852
H3c Shares	RF	31.235	2.269	0.064	13.766	0.000	0.004	189.502	0.000	1.925
	GB	25.598	2.593	0.046	9.873	0.000	0.002	97.478	0.000	1.923
	AD	45.667	1.556	0.135	29.350	0.000	0.018	861.452	0.000	1.928

Table 3. Linear regression coefficient of determination and beta (marketing cues).

Marketing Cues		B	SE	Beta	T	Sig.	R^2	ΔF	F Change	Durbin–Watson
Retail Food Brands' Posts										
H4a Likes	RF	626.394	517.073	0.009	1.211	0.226	0.000	1.468	0.226	1.194
	GB	488.883	618.452	0.006	0.790	0.429	0.000	0.625	0.429	1.195
	AD	−2391.978	550.624	−0.033	−4.344	0.000	0.001	18.871	0.000	1.196
H4b Comments	RF	−103.018	31.390	−0.025	−3.282	0.001	0.001	10.771	0.001	1.523
	GB	79.512	37.550	0.016	2.117	0.034	0.000	4.484	0.034	1.520
	AD	−119.137	33.441	−0.027	−3.563	0.000	0.001	12.692	0.000	1.523
H4c Shares	RF	−74.281	45.537	−0.012	−1.631	0.103	0.000	2.661	0.103	1.573
	GB	237.959	54.439	0.033	4.371	0.000	0.001	19.107	0.000	1.570
	AD	−104.903	48.513	−0.016	−2.162	0.031	0.000	4.676	0.031	1.572
Retail Home Improvement Brands' Posts										
H5a Likes	RF	544.878	69.576	0.070	7.831	0.000	0.005	61.332	0.000	1.600
	GB	721.046	52.711	0.121	13.679	0.000	0.015	187.122	0.000	1.623
	AD	819.504	83.542	0.087	9.810	0.000	0.008	96.226	0.000	1.610
H5b Comments	RF	−48.046	6.276	−0.068	−7.655	0.000	0.005	58.602	0.000	1.694
	GB	−28.110	4.783	−0.052	−5.877	0.000	0.003	34.540	0.000	1.690
	AD	−39.189	7.556	−0.046	−5.187	0.000	0.002	26.900	0.000	1.689
H5c Shares	RF	64.849	15.815	0.037	4.100	0.000	0.001	16.814	0.000	1.715
	GB	87.347	12.024	0.065	7.265	0.000	0.004	52.773	0.000	1.723
	AD	72.656	19.017	0.034	3.820	0.000	0.001	14.596	0.000	1.717
Retail Warehouse Club Brands' Posts										
H6a Likes	RF	315.498	14.712	0.099	21.445	0.000	0.010	459.876	0.000	1.793
	GB	283.907	14.420	0.091	19.689	0.000	0.008	387.644	0.000	1.793
	AD	426.938	21.349	0.093	19.998	0.000	0.009	399.909	0.000	1.786
H6b Comments	RF	5.710	1.021	0.026	5.591	0.000	0.001	31.262	0.000	1.854
	GB	5.107	1.000	0.024	5.105	0.000	0.001	26.065	0.000	1.854
	AD	12.007	1.481	0.038	8.110	0.000	0.001	65.764	0.000	1.852
H6c Shares	RF	72.219	3.287	0.102	21.971	0.000	0.010	482.705	0.000	1.937
	GB	63.216	3.223	0.091	19.616	0.000	0.008	384.798	0.000	1.936
	AD	58.663	4.784	0.057	12.262	0.000	0.003	150.364	0.000	1.923

Fifth, the influence of the marketing cues in retail home improvement brands' posts on the behavioral involvement of social media users (H5) was verified. The association between the marketing cues in retail home improvement brands' posts, the "Likes" (random decision forests: $\beta = 0.070$, $p < 0.000$; extreme gradient boost: $\beta = 0.121$, $p < 0.000$; adaboost: $\beta = -0.087$, $p < 0.000$), the "Comments" (random decision forests: $\beta = -0.068$, $p < 0.000$; extreme gradient boost: $\beta = -0.052$, $p < 0.000$; adaboost: $\beta = -0.046$, $p < 0.000$), and the "Shares" (random decision forests: $\beta = 0.037$, $p < 0.000$; extreme gradient boost: $\beta = 0.065$, $p < 0.000$; adaboost: $\beta = 0.034$, $p < 0.000$) were found to be significant.

Lastly, the influence of the marketing cues in retail warehouse club brands' posts on the behavioral involvement of social media users (H6) was verified. The association between the marketing cues in retail brands' posts, the "Likes" (random decision forests: $\beta = 0.099$, $p < 0.000$; extreme gradient boost: $\beta = 0.091$, $p < 0.000$; adaboost: $\beta = 0.093$, $p < 0.000$), the "Comments" (random decision forests: $\beta = 0.026$, $p < 0.000$; extreme gradient boost: $\beta = 0.024$, $p < 0.000$; adaboost: $\beta = 0.038$, $p < 0.000$), and the "Shares" (random decision forests: $\beta = 0.102$, $p < 0.000$; extreme gradient boost: $\beta = 0.091$, $p < 0.000$; adaboost: $\beta = 0.057$, $p < 0.000$) were found to be significant.

6. Results, Hypothesis Verification, and Discussion

6.1. Results

This section compares the estimation results for the studied brands.

For Costco, fans appear to prioritize practical needs and product-related information (e.g., "recipes", "items", and "packages"). In addition to their own needs, they are happy to share the information with friends who like the brand, indicating high interactive value. The use of clear rewards information (e.g., "member", "today", "comment", "FridayFind", and "chance") successfully promotes physical products (Table A1, Figures A1–A3).

In the case of Walmart, the construction of corporate image through the image cues of "ethics", "best brand", and "realization" gradually builds a sense of trust and enhances the willingness to share the information. In addition, marketing cues (e.g., "tip", "here", "find", or "http") increase fans' attention space and the time spent browsing through information (Table A2, Figures A4–A6).

For KFC, the analysis results for Starbucks show that, in addition to the promotion of main products, the brand incorporates positive cues (e.g., "holiday" and "happy") to develop a pleasant and positive image (Table A3, Figures A7–A9).

For Starbucks, compared with KFC′s marketing cues, those of Starbucks (e.g., "share" and "free") are more effective in communicating information. Nevertheless, KFC demonstrates precise performance in setting key cues, particularly marketing cues (e.g., "friend", "now", "only", and "free"), and in promoting cheap products to attract the public. Through designed action, the brand encourages participation through likes and comments (Table A4, Figures A10–A12).

Lowe′s Home Improvement shows similar results to those for Home Depot: "Vine", "DIY", "garden", "paint", likes, and shares report good interactive performance (Table A5, Figures A13–A15).

Finally, Home Depot can enhance its brand image while strengthening its information characteristics by encouraging interactions with its products (e.g., "workshop", "DIY", and "Vine"). However, providing brand cues (e.g., "workshop", "depot", and "retail") that are less relevant to physical needs will deter the public from participating (Table A6, Figures A16–A18).

In sum, this study measures users′ response behaviors to information [72], evaluates the focus of user interactions with brand community information, and analyzes if such information is in line with user needs [73]. The results identify behavioral tension among community posts on fan pages. The analysis also confirms that user preferences for image- and information-based posts tend to differ and these differences influence participation levels [74]. This finding not only contributes to the literature on social media content, but also reiterates the importance of community content planning for brands. A further analysis of brand cue reveals a majority of information is utilized and adjusted according to brand positioning and content needs rather than repeatedly promoted to better fit the definition of diverse information.

The recent years have witnessed a growing amount of social media research [75] on community needs [76] and the benefits of brands' social communication. These two topics have received particular academic attention [77] given the critical role of communities in enhancing public dialogue [78]. Social media positioning and needs tend to differ by brand [79,80]. Nevertheless, numerous studies have confirmed that social media effectively generates secure communication and interactions between brands and the public and strengthens the impact of relationship marketing [81,82]. With increasing importance being assigned to public participation, researchers are paying more attention to brand interactions with communities and exploring ways to successfully communicate brand information to increase brand loyalty [83].

6.2. Hypothesis Verification

This study verifies the importance of consistent image and information positioning. Images can be used to reflect the impact of information on users [84]. Information in line with a brand's image is easier to recall than misaligned information, a finding supported by past research on advertising information and memory recall [85]. Information organization theory and information processing research have repeatedly demonstrated the relationship between consistent information and imagery and higher memory recall. In addition, clearer and more explicit content contributes to long-term brand memory and achieving a successful brand link [86]. The result for marketing cues shows that different marketing plans, such as promoting high-quality attributes of a product, strengthen brand identity [87] and that marketing activities induce certain user behaviors. Image cues also symbolize important judgments in brand emotions [88]. Emotional identification with brands can be used to determine if a crowd positively or negatively perceives a brand and critically influences subjective impression.

6.3. Discussion

This study contributes a model that classifies brand community posts and mines related data to predict public needs and preferences. More specifically, it proposes a framework with supervised and ensemble learning to classify information and predict users′ behavioral characteristics. A social network analysis is conducted on brand fan pages and a crowd-based model with an F-score is used to predict and cross-validate the relationship between post information and user behavior. The research employs a big data analysis with AI machine learning to review the information characteristics of brand communities and provides model tools for complete data collection, analysis, and operation. The model is premised on user needs that often differ in learnings and emotions over time. To address the potential for unexpected results, the model uses big data to access information that is not easily available and perform high-speed calculations, thus reducing the time and financial burden. Nevertheless, new decision-making and management methods are needed to promote the development of a data economy. Given the continuous flow of data, digital smoke signals can be used as an early warning system, although they are unable to confirm actual situations. Therefore, the contribution of this research lies in its construction of a predictive model, which can be used as a reference tool to determine decisions and actions on the basis of early warning signals, identify problems and related solutions, and enhance brand community management.

6.4. Conluclusions and Limitations

This study is not free from limitations and, accordingly, offers suggestions for future research. First, accounting for the restrictions of the Facebook API, the collected data are limited to specific time periods and may be subject to and dominated by hot topics. To improve the stability of the results, cross-comparisons are needed over an extended period to verify the general value of the model. Second, the sample focuses on well-known brands and a majority of the content is published in English. While the English language is predominantly used on social media around the world, future research should consider other languages to conduct a comparative analysis.

In addition, the researcher provides two suggestions for information management. Social media experiences tend to increase public acceptance or rejection of information, and users' interactive behaviors are expected to reflect their satisfaction levels (Jiang et al., 2010). Therefore, information rich in marketing elements is more likely to trigger positive comments and even stimulate potential revisits [89]. Links, messages, and sharing also critically stimulate user behaviors [90]. Image cues enhance public dialogue, which in turn stimulate good brand communication [91,92]. Users actively express emotions or relay information through interactions [93], a notion in line with community exchange theory. In addition to generating social interactions, community information promotes self-expression and support and contributes toward strong emotional interactions [94] and a safe environment [93]. Given today′s dynamic market conditions, consumer expectations exceed brand positioning. Individuals develop trust in a brand by evaluating its actions rather than claimed appeals. Thus, the loss of consumer confidence detrimentally impacts brands whose business models are built on trust. In other words, the existence of a brand largely depends on its consumers. Impressions of and attitudes toward a brand differ by corporate attitudes. One such attitude is cultivating fan culture by returning brands to consumers. It is important for brands to remain open and transparent and use online platforms and communities to encourage consumer participation and sharing.

Funding: This study was funded by the Ministry of Science and Technology, Digital Humanities Program (MOST 110-2410-H-032-051).

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A Measurement and Items

Table A1. Brand cues (Costco).

Brand Cues	Likes	Brand Cues	Comments	Brand Cues	Shares
recipe	102.09	http	53.74	recipe	122.38
http	39.47	Costco	26.97	http	30.04
Costco	31.18	member	23.44	Costco	33.43
love	22.72	love	26.54	warehouse	19.8
day	17.36	day	16.48	love	26.46
available	9.99	feature	8.85	available	16.13
new	20.21	recipe	20.09	day	18.24
warehouse	6.72	favorite	28.85	now	17.83
item	14.22	Kirkland	27.46	book	16.98
Kirkland	25.11	item	16.14	receive	21.91
book	13.34	comment	13.88	item	17.17
member	17.59	pick	4.37	year	17.34
month	−3.42	available	10.74	new	16.84
Signature	21.5	warehouse	13.01	last	13
FridayFind	12.93	month	−5.62	offer	15.88
feature	0.67	chance	3.04	Kirkland	17.02
CostcoConnection	20.88	today	10.39	Facebook	12.21
year	13	book	11.16	today	12.82
last	14.14	select	8.04	package	13.52
pick	6.01	new	17.77	pick	16.95
today	8.23	year	18.94	save	10.19
local	3.35	Facebook	11.98	local	5.31
value	13.84	tip	16.12	select	11.28
select	8.73	value	19.63	Signature	14.84
package	12.3	Signature	21.28	favorite	12.59
card	6.21	time	14.59	time	12.27
time	15.76	now	15.53	Available	9.87
save	8.07	last	14.19	Sunday	8.69
now	9.37	live	11.59	live	12.74
Facebook	9.42	local	7.09	help	15.16
offer	13.95	receive	12.76	CostcoConnection	13.82
chance	−1.42	holiday	9.53	member	18.71
find	16.41	package	8.69	holiday	8.27
receive	12.35	find	15.66	feature	9.17
live	10.77	photo	7.98	tip	11.63
vacation	9.44	card	8.41	comment	5.92
gift	8.1	cover	6.7	FridayFind	8.66
favorite	9.58	home	5.33	home	7.09
Sunday	6.74	save	0.06	photo	5.31
cover	0.64	CostcoConnection	7.22	month	7.61
Available	3.7	learn	6.35	chance	−0.45
help	13.47	offer	7.07	gift	8.39
tip	11.1	FridayFind	15.17	card	5.44
home	9.27	Sunday	6.78	vacation	9.44
holiday	9.48	vacation	6.49	find	9.68
photo	−3.73	help	10.4	cover	17.14
comment	8.76	start	6.44	value	8.82
learn	6.26	Available	5.11	start	2.72
start	6.15	gift	7.88	learn	5.61

Table A2. Brand cues (Walmart).

Brand Cues	Likes	Brand Cues	Comments	Brand Cues	Shares
Tuesday	37.34	Tuesday	30.74	here	44.96
http	52.42	recommendation	26.55	http	30.99
tienda	48.67	SIEMPRE	29.29	SIEMPRE	24.87
fruit	43.19	http	37.96	recipe	27.95
mejor	24.86	mejor	13.33	tip	9.2
encuentra	14.65	encuentra	2.63	mejor	9.44
SIEMPRE	22.65	brand	13.38	tienda	24.55
walmart	19.36	fruit	35.65	recommendation	4.2
here	30.07	precio	16.19	Tuesday	8.1
availability	17.84	tip	−2.8	style	5.12
recommendation	16.22	producto	22.23	come	9.91
precio	23.57	tienda	17.47	sale	13.24
lifetime	−2.05	walmart	15.93	encuentra	−7.21
producto	20.97	lifetime	7.46	find	14.98
brand	16.78	cat	25.12	availability	18.2
shape	19.43	prepare.1	−0.46	lifetime	5.25
recipe	29.78	availability	2.84	prepare	11.9
style	−14.79	baby	13.16	prepare.1	11.06
tip	9.74	prepare	−0.8	subject	7.63
subject	−0.44	color	−4.2	ethics	7.68
prepare	6.45	style	−5.4	baby	13.11
sale	16.27	come	6.19	realization	15.82
prepare	5.05	query	17.26	responsabilidad	14.85
come	10.93	great	−5.73	ingredient	15.76
ethics	13.21	subject	5.79	walmart	5.8
responsabilidad	18.23	here	20.61	shape	−2.03
realization	14.43	recipe	14.91	precio	1.43
great	−1.63	purchase	1.63	producto	21.01
cat	13.81	responsabilidad	13.41	family	1.37
months	1.05	without	5.03	months	−1.38
ingredient	20.84	months	−7.16	House	11.54
find	9.57	ethics	16.33	great	0.82
variety	10.09	fresh	−4.53	fruit	2.52
without	14.64	shape	11.48	Go.ahead	−1.73
Favourite	8.38	realization	13.78	purchase	7.78
family	5.2	Go.ahead	2.35	brand	18.06
Go.ahead	2.64	family	2.71	fresh	6.28
discover	6.1	variety	7.94	without	5.33
interests	14.28	sale	8.66	interests	9.27
fresh	11.29	ingredient	2.94	variety	1.44
House	9.05	House	5.75	Favourite	6.33
baby	5.2	discover	−1.11	color	−2.77
purchase	12.86	find	2.83	Health	4.82
Water	−1.74	interests	6.98	cat	2.45
Health	0.53	Favourite	12.77	discover	2.68
query	1.93	Health	−2.23	query	−0.53
kitchen	−0.65	Water	2.61	Water	0.29
color	−0.51	kitchen	5.17	kitchen	−5.1

Table A3. Brand cues (KFC).

Brand Cues	Likes	Brand Cues	Comments	Brand Cues	Shares
only	22.21	only	19.48	only	9.54
dip	24.86	chicken	18.16	online	−26.13
order	−5.59	http	21.71	yummy	0.81
chicken	16.63	want	17.24	http	16.94

Table A3. *Cont.*

Brand Cues	Likes	Brand Cues	Comments	Brand Cues	Shares
win	12.38	friend	1.84	order	−12.1
http	10.77	code	−18.84	chicken	4.72
offer	−0.97	KFC	1.95	friend	−4.19
friend	6.78	online	−16.01	KFC	−6.4
online	−9.33	order	−9.49	offer	−6.29
day	13.77	dip	17.79	enjoy	−7.34
today	5.28	yummy	−2.72	dip	5.42
want	10.17	day	9.48	free	−11.35
enjoy	7.71	win	8.11	want	8.98
meal	6.65	right	−0.92	win	10.47
yummy	−2.04	enjoy	7.21	meal	4.75
KFC	−0.01	hot	1.69	Zinger	−1.75
free	7.21	offer	−5.24	hot	−1.47
treat	−4.74	free	−9.1	Use	−1.9
here	4.27	now	−5.95	code	−5.38
code	−3.24	start	14.14	click	−6.71
hot	1.96	good	7.03	now	−6.78
new	9.08	today	5.8	right	−0.05
good	0.78	coupon	7.61	new	10.89
Use	10.19	click	−6.15	day	−1.8
Zinger	3.7	Use	−2.2	good	3.13
now	−2.68	new	3.01	time	2.22
right	1.7	time	5.74	coupon	6.36
time	2.05	first	−3	treat	−5.7
coupon	6.37	Zinger	2.45	bucket	0.95
share	6.19	treat	−3.84	today	3.36
call	−0.28	share	−0.34	start	12.1
like	2.03	come	0.18	here	−2.8
click	1.87	call	−0.58	like	−0.77
bucket	7.36	here	1.04	come	1.07
come	1.28	photo	10.69	call	−4.33
hunger	−4.11	bucket	−0.89	photo	9.59
photo	8.45	meal	−0.36	first	−6.88
start	8.17	love	−5.53	share	−0.74
first	−4.95	hunger	0.11	love	0.62
love	−2.84	like	−3.08	hunger	−6.6

Table A4. Brand cues (Starbucks).

Brand Cues	Likes	Brand Cues	Comments	Brand Cues	Shares
caramel	9.52	caramel	13.13	caramel	22.51
Iced	25.24	Frappuccino	12.66	Frappuccino	9.47
share	10.02	Starbucks	12.46	Starbucks	11.17
Starbucks	14.45	Iced	8.8	free	2.46
sweet	9.53	holiday	10.84	any	13.98
http	16.95	friend	0.05	share	6.93
here	1.3	here	−1.28	cold	6.29
pumpkin	2.33	share	9.78	all	12.01
cup	5.14	any	7.47	holiday	11.48
any	8.21	like	3.58	drink	1.9
drink	1.9	cold	1.44	here	−0.32
year	7.69	time	1.39	espresso	0.75
Frappuccino	3.43	come	3.07	like	2.68
coffee	1.35	free	9.76	http	4.01
friend	1.74	drink	1.41	friend	0.35
help	8.48	espresso	−0.77	thank	5.19

Table A4. *Cont.*

Brand Cues	Likes	Brand Cues	Comments	Brand Cues	Shares
all	1.82	sweet	4.39	today	6.5
cold	1.33	today	3.38	join	−0.78
today	5.37	http	6.44	sweet	4.22
espresso	−1.08	help	5.7	new	6.91
brew	−2.14	new	5.78	come	1.97
time	−2.13	community	0.41	happy	−0.4
new	0	coffee	−2.36	store	0.51
like	−3.73	now	3.9	time	−5.16
happy	−3.5	year	−0.24	help	0.66
only	−2.12	brew	−1.89	love	−0.94
holiday	3.46	happy	−3.74	coffee	−1.1
thank	0.6	store	4.58	year	0.88
buy	−2.15	buy	0.37	buy	−6.63
join	−1.59	pumpkin	−1.84	pumpkin	−2.78
come	−1.82	join	−4.04	only	−0.04
love	−4.53	love	−2.66	brew	−4.07
free	0.35	good	−4.29	Iced	−1.65
store	3.09	all	3.08	now	1.17
now	−2.46	only	−1.88	day	−2.76
day	−1.45	cup	−2.23	good	−4.6
tea	0.31	thank	2.28	cup	3.19
good	−6.35	day	−4.3	community	−3.91
community	−1.86	tea	−3.69	tea	−3.5

Table A5. Brand cues (Lowe’s Home).

Brand cues	Likes	Brand Cues	Comments	Brand Cues	Shares
look	18.3	today	0.69	Vine	54.36
fall	9.1	http	8.93	http	22.08
detail	9.54	low	4.33	DIY	16.62
low	16.69	paint	−0.56	store	7.72
idea	5.21	project	0.68	help	5.15
keep	6.96	Vine	4.89	like	1.13
build	8.61	store	−1.13	garden	9.65
paint	0.66	love	8.16	now	0.74
color	3.42	look	13.51	look	12.32
love	9	detail	9.47	detail	14.49
like	−3.22	now	−0.24	keep	4.26
kitchen	5.26	here	2.62	kitchen	4.7
save	−0.38	keep	10.16	save	7.81
today	−3.78	color	−0.91	light	4.8
now	−1.88	create	−3.16	give	−0.03
DIY	11.72	garden	−2.18	fall	10.31
project	2.96	spring	5.58	tip	−0.94
here	5.39	time	2.86	start	2.72
http	3.05	idea	−1.78	love	9
just	5.3	just	−4.65	create	−0.87
perfect	1.47	design	0.88	just	4.25
Vine	−1.92	need	1.51	low	6.29
store	−8.06	home	−2.81	project	−0.34
create	−5.33	great	−1.04	idea	3.47
garden	−0.53	tip	−4.19	paint	1.22
start	−4.05	light	−2.77	bathroom	3.46
spring	−3.5	save	−5.47	time	−3.7
tip	−1.61	build	1.59	build	5.83

Table A5. *Cont.*

Brand cues	Likes	Brand Cues	Comments	Brand Cues	Shares
bathroom	8.02	perfect	−3.49	home	0
time	−3.85	give	−2.17	great	−4
design	0.28	help	2.96	design	2.01
give	−3.14	kitchen	−2.19	today	0.17
year	−1.56	like	−4.83	perfect	3.28
great	−0.68	fall	−0.62	color	−0.05
home	−1.29	new	−5.29	here	3.41
help	−1.86	DIY	2.66	year	−0.34
light	−7.12	family	−1.27	need	0.73
new	−3.2	start	−4.22	new	−3.69
shop	−2.08	shop	−2.93	family	0.19
family	−4.28	year	1.39	spring	−4.46
need	−2.25	bathroom	4.38	shop	0.3

Table A6. Brand cues (Home Depot).

Brand Cues	Likes	Brand Cues	Comments	Brand Cues	Shares
http	0.21	http	31.11	workshop	29.58
full	−8.66	room	10.67	DIY	5.66
home	0.32	free	12.26	light	16.26
garden	9.22	space	−3.83	http	8.5
post	3.83	depot	9.46	full	−3.6
now	0.35	now	13.97	post	6.4
know	−2.97	season	−7.58	garden	7.25
spring	−0.58	post	−3.29	season	4.71
space	−7.09	home	−4.22	need	−0.46
depot	2.83	style	−7.8	free	9.9
start	−2.61	full	−6	know	−0.71
today	−2.05	here	7.88	here	4.73
year	4.01	know	5.31	build	12.73
light	4.02	help	2.49	space	−5.84
need	−7.34	garden	5.63	depot	2.36
DIY	−0.71	look	−0.24	home	5.71
project	−3.03	Christmas	2.02	tip	1.21
patio	7.87	photo	−4.33	today	2.39
season	−5.68	tip	6.12	project	0.61
tip	0.57	store	3.38	patio	0.72
here	1.05	DIY	4.68	photo	−0.35
holiday	−2.89	paint	4.98	outdoor	0.54
store	−4.1	build	12.78	create	−4.46
bathroom	−4.84	tool	4.55	SpringMadeSimple	0.06
room	−5.58	patio	5.43	time	3.95
SpringMadeSimple	5.72	today	2.15	start	−2.69
help	0.73	create	2.5	holiday	4.16
create	−1.87	new	−5.2	now	−3.29
Christmas	−1.54	decor	−6.21	Christmas	0.66
gift	2.69	year	−1.51	year	−1.69
workshop	1.09	spring	−5.26	spring	−4.83
paint	−0.66	time	−1.97	new	3.35
learn	−2.38	project	3.61	learn	−3.43
look	−3.65	need	−2.15	store	−4.11
tool	0.26	start	1.43	gift	1.74
build	−0.8	gift	−0.15	decor	−3.99

Table A6. *Cont.*

Brand Cues	Likes	Brand Cues	Comments	Brand Cues	Shares
photo	−2.44	bathroom	−7.11	tool	−2.1
decor	−3.05	outdoor	−6	help	−0.82
new	−6.55	light	−3.99	look	0.13
time	−5.95	SpringMadeSimple	4.49	room	3.48
outdoor	0.65	workshop	9.64	style	0.4
free	−1.97	holiday	−5.11	paint	6.44
style	−2.77	learn	0.9	bathroom	1.23

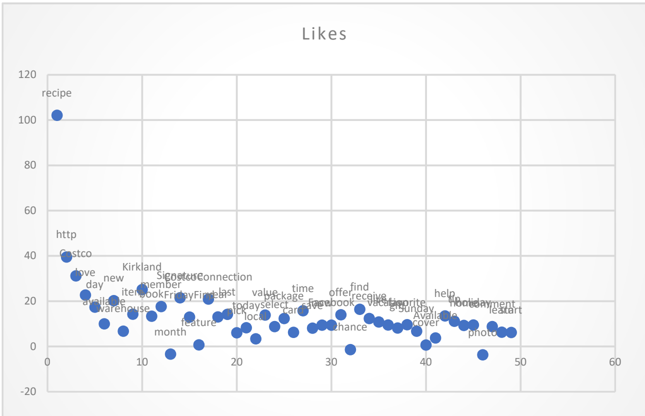

Figure A1. Cues of Costco (Likes).

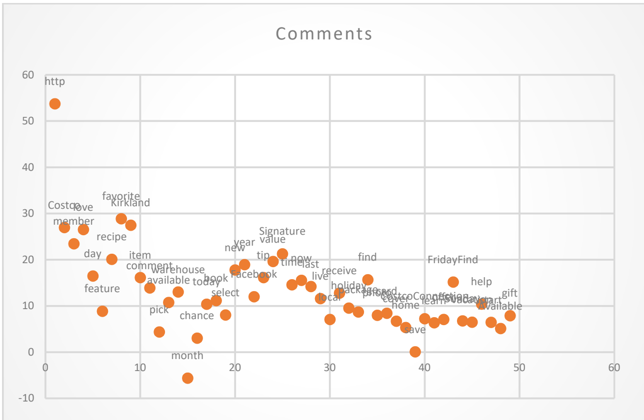

Figure A2. Cues of Costco (Comments).

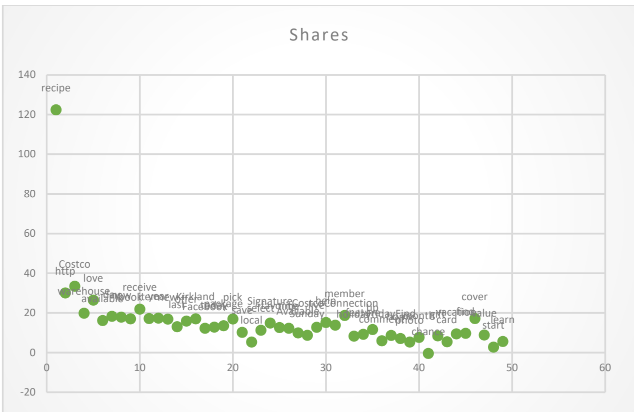

Figure A3. Cues of Costco (Shares).

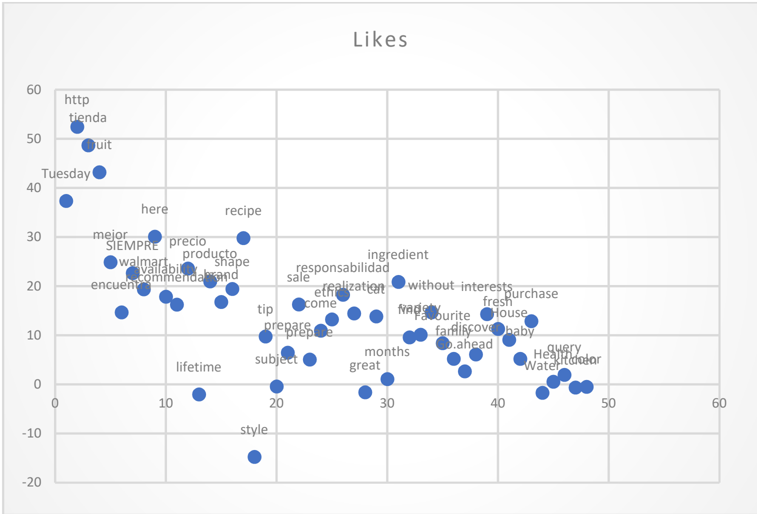

Figure A4. Cues of Walmart (Likes).

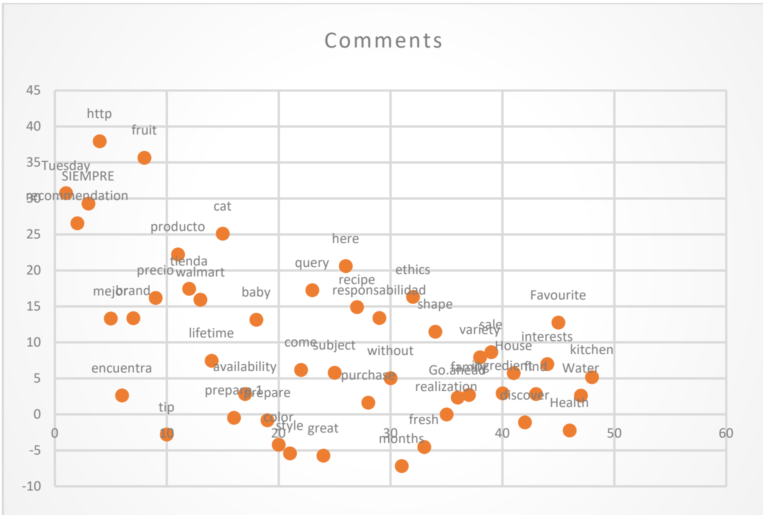

Figure A5. Cues of Walmart (Comments).

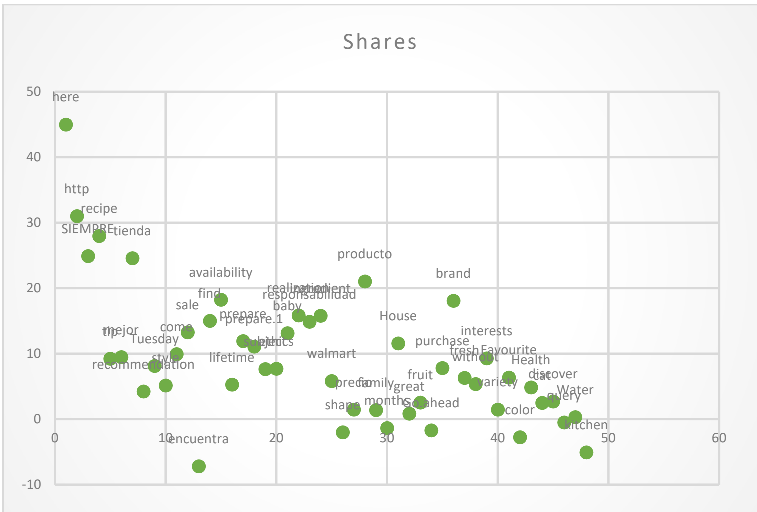

Figure A6. Cues of Walmart (Shares).

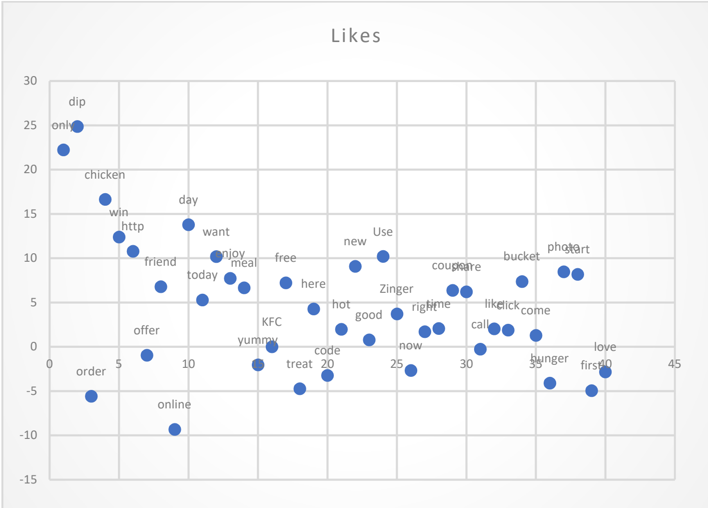

Figure A7. Cues of KFC (Likes).

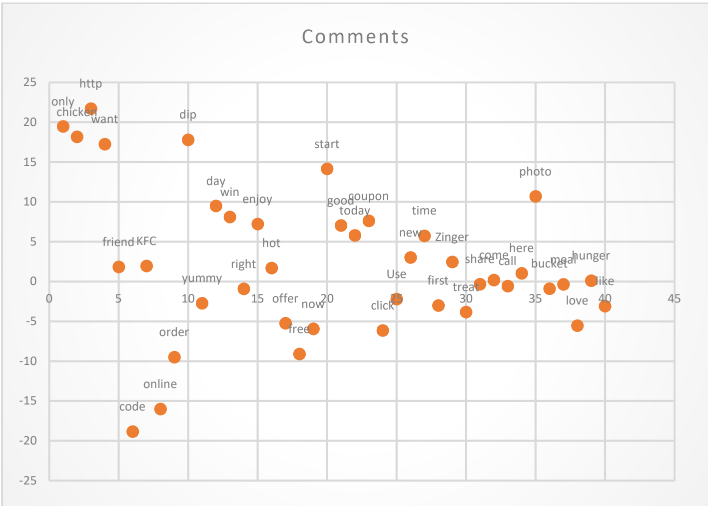

Figure A8. Cues of KFC (Comments).

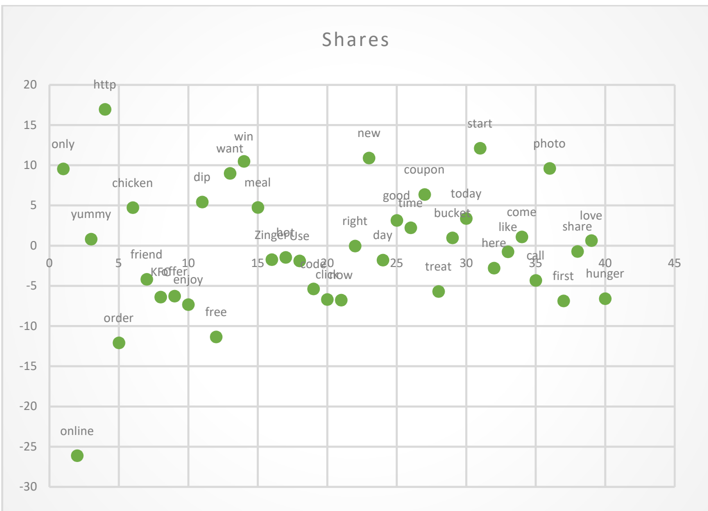

Figure A9. Cues of KFC (Shares).

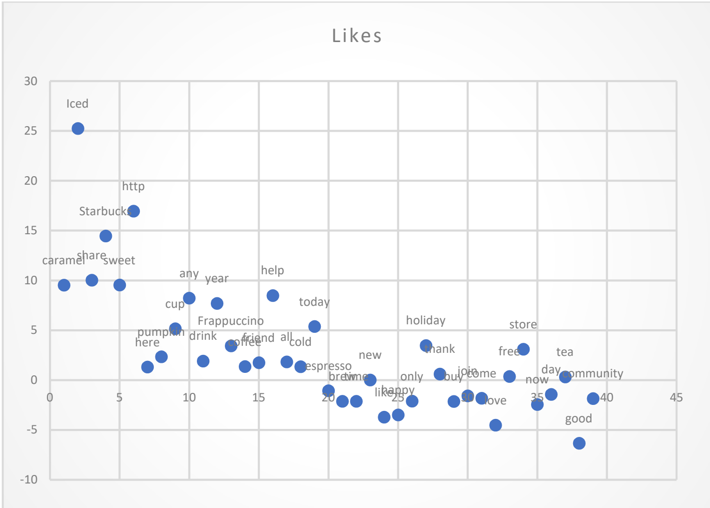

Figure A10. Cues of Starbucks (Likes).

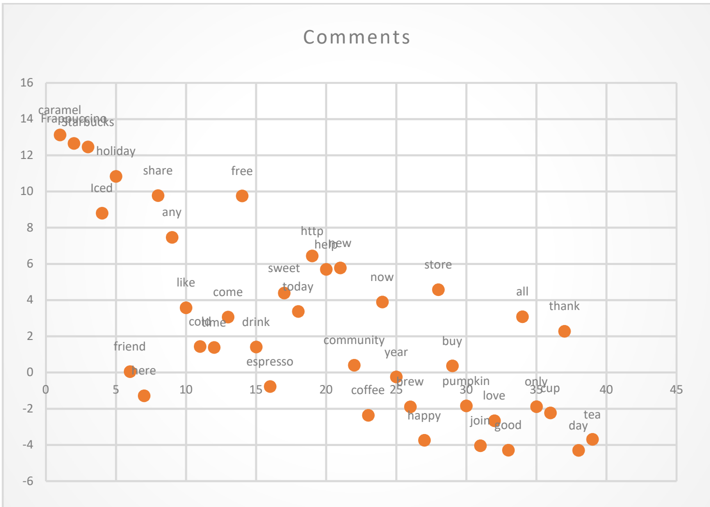

Figure A11. Cues of Starbucks (Comments).

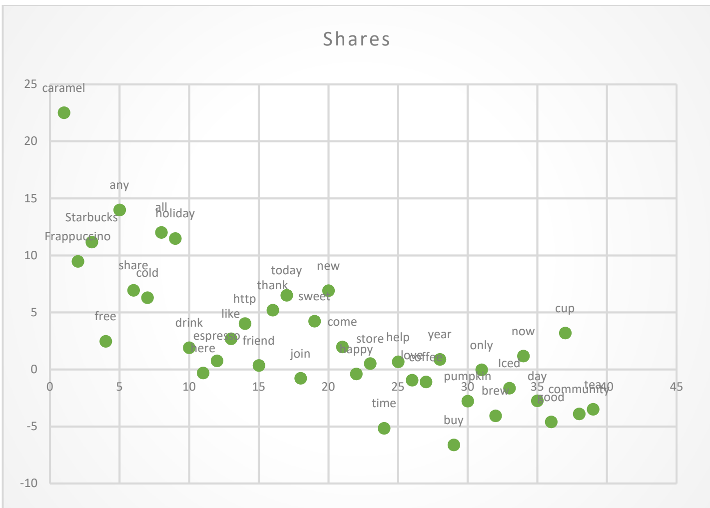

Figure A12. Cues of Starbucks (Shares).

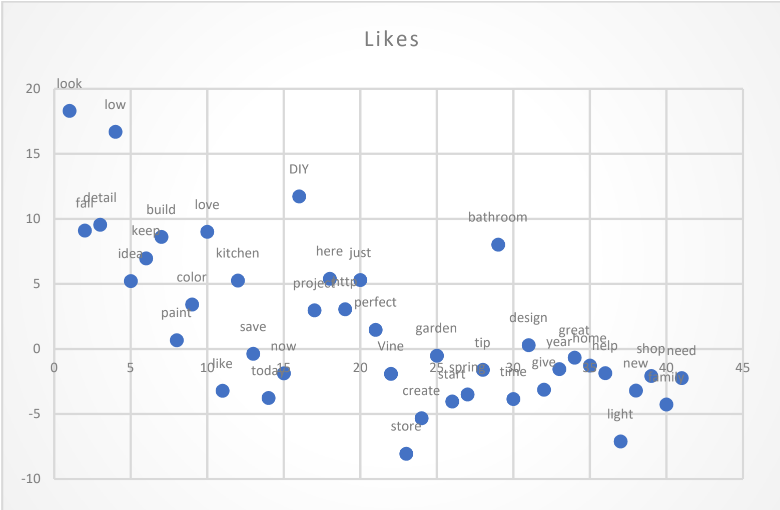

Figure A13. Cues of Lowe's Home (Likes).

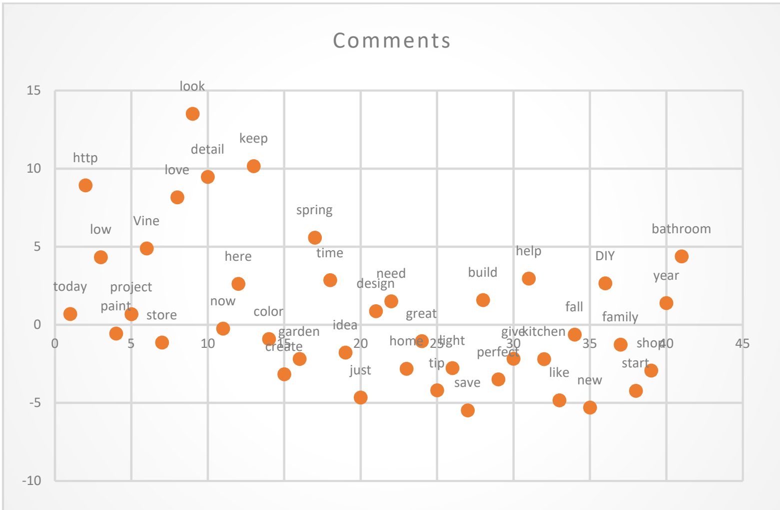

Figure A14. Cues of Lowe's Home (Comments).

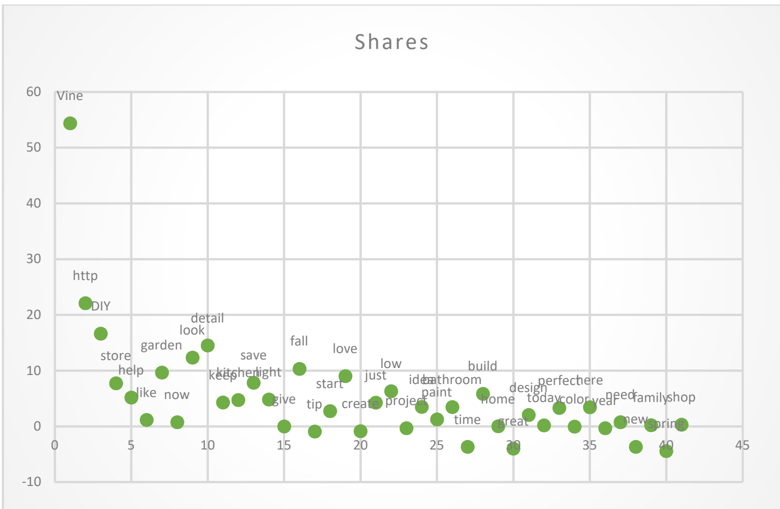

Figure A15. Cues of Lowe's Home (Shares).

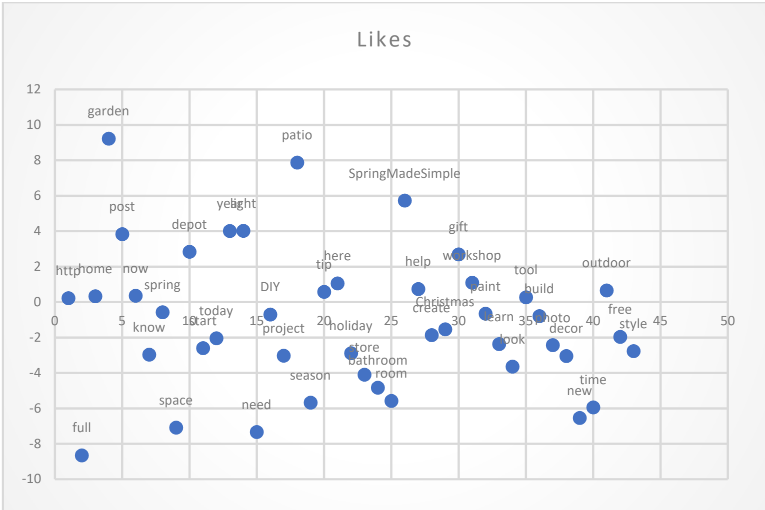

Figure A16. Cues of Home Depot (Likes).

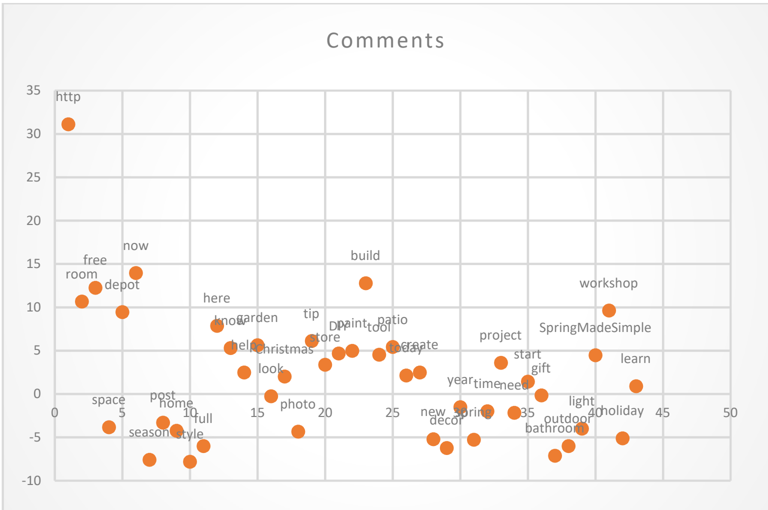

Figure A17. Cues of Home Depot (Comments).

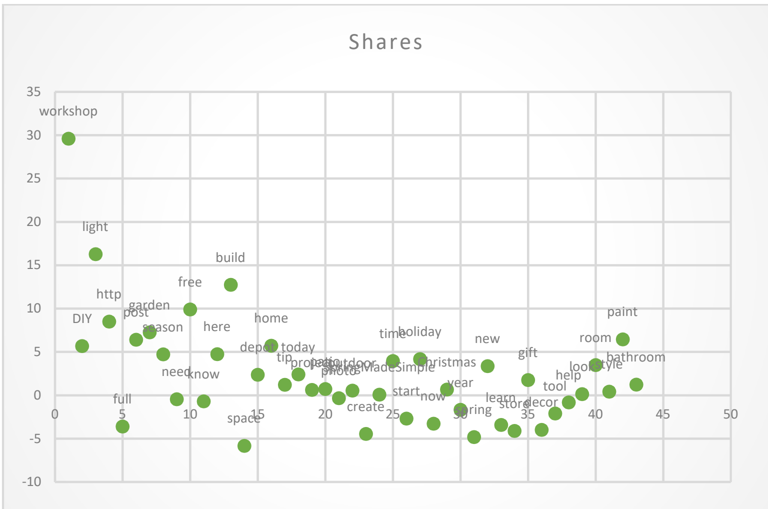

Figure A18. Cues of Home Depot (Shares).

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