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A Social Media Mining and Ensemble Learning Model: Application to Luxury and Fast Fashion Brands

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Abstract: This research proposes a framework for the fashion brand community to explore public participation behaviors triggered by brand information and to understand the importance of key image cues and brand positioning. In addition, it reviews different participation responses (likes, comments, and shares) to build systematic image and theme modules that detail planning requirements for community information. The sample includes luxury fashion brands (Chanel, Hermès, and Louis Vuitton) and fast fashion brands (Adidas, Nike, and Zara). Using a web crawler, a total of 21,670 posts made from 2011 to 2019 are obtained. A fashion brand image model is constructed to determine key image cues in posts by each brand. Drawing on the findings of the ensemble analysis, this research divides cues used by the six major fashion brands into two modules, image cue module and image and theme cue module, to understand participation responses in the form of likes, comments, and shares. The results of the systematic image and theme module serve as a critical reference for admins exploring the characteristics of public participation for each brand and the main factors motivating public participation.

Keywords: fashion brands; luxury brands; masstige; key image cues; social media mining; ensemble earning

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Citation: Chen, Y. A Social Media Mining and Ensemble Learning Model: Application to Luxury and Fast Fashion Brands. *Information* **2021**, *12*, 149. https://doi.org/10.3390/info12040149

Academic Editor: Arkaitz Zubiaga

Received: 9 March 2021
Accepted: 29 March 2021
Published: 31 March 2021

1. Introduction

In recent years, social networking sites have become a key communication channel between brands and the public [1,2]. Consumers' increased proficiency in using social networking sites has enhanced the importance of brand communities. About 90% of the world's leading brands have their own brand communities. A brand community facilitates exclusive brand experiences [3], information sharing, and stronger public relations through an widening follower base [4,5]. Studies have shown that a growing number of brands, irrespective of their size, are using social media to expand their businesses. About 80% SNS users believe that their purchase decisions can be influenced by reliable community reviews, indicating the effectiveness of brand community in enhancing brand trust, reputation, and loyalty [6–8]. Therefore, examining factors motivating public participation [9] can help understand the causes and consequences of their actions [10].

Numerous fashion brands consider social communities an important medium for marketing and to increase brand awareness and public participation. Social communities are also platforms that promote brand interactions with the public through fan pages and prompt responses to user comments [11]. The function of brand pages is mainly to establish contact with the masses and to disseminate information through social networks [12]. Studies have confirmed the impact of entertainment, interaction, personalization, and reputation on Louis Vuitton's fan pages [13–15]. Social media activities not only promote public interactions but also improve brand image. Therefore, when used well, social media can be an effective tool to enhance brand value and establish strong consumer relations. Coach, for example, uses its fan page to share community information, including videos and images, that emphasize the uniqueness and exclusivity of the brand and satisfies information demands including functionality, hedonism, and symbolism [16].

Brand community analyses largely focus on the intentions of public participation [17], the intensity of motivation [18], and ways to attract potential community members [19,20]. Few analyze the potential effects of community information. It is necessary to expand the scope of brand community analyses to confirm the inextricable relationship between public participation and information. Therefore, using public behavior data, this study examines how key image cues in community information can be used to increase public interactions. The sample comprises six fashion brands, of which three are luxury fashion brands (Chanel, Hermès, and Louis Vuitton) and the remaining are fast fashion brands (Adidas, Nike, and Zara). By analyzing luxury fashion brands and their unstructured data on Facebook, this study attempts to answer the following two questions:

(A) Do luxury fashion brands and fast fashion brands use image cues in their posts on fan pages to establish brand positioning?

(B) Can data analysis and machine learning techniques be applied to interactive public data to identify information preferences as well as analyze and predict participation characteristics?

This study proposes a set of information models that are based on the concept of public participation in brand communities [21] to meet the following objectives: (a) reveal how fashion brands position information in line with brand image to prompt positive public attitudes and behaviors; (b) examine the consistency of fashion brand images and its impact on strengthening brand identity in the community; and (c) explore the relationship between key image cues and behaviors in the brand community to determine common rules for module verification.

While studies have proposed various theories related to information analysis, such as relations marketing, service introduction, and community analysis, this research examines public participation from a different theoretical perspective. It focuses on information image and public participation to examine the information effects of media, public perception, and the main factors motivating participation. The results of the integrated approach, including artificial intelligence data analysis and community content exploration, verify the effectiveness of the proposed framework. This research combines social media exploration and artificial intelligence data analysis to verify cues in brand information and the relationship between images and themes. It also examines the interactive characteristics of various luxury and fast fashion brands to discuss the different types of key image cues.

The remainder of this study is organized as follows. Section 2 reviews the literature on community participation and information image. Section 3 proposes the hypotheses. Section 4 describes the research methods and data collection tools. Section 5 explains the research results and findings. Section 6 concludes with the academic and practical implications of this research.

2. Literature Review

2.1. Brand Community Participation

Several studies have been conducted on the different forms and characteristics of social media. Social networking sites continuously and steadily strengthen ties among members [15]. Users choose information on the basis of their personal preferences and thus, SNSs such as Facebook actively present diverse information to create more opportunities for dialogue between the public and brands [22]. In addition to establishing clear brand communication, brand pages have become a critical community tool and an effective channel for interaction between consumers and brands across the world [23]. The platform also allows brands to convey important information [24]. Admins of fan pages can identify problems through community interactions and such information can be used to innovate and improve brand products and services [25,26].

Consumers can actively express their preferences through likes, comments, and shares [27]. These interactive features can be used to assess the popularity of brand posts and have become a common strategy of viral marketing [28,29]. Users who like a post tend to exhibit stronger willingness to purchase and brand loyalty in the future [30], which adds further value to a brand [31]. Therefore, likes, comments, and shares provide insight into public willingness to participate and can help brands explore themes and images aligned with consumer expectations.

Three key factors motivating participation are consumption, contribution, and creation [27]. Consumption refers to reading, viewing, checking, or commenting on brand-related information. Users actively browse for content and convert it into valuable brand information for absorption [32]. Contribution refers to stimulating continuous public participation. Brand-related information facilitates interactions among users through, for example, likes and comments, and such interactive contributions highlight public preferences for information [33,34]. Public participation in a brand's content on SNSs is considered a means to create self-identity—this is a typical case of hierarchy creation [35]. Further, individuals who associate with a brand tend to influence others' personal impression of it [12,36,37].

Community interaction is an important driving force, for example, through information creation. Users not only connect with each other but also become part of a virtual community [27,38]. Thus, contribution and creation are key factors influencing information positioning. Often, motivation to participate emanates from gratification gained from the pursuit of information [39]. Some studies suggest that information participation is largely driven by information demands [40], information exchanges [41], or the search for reliable information sources [39]. Consumers can peruse information shared within brand communities to learn more about a brand's products [42], which may increase their willingness to purchase [27]. Even if users do not actively participate in the communities, their reading behaviors can accelerate a brand's objective to achieve publicity.

Studies suggest that social media has relaxing effects [43] and entertainment effects [39] on users. Positive entertainment effects contribute to public participation and attitudes, continued willingness to participate, and user sign-ups on other SNSs. The e-commerce literature clearly highlights the positive impact of information on public perception [44]. Diversified information is more effective in satisfying public curiosity and even inducing stronger entertainment effects [35]. The more complete the information is the stronger the possibility of accomplishing a task and of evoking emotional responses among the public. Abstract information is more suitable when conveying entertainment effects, whereas clear information positioning promotes positive content experiences [45].

Entertainment has a more obvious effect on facilitating public interactions. A good brand page provides entertainment information, attracts users to the page, and stimulates consumer intentions [38]. Entertainment increases brand loyalty as well as consumption, contribution, and creation as participation motivators. Social media is currently perceived as a reliable source of brand information. Trust is the basic driving force in a virtual community, and continuous information exchanges strengthen the interpersonal relationships among members [46]. The level of trust generated by the website impacts the willingness to participate.

Moreover, when there are higher levels of trust, members are more likely to view other members as reliable and active sharing and dialogue becomes easier. Such word-of-mouth promotion enhances brand image and loyalty [47]. The information cueing effect is based on possible crowd behaviors and interactions in response to text information shared in the community [48]. To conceptualize information cues [49], the research transforms vague information cues into definite text concepts [50], a problem emphasized in numerous image studies evaluating the individual attributes of information to obtain specific factors composing an image [51]. Information cues are commonly defined as potential ideal information in the minds of the public [52] that may be transformed into a specific image or concept [53].

2.2. Information Image and Cues

Information image is a key factor influencing public participation and can effectively drive public perception, impression, and cognition. Information image reflects public psychology [54], and thus, is an effective guiding tool. It represents ideas and concepts gathered by individuals [55] and can continuously influence decisions through various publicity methods [56]. Discussions on the concept of information image and its influence and information image composition are not limited to the information image literature. In fact, decision-making research explores the impact of information images on the public and the resultant behavioral differences [57]. A majority of information research focuses on information assessment and measurement [58,59], information theory, and information case studies [60].

Studies in the field of cognitive psychology have attempted to distinguish between the cognitive and emotional associations of different types of information [61]. Information triggers sensory perceptions (e.g., smell, hearing, touch, and taste) and has complex interactive effects on human visual perceptions. Information can freely transform personal experiences and shape the unique image of a community. Thus, information used to shape the cognition and imagination of a community [62] creates symbolic impressions in viewers' memories and evokes the most direct and perceptual responses among the masses [63]. Further, it gradually increases familiarity and trust within the community. [64] states that images can be used to present an ideology. Thus, an image analysis of community information will help admins understand the various dimensions of information images (i.e., text, image, abstract, and concrete) [65]. Integrating explorations of social media sharing in the form of likes and comments and other behaviors can provide further insight on the characteristics of information.

Studies suggest that information cues can be used to enhance gratification derived from information [66]. Cognitive and emotional responses to visual cues can serve as a reference to assess if the information satisfies the requirement of a task, the finding of which can help expand public perceptions and attitudes [67]. Information is generally divided into cognitive and emotional information. Cognitive information refers to the cognitive and knowledge aspects of information generation and is related to information characteristics (e.g., themes and symbols) derived from the cognition of information images. Cognitive information significantly affects consumer choices, decision making [68], subsequent evaluations, and behavioral intentions. Existing research discusses the characteristics of cognitive information from various viewpoints, including the impression and perception of information [20]; knowledge, thoughts, and emotions; and interactions between consumer cognition and intentions [69,70].

Cognition affects emotions and intentions, and emotions impact the degree of cognition. This correlation is further contingent on information. To elaborate, information cues are key factors guiding cognition [71] and complement emotional cues, which satisfies the objective of information notification and advances the emotional identity of the public. This also increases the frequency of interactions between consumers and brands, which is often associated with the degree of coordination of information received and the extent to which the public identifies with a brand when interpreting information cues [72]. The above-mentioned theories highlight the importance of understanding how information positioning impacts the public and way for brand to package and share appropriate content.

Studies suggest that the motivations underpinning information searches include satisfaction [73], participation [41], and the gaining of trust [39]. Consumers read information to understand a brand [27], analyze product characteristics [74], and make purchase decisions. The value of brand fan pages depends on whether the information drives fans toward active participation [75]. 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 [46] to share and exchange opinions.

3. Hypotheses

This section may be divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation, as well as the experimental conclusions that can be drawn.

Brand communities serve as an interactive platform for like-minded individuals. For brands, the function of a brand community is to promote public participation and strengthen public ties with the brand [3,76]. Community interaction is a "state of mind" that generates specific feelings and experiences through interactions [3,10,77–79] and creates interactive value from the viewpoints of cognition, emotion, behavior, and social knowledge. This study defines public participation as the active generation of brand-related cognition, emotions, and behaviors attributable to factors motivating participation [80].

Familiarity with brands is another key factor influencing public participation. Therefore, social media information (cognition) and engagement with the information (behavior) can strengthen public interest [81,82]. Some studies define public participation as a "three-dimensional structure of cognition, emotion and behavior" [83,84]. The proliferation of brand communities [80] has led to a growing number of brand community analyses [34,81,85]. Accounting for market demands and technological developments, this study proposes an association model that is based on fashion brand information and community behavior to evaluate interactions between brand communities and key image cues.

Lee and Jeong [21] assume that consistent brand information and image strengthens the relationships among community members. [86] states that individuals are eager to realize their ideal self-worth through brand interaction and affirm their self-existence. Therefore, consistent value results in congruence between self-value and brand value [87]. This study conducts a data analysis to identify key information cues in existing fashion brands. More specifically, it explores how information can be used to establish consistent brand relationships and develop an ideal brand identity.

The literature contains numerous information-related studies on social media, a majority of which employ methods that convert original data into useful structured data that are interpreted using corresponding analysis technologies [88]. Given that social media data often consist of keywords and high-frequency words [89], unstructured data analysis is considered particularly suitable in social media research and provides unprecedented advantages in community-based research. Using the approach to identify issues in the content provides researchers and analysts with operational insights [90]. For example, community data can be collected and cleaned up to conduct text mining and content analyses and extract influential topics and categories [91]. In addition, data from various social platforms can be extracted and compared to check for content problems that are not easily observable.

However, few studies focus on brand information image. Considering the vastness of existing information, this research attempts to revisit the relationship between brands and key information. Further, it conducts a community content exploration and artificial intelligence data analysis along with multiple verifications of the community and behavioral data. On the basis of cues identified using artificial intelligence and ensemble learning technology, the research proposes a classification approach with focus on luxury fashion brands and fast fashion brands. The analysis provides insights on key image cues in the context of brand communities and their varying influences on the public. Accordingly, this study tests the following hypotheses (Table 1 and Figure 1):

Table 1. Summary of hypothesis.

ID	Hypothesis	Hypothesis Verification
H1.	Luxury fashion brands actively use key image cues when packaging information for their fan pages, and these cues impact community participation in the form of likes, comments, and shares.	Established
H1a.	Luxury fashion brands actively use key image cues when packaging information for their fan pages, and these cues impact community participation in the form of likes.	Established
H1b.	Luxury fashion brands actively use key image cues when packaging information for their fan pages, and these cues impact community participation in the form of comments.	Established
H1c.	Luxury fashion brands actively use key image cues when packaging information for their fan pages, and these cues impact community participation in the form of shares.	Established
H2.	Fast fashion brands actively use key image cues when packaging information for their fan pages, and these cues impact community participation in the form of likes, comments, and shares.	Partially established
H2a.	Fast fashion brands actively use key image cues when packaging information for their fan pages, and these cues impact community participation in the form of likes.	Not established
H2b.	Fast fashion brands actively use key image cues when packaging information for their fan pages, and these cues impact community participation in the form of comments.	Established
H2c.	Fast fashion brands actively use key image cues when packaging information for their fan pages, and these cues impact community participation in the form of shares.	Not established

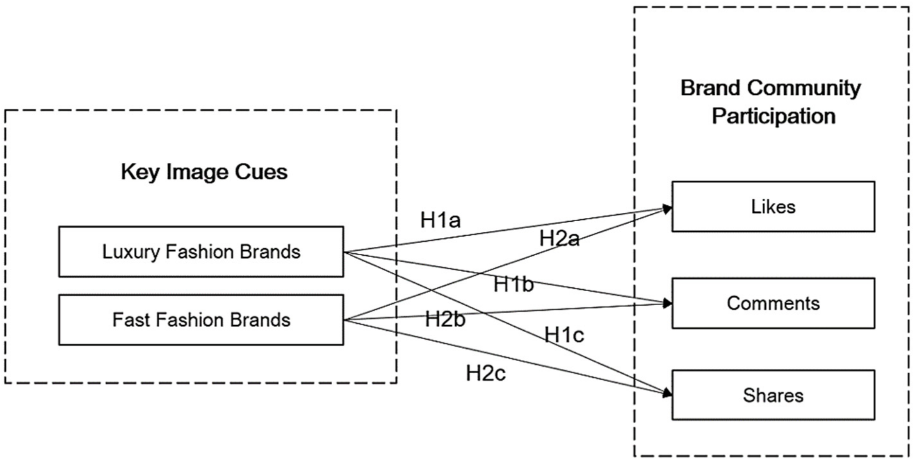


Figure 1. Extended research model.

4. Methodology

This study empirically analyzes the brand pages of luxury and fast fashion brands to identify key information cues in posts and their impact on public participation. Information on Facebook's fan pages are generally presented in four major forms: text, photos, videos, and links. Facebook's terms of service allow app designers to monitor interactions [92,93]. This research acquires post data and content in line with Facebook's terms of service and allows application designers to monitor interactions for the purpose of this study [92,93]. The behavioral benchmarks to measure online participation include likes, comments, and shares [12]. To ensure information accuracy, Facebook's graphics API is used to collect daily post data including post content, type, time, likes, shares, and comments, which are stored in a database for classification. Data are collected for six fashion brands, of which three are luxury fashion brands (Chanel, Hermès, and Louis Vuitton) and the remaining are fast fashion brands (Adidas, Nike, and Zara). The brand page must meet the characteristics of consistent and continuous posting. Web crawlers are used to obtain post content and the number and content of public responses corresponding to the posts from 1 January 2011 to 31 December 2019. A total of 21,670 posts were acquired, among which 9153 are posts by the luxury fashion brands and 12,517 are those by the fast fashion brands.

The model implementation focuses on content posted by each brand on their Facebook fan pages. First, a data mining program is used to gather post data. This study runs a series of natural language processing (NLP) programs to examine the unstructured data [94,95]. The unstructured data are transformed, and separable sentences are tokenized and converted into words and punctuations [96]. It entails editing, organizing, and analyzing expansive data and offers in-depth information on, for example, representative indicators. 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. The distributed vertical frequent mode, in particular, applies an array method to process large amounts of data and target variables. This mode can be used to optimize problems in the original groups of a data warehouse, and thus, is widely applied in social network analyses to mine consistent characteristics from social interaction content.

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. The three most commonly used exploration techniques are mass data, clickstream, and classification analyses. Exploration processes also include data cleaning and preprocessing. 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 experiences. Therefore, this study adjusts the content to a community service enhancement model 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).

A fashion brand model is then constructed to determine key image cues. Then, using the evaluation results for the image cues, multiple ensemble analyses are conducted (i.e., random decision forests, extreme gradient boosting, and AdaBoost) to predict indicators of public participation. The cues are evaluated to determine the behavioral impact of the different types of information. Finally, the measurement items are based on Facebook's functional classification of behavioral responses (likes, comments, and shares). This research refers to the extant literature on information dimensions [65] and the degree of information harmony in the masses.

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 luxury fashion brands had a total variance of 88.909% and a KMO value of 0.877. The factor characteristic value of fast fashion brands had a total variance of 74.070% and a KMO value of 0.915. 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 0.915 for luxury fashion brands, and 0.897 for fast fashion brands. Each of these results shows good reliability.

5.2. Hypotheses Testing

The findings support H1, that is, luxury fashion brands use image cues when packaging information for their brand pages, and these cues impact community participation (likes, comments, and shares). The key cue analysis based on ensemble learning presents the following results. The image cues highlighted significantly impact the behavioral response of likes, comments, and shares. Thus, the three types of ensemble learning approaches fully establish H1. They suggest that luxury fashion brands use key image cues in their fan page posts, and these cues significantly affect participation and behavioral responses in the form of likes, comments, and shares (Table 1). The findings support H2, fast fashion brands, the image cues highlighted significantly influence interactions among comments (Figure 2).

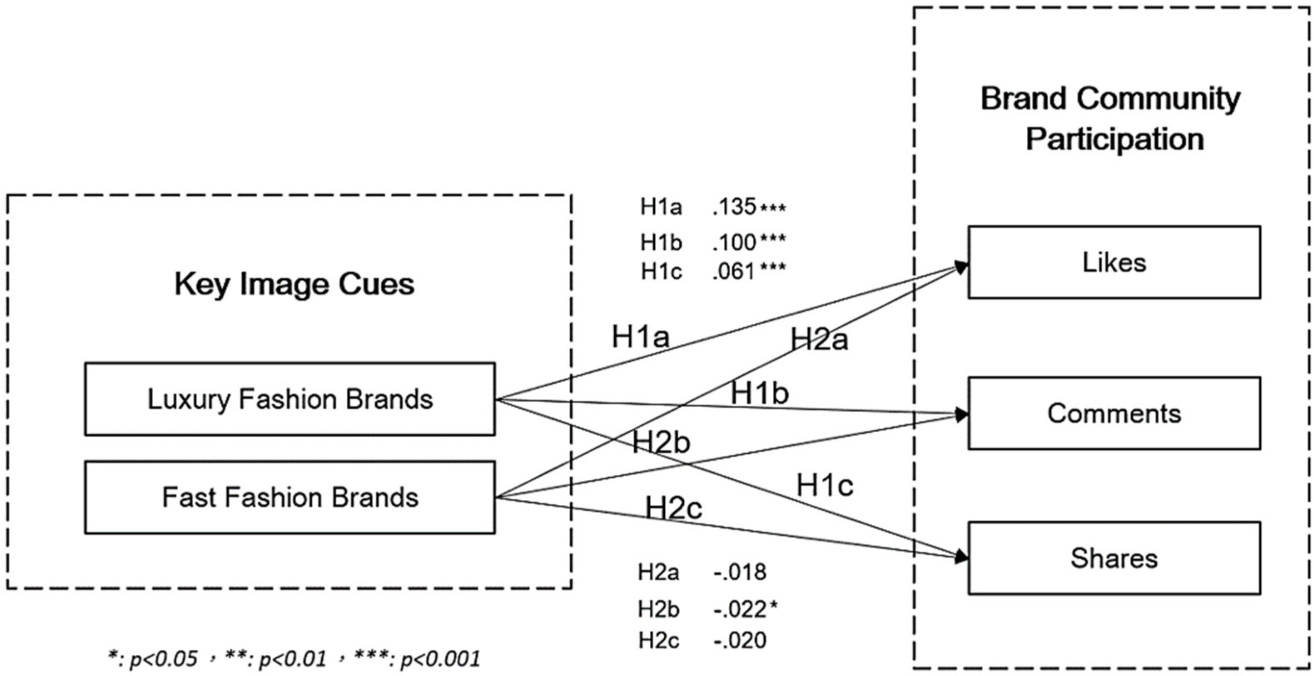


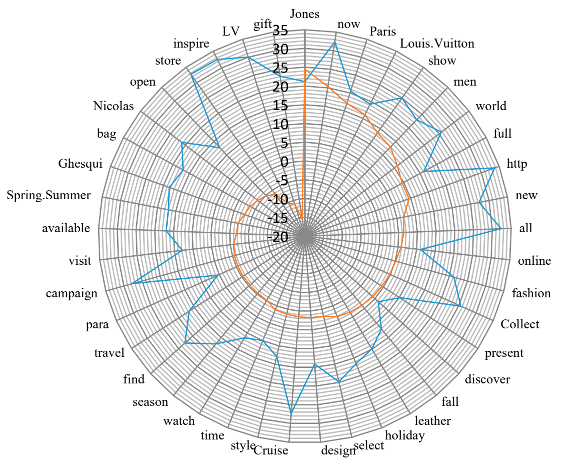
Figure 2. Model results.

5.3. Data Findings

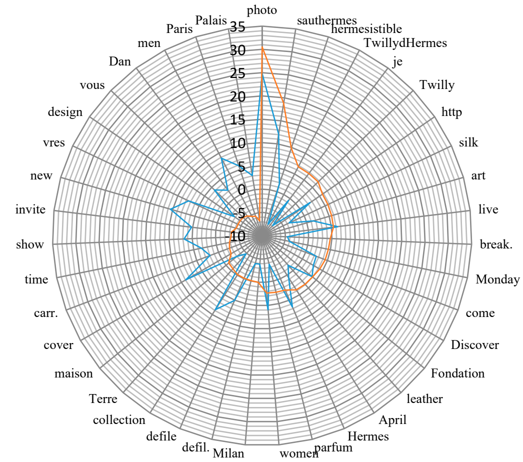
This study further integrates the recommendations and significant key image cues derived from the ensemble analysis (Figure 3a–f). This study uses three integrated analyses to compare the posts with more interactions than the average of each brand on positive cues (orange) and negative cues (blue). It was found that there are some similarities and differences in the operation of key cues of each brand. The main characteristics of the cues after comparison are as follows:

5.4. Data Verification

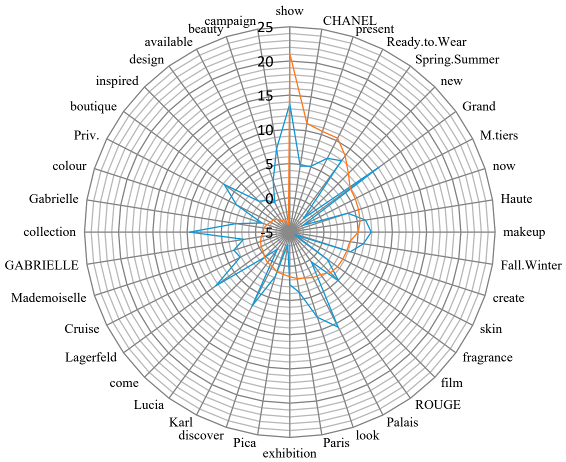
The results show that key image cues significantly influence behavioral responses. The analysis presents significant results for the impact of image cues in luxury fashion brands posts on likes. The results are $\beta = 0.135$, $p < 0.000$ made by users. Comments was found to have a significant impact $\beta = 0.100$, $p < 0.000$. Shares was found to have a significant impact $\beta = 0.061$, $p < 0.000$ (Table 2a). Next, the hypothesis information among fast fashion brands is supported. The behavior of users (comments) was found to have a significant impact $\beta = -0.022$, $p < 0.042$ made by users (Table 2b).



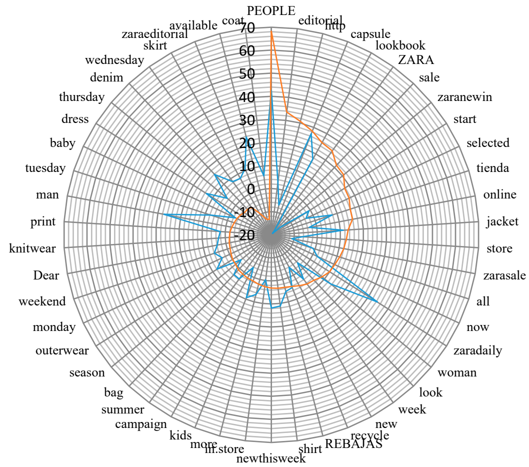
(**a**) Cues of Louis Vuitton



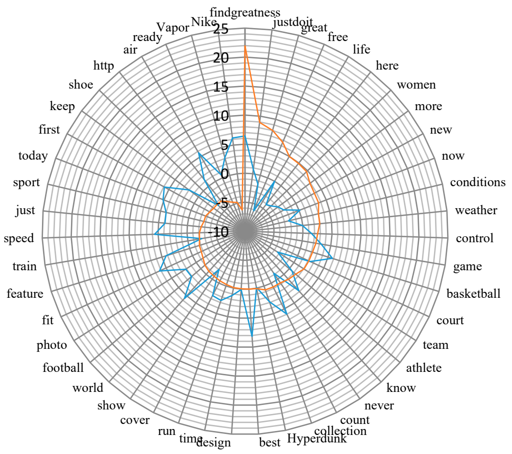
(**b**) Cues of Hermès



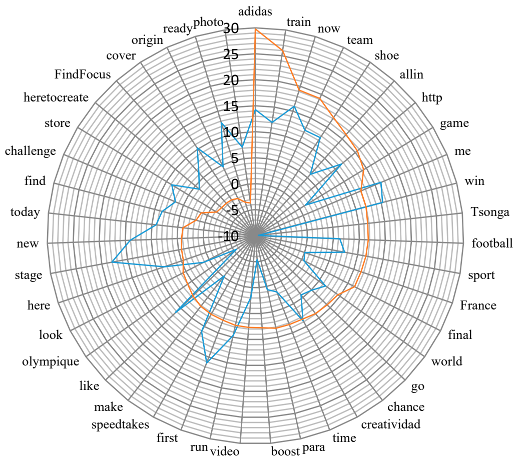
(**c**) Cues of Chanel



(**d**) Cues of Zara



(**e**) Cues of Nike



(**f**) Cues of Adidas

Figure 3. Cues of six brands.

Table 2. (**a**) Linear regression coefficient of determination and beta (luxury fashion brands), (**b**) Linear regression coefficient of determination and beta (fast fashion brands).

(a)

Luxury Fashion Brands		R	R^2	Adjusted R^2	F Change	ΔF	Durbin-Watson	B	Standard Error	Beta	T	Sig.
Chanel	Likes	0.190	0.036	0.035	0.036	34.587	1.337	7689.184	1307.446	0.190	5.881	0.000
	Comments	0.132	0.017	0.016	0.017	16.387	1.488	100.256	24.766	0.132	4.048	0.000
	Shares	0.153	0.023	0.022	0.023	21.981	1.461	902.988	192.602	0.153	4.688	0.000
Hermès	Likes	0.042	0.002	0.001	0.002	1.942	1.858	−265.680	190.664	−0.042	−1.393	0.164
	Comments	0.037	0.001	0.000	0.001	1.530	1.694	−3.940	3.185	−0.037	−1.237	0.216
	Shares	0.047	0.002	0.001	0.002	2.461	1.953	−112.075	71.444	−0.047	−1.569	0.117
LV	Likes	0.162	0.026	0.026	0.026	191.209	1.768	2685.782	194.230	0.162	13.828	0.000
	Comments	0.158	0.025	0.025	0.025	180.952	1.664	31.560	2.346	0.158	13.452	0.000
	Shares	0.162	0.026	0.026	0.026	191.040	1.781	130.064	9.410	0.162	13.822	0.000

(b)

Fast Fashion Brands		R	R^2	Adjusted R^2	F Change	ΔF	Durbin-Watson	B	Standard Error	Beta	T	Sig.
adidas	Likes	0.012a	0.000	0.000	0.627	0.428	1.868	149.759	189.104	0.012	0.792	0.428
	Comments	0.014a	0.000	0.000	0.821	0.365	1.688	−2.838	3.132	−0.014	−0.906	0.365
	Shares	0.022a	0.001	0.000	2.147	0.143	1.705	25.057	17.099	0.022	1.465	0.143
NIKE	Likes	0.001a	0.000	−0.001	0.001	0.976	1.347	−16.397	535.541	−0.001	−0.031	0.976
	Comments	0.059a	0.003	0.003	5.151	0.023	1.880	101.934	44.913	0.059	2.270	0.023
	Shares	0.015a	0.000	0.000	0.312	0.576	1.836	79.192	141.726	0.015	0.559	0.576
ZARA	Likes	0.008a	0.000	0.000	0.152	0.696	0.958	24.658	63.210	0.008	0.390	0.696
	Comments	0.110a	0.012	0.012	32.156	0.000	1.542	−8.276	1.459	−0.110	−5.671	0.000
	Shares	0.123a	0.015	0.015	40.736	0.000	1.035	−12.799	2.005	−0.123	−6.382	0.000

5.4.1. Luxury Fashion Brand: Louis Vuitton

According to the random decision forests, "Jones, now, Paris, Louis Vuitton, show" are key image cues impacting likes; "Jones, now, http, show, world" influence comments; and "Paris, now, Jones, show, Louis Vuitton" affect shares. Extreme gradient boosting suggests that likes are affected by "now, http, all, new, Paris"; comments are impacted by "http, now, Louis Vuitton, all, new"; and shares are influenced by "Louis Vuitton, now, all, http, LV." AdaBoost indicates that the key image cues influencing likes, comments, and shares, respectively, are "available, Spring Summer, fashion, fall, world"; "available, discover, fall, fashion, present"; and "available, time, present, world, and discover."

The image cues common to both the random decision forests and extreme gradient boosting are "Jones, now, show, Paris, Louis Vuitton". Thus, Louis Vuitton should focus on "Jones, Paris, Louis Vuitton" to construct its brand image and maintain brand impression. In addition, the brand should share the latest information to keep viewers continually engaged. AdaBoost further indicates that, once the above-mentioned image is constructed, the brand should discuss specific topics related to "Spring Summer, fashion, world." Aligning information cues with the public's unique demands can increase the willingness to share (Table A1).

5.4.2. Luxury Fashion Brand: Hermès

Extreme gradient boosting recommends "Hermès, cover, live" as key image cues, whereas AdaBoost suggests "Discover, photo, Monday, Twilly, Milan". Following the image construction with focus on "Hermès" and "live," the brand should explore themed packaging with keywords such as "Twilly" and "Milan" or regularly post the latest information and updates using cues such as "Monday" and "Discover." Image construction, themed packaging, the proper use of repetitive information contributes toward cultivating regular tracking habits among the public (Table A2).

5.4.3. Luxury Fashion Brand: Chanel

Both the random decision forests and extreme gradient boosting recommend "show, present, Chanel, Spring Summer." The main image cues include "Chanel, Spring Summer, show, present." These cues can not only transform the public's brand impression, but also elevate Chanel to the most endorsed brand in the world. AdaBoost, on the other hand, recommends "Palais, Ready to Wear, Grand, discover." Thus, the brand should focus on the demands of niche groups by personalizing the information packaging using the key image cues. Posting the latest information and carefully curating theme characteristics can increase fans' willingness to actively share (Table A3).

5.4.4. Fast Fashion Brand: Zara

Both random decision forests and extreme gradient boosting list "lookbook, PEOPLE, capsule, zaradaily" as key image cues. AdaBoost, on the other hand, suggests "zarasale, woman, Tuesday." For fast fashion brands, in addition to image construction and themed packaging, strengthening promotions using keywords such as "zarasale" or "zaradaily" or sharing information on a daily basis encourages behavioral responses in the forms of comments and motivates users to share (Table A4).

5.4.5. Fast Fashion Brand: Nike

While random decision forests suggest "here, basketball, now," AdaBoost lists "speed, sport, life, feature" as key image cues. It appears that Nike seldom uses specific key image cues in their information packaging for the community, and thus, the recommendation results in terms of interaction are few. Although the results highlight the use of "sport" and "feature" in the image construction, the lack of specificity makes it difficult to derive clear findings on the benefits of the posts (Table A5).

5.4.6. Fast Fashion Brand: Adidas

Adidas is the only fast fashion brand whose key image cues have no significant result. It is also the only brand whose image construction is relatively unclear (Table A6).

6. Conclusions

6.1. Finding and Discussion

Drawing on the findings from the ensemble analysis, this research further divides the cue characteristics of six major fashion brands under an image cue module and an image and theme cue module.

(A) Image cue module: The image cue module focuses on the behavioral response of comments and image cues in the content. Brand pages with significant findings include the luxury fashion brand Hermès and the fast fashion brand Nike. Image information reflects the extent to which information impacts the public [97], and information evoked in viewer memory often influences public attitudes and behaviors. Familiar information is more likely to be recalled than unfamiliar content [98]. Research on information management processing clearly demonstrates a high correlation between information familiarity and memory recall. Therefore, brand pages that continuously provide key information along with brand familiarity are more likely to evoke stronger recall [99] and more easily trigger participation in the form of comments.

(B) Image and theme cue module: The image and theme cue module effectively combines the three types of interactions of likes, comments, and shares. The module highlights image and theme cues that generate public focus on and interest in the brand. Luxury fashion brands Chanel and Louis Vuitton and the fast fashion brand Zara best exemplify the module. This primary aim of the image and theme cue module is to transform image cues into a unique brand personality. Information cues can be generated through different marketing plans such as the continuous disclosure of product-related cues, prices, features, and other information [100]. Information cognition represents not only public beliefs and ideas but also emotional or behavioral responses and thus, is the main factor determining the effectiveness of posts [101]. The module strengthens benefits common to both images and themes and uses information to promote representative behaviors such as sharing and commenting. The social media activities of luxury fashion brands employ various dimensions including entertainment, interaction, fashion, and personalization to create brand stories and establish a connection between brands and emotions [13–15]. Image cues also help enhance user trust [13–15] and brand equity [102]. In summary, the appropriate use of image and theme cues is the most effective way to evoke public participation.

6.2. Theoretical Implications

This research performs a social media exploration and artificial intelligence data analysis to verify information cues in brand pages and the relationship between images and themes. Social media provides marketers with the opportunity to increase brand exposure and promotes continuous interaction between brands and consumers irrespective of time, location, and medium [103]. Information interaction enhances the relationship between brands and the public [15], and active public participation affects the perceived value of information [104,105]. Information communication that is positive and frequent tends to have a stronger influence on consumers' brand associations and attitudes [106]. Therefore, brands should conduct accurate evaluations of information benefits to mitigate any misunderstanding or prejudice and enhance brand value through key information positioning [13]. This research combines artificial intelligence data analysis and community content exploration, and the results successfully verify the effectiveness of the model.

This study examines the interactive characteristics of various luxury and fast fashion brands as well as the different types of key image cues to theoretically verify cognitive, emotional, and behavioral stimulations. Importantly, this research explores public participation from a different theoretical perspective [10,107]. 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. Emotional identification with brands can be used to determine if a crowd positively or negatively perceives a brand and critically influences subjective impressions. While the information analysis literature addresses relationship marketing [108], service introduction [79], and social analysis [109], this study focuses on public cognition, emotions, and behaviors [23,110] to examine the information effects of media on public perception and the motivation to participate.

6.3. Practical Implications

This research proposes a framework for the existing fashion brand community to explain public participation and behaviors in response to information and to reiterate the importance of key image cues and brand positioning. The study evaluates differences in the interactions between brands and the public, examines whether information on social media is aligned with public demands, and verifies why information cues affect public participation. Information can be actively used to trigger interactions and thus, can certainly increase the willingness to comment and share and generate more access opportunities on Facebook [111].

The study also examines behavioral responses in the form of likes, comments, and shares to construct systematic image and theme modules. To evaluate the core values of the public in the context of a specific brand, relevant tests should be conducted to explore the public's current thinking [112]. Through the systematic modules of images and themes, this study serves as a substantial reference basis to understand the different types of participation responses (likes, comments, and shares). The modules will help brand managers promptly grasp the characteristics of public participation and understand the main factors motivating participation.

6.4. Research Limitations and Suggestions for Future Research

Despite its numerous contributions, this research is not free from certain limitations. The analysis is limited to the Facebook brand community. Thus, further research investigating various social media platforms and customized content production for different information types is needed. This study can also be extended to specific industries (e.g., consumer electronics) and enterprises (e.g., non-profit organizations or academic institutions) to confirm the model's effectiveness. The machine learning algorithm largely depends on the manner in which data are presented, and data classification is subject to a high degree of difference and relevance. Thus, the model can be used to identify information that evokes high and low participation. Data from different communities can be gradually added for further verification [113]. The results could prove that the definition of the proposed model is current and accordingly, more appropriate prediction models can be derived by combining various characteristics of social interactions [114,115].

This study confirms the importance of consistent direction in information and its role in driving the masses. Therefore, brands should analyze the members of their brand community to evaluate the core values of the brand and delivery methods. Consumers' whose personal value is consistent with that of the brand are more likely to develop a favorable impression. Second, to strengthen the consistency between brand image and public expectations, brands should regularly review the interest trends of community members and create brand posts that align with their preferences. Page admins should focus on personalized marketing. Brands can create a sense of belonging by exploring and incorporating core values prioritized by different user groups.

Funding: This research was funded by the Ministry of Science and Technology—Digital Humanities Program (No. 0510234) (No. 0610234).

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

Appendix A. Measurement and Items

Table A1. Negative and positive cues for Louis Vuitton.

Likes	Negative	Positive	Comments	Negative	Positive	Shares	Negative	Positive
Jones	21.16	24.54	Jones	21.4	19.67	Paris	21.97	23.23
now	32.39	20.32	now	24.55	17.61	now	31.28	23.2
Paris	20.55	17.14	http	40.14	17.59	Jones	18	22.16
Louis.Vuitton	19.22	16.1	show	25.97	12.8	show	24.85	16.37
show	25.02	13.65	world	26.82	11.26	Louis.Vuitton	17.39	15
men	23.02	12.98	full	16.77	10.19	world	27.75	13.68
world	25.76	10.97	all	29.18	9.56	http	34.3	13.32
full	16.11	9.55	style	25.13	8.31	full	20.84	11.51
http	33.74	9.54	Louis.Vuitton	24.36	7.5	bag	15.7	8.59
new	27.32	6.85	Paris	13.61	5.93	all	27.5	8.38
all	32.3	6.42	new	25.9	5.52	men	23.33	7.15
online	11.03	5.79	watch	22.59	4.6	fall	15.16	6.54
fashion	21.23	5.16	men	25.7	4.17	style	12.21	6.18
Collect	25.58	4.78	discover	5.08	4.15	Spring.Summer	16.07	5.82
present	10.15	4.55	fall	15.04	4.05	design	15.76	5.14
discover	6.23	4.24	open	12.61	4.01	online	8.97	4.93
fall	12.07	3.9	present	7.12	3.27	leather	13.66	4.62
leather	14.93	3.55	Collect	21.36	1.74	discover	5.78	4.5
holiday	16.64	3.13	Spring.Summer	16.02	1.74	new	26.52	4.35
select	19.83	1.89	para	5.91	1.51	campaign	24.94	3.73
design	14.14	1.7	holiday	15.15	0.76	watch	11.63	3.21
Cruise	27.39	1.56	online	4.75	0.21	Collect	22.66	2.45
style	12.89	1.35	design	11.81	−0.08	fashion	14.27	2.18
time	9.96	1.1	leather	11.84	−0.27	Cruise	28.16	1.99
watch	11.5	−0.15	visit	9.64	−0.61	holiday	15.71	1.91
season	17.17	−0.33	campaign	27.08	−0.82	para	5.18	1.72
find	22.79	−0.42	select	14.51	−1.16	visit	13.47	1.67
travel	16.67	−0.42	time	9.08	−2	season	20.2	0.99
para	5.37	−0.44	find	15.38	−2.41	select	18.84	−0.25
campaign	27.73	−0.56	available	17.65	−2.5	travel	15.95	−2.64
visit	12.85	−0.87	season	16.76	−2.73	time	9.21	−3.3
available	16.96	−1.77	travel	12.68	−3.04	present	12.81	−3.39
Spring.Summer	17.02	−1.86	fashion	18.45	−3.49	Ghesqui	21.66	−3.42
Ghesqui	18.4	−2.94	Cruise	28.6	−5.06	Nicolas	19.82	−3.58
bag	16.89	−3.43	Ghesqui	18.6	−6.86	open	13.16	−3.96
Nicolas	21.22	−4.31	Nicolas	18.33	−7.93	find	16.95	−4.56
open	12.71	−5.06	store	25.74	−8.35	inspire	29.65	−7.64

Table A2. Negative and positive cues for Hermès.

Likes	Negative	Positive	Comments	Negative	Positive	Shares	Negative	Positive
photo	24.83	30.54	live	2.89	11.31	Milan	−7.29	8.41
sautHermès	12.11	18.84	Hermèsistible	0.07	8.41	maison	−0.12	6.63
Hermèsistible	1.77	9.84	Herm.s	7.42	7.62	Twilly	−5.8	6.01
TwillydHermès	−7.2	6.72	Discover	0.31	7.54	TwillydHermès	−3.49	4.35
je	−0.53	6.7	http	3.97	6.26	carr.	3	4.28
Twilly	−6.85	6.7	Fondation	8.03	5.87	Discover	1.12	3.89
http	2.51	5.74	Terre	−8.83	4.95	invite	3.62	3.18
silk	−3.56	5.65	photo	14.74	4.44	parfum	−2.68	2.84
art	1.43	5.52	show	7.66	4.4	Fondation	4.83	2.34
live	6.33	5.45	break.	−4.33	4.13	break.	−2.32	2
break.	−4.55	4.67	parfum	−2.04	3.82	collection	5.79	1.97
Monday	−4	4.53	Twilly	−2	3.32	new	2.51	1.81
come	2.43	4.5	je	3.61	2.96	je	1.26	1.79
Discover	2.71	4.29	d.fil.	7.54	1.59	Monday	−2.24	1.73
Fondation	3.85	3.98	men	8.74	1.32	April	−1.36	1.28
leather	−1.56	3.92	Monday	−0.48	0.88	photo	10.81	1.23
April	0.68	3.74	TwillydHermès	−4	0.84	Paris	10.44	1.21
Herm.s	6.63	2.67	maison	−5.83	0.72	Herm.s	2.66	1.14
parfum	−3.68	2.48	Palais	−4.04	0.05	live	0.75	1.11
women	5.92	2.33	carr.	1.01	−0.58	art	−3.02	−0.19
Milan	−3.91	0.02	silk	−5.46	−0.63	silk	−2.45	−0.33
d.fil.	−3.85	−0.09	vous	11.68	−0.94	leather	−1.44	−1.18
defile	5.1	−0.11	time	2.64	−0.98	sautHermès	13.29	−1.56
collection	8.78	−0.15	women	7.5	−1.01	men	5.38	−1.57
Terre	−4.8	−0.56	art	−1.86	−1.47	show	0.61	−1.67
maison	−2.97	−0.75	Milan	−2.54	−1.53	http	−3.05	−1.68
cover	8.88	−2.33	April	0.45	−1.56	defile	9.66	−1.72
carr.	1.94	−2.52	leather	−3.76	−2.03	come	−0.97	−1.75
time	3.32	−2.87	sautHermès	13.34	−2.97	Terre	−4.44	−1.84
show	6.76	−3.33	Dan	3.68	−3.43	Hermèsistible	−4.05	−1.93
invite	5.25	−3.36	defile	12.59	−3.91	women	3.31	−2.17
new	10.48	−4.21	cover	19.43	−4.21	vous	−1.54	−2.2
vres	7.43	−4.29	come	5.03	−4.45	design	1.45	−2.24
design	−2.74	−4.31	Paris	11.04	−5.21	time	3.3	−2.98
vous	4.18	−4.36	design	0.55	−5.66	d.fil.	3.56	−3.18
Dan	2.22	−4.7	new	12.23	−7.37	Palais	3.15	−3.38
men	8.81	−5.3	collection	15.76	−7.48	Dan	4.83	−5.18
Palais	3.1	−6.74	invite	5.11	−7.86	cover	11.17	−8.67

Table A3. Negative and positive cues for Chanel.

Likes	Negative	Positive	Comments	Negative	Positive	Shares	Negative	Positive
show	13.75	21.13	show	13.38	22.89	show	13.64	24.76
CHANEL	4.76	11.07	present	9.68	17.75	present	7.71	19.42
present	5.13	10.46	CHANEL	1.88	10.76	Spring.Summer	11.91	14.75
Ready.to.Wear	7.1	10.4	Spring.Summer	11.39	10.43	CHANEL	4.54	10.03
Spring.Summer	7.87	8.77	film	2.82	8.19	Haute	11.14	9.95
new	−2.15	7.12	Ready.to.Wear	4.62	6.37	new	−3.99	5.88
Grand	11.14	5.92	Haute	11.89	6.15	Paris	5.78	5.13
M.tiers	−2.84	5.74	skin	−7.46	5.87	skin	−6.49	5.03
now	3.92	5.58	Paris	3.16	5.84	makeup	9.53	4.29
Haute	6.2	5.39	new	−4.17	5.53	ROUGE	0.23	4.07
makeup	6.92	5.03	makeup	7.41	4.26	look	6.89	3.82
Fall.Winter	5.91	3.9	Cruise	1.2	3.36	design	5.9	3.71
create	4.34	3.78	now	4.15	3.1	Ready.to.Wear	3.61	3.36

Table A3. *Cont.*

Likes	Negative	Positive	Comments	Negative	Positive	Shares	Negative	Positive
skin	−4.12	3.69	ROUGE	2.23	2.76	now	−1.22	3.28
fragrance	1.8	3.63	M.tiers	1.75	2.46	Cruise	2.06	2.96
film	5.13	3.4	create	1.25	1.96	GABRIELLE	−0.17	2.72
ROUGE	0.36	2.66	fragrance	−2.75	1.61	Lucia	−4.58	2.23
Palais	10.59	2.45	GABRIELLE	1.76	1.16	Fall.Winter	5.45	2.07
look	8.08	2.06	Mademoiselle	3.86	0.83	inspired	0.23	1.8
Paris	3.92	1.87	come	3.39	0.71	create	1.64	1.65
exhibition	2.68	1.53	colour	−1.35	0.41	Palais	8.52	1.42
Pica	−3.2	1.26	Grand	12.04	0.23	Grand	9.61	1.39
discover	1.78	1.11	look	3.85	0.2	come	0.35	1.24
Karl	7.12	0.62	Lucia	−3.95	0.16	colour	−3.83	1.08
Lucia	−1.94	0.51	Pica	−3.09	−0.15	campaign	6.81	0.8
come	0.26	0.21	Gabrielle	4.63	−0.71	Pica	−3.41	0.8
Lagerfeld	8.36	−0.21	discover	2.84	−0.93	Lagerfeld	8.09	0.77
Cruise	3.11	−0.32	design	1.09	−0.97	M.tiers	−0.31	0.55
Mademoiselle	3.6	−0.5	exhibition	5.61	−1.21	fragrance	−3.75	0.36
GABRIELLE	1.83	−0.79	inspired	−3.22	−1.23	collection	6.03	0.04
collection	9.64	−1.15	available	0.49	−1.33	discover	2.01	0
Gabrielle	2.94	−1.15	Palais	9.16	−1.38	exhibition	4.06	−0.89
colour	−0.74	−1.51	Karl	7.83	−1.56	available	−0.52	−0.91
Priv.	3.71	−1.8	beauty	4.32	−1.58	Gabrielle	2.17	−1.01
boutique	6.83	−2.05	Priv.	5.41	−2.05	Priv.	3.7	−1.83
inspired	1.36	−2.36	collection	10.11	−2.31	Mademoiselle	2.62	−1.84
design	0.73	−2.97	boutique	5.15	−2.5	film	0	−1.88
available	−0.18	−3.1	Fall.Winter	8.44	−2.69	boutique	5.67	−2.2

Table A4. Negative and positive cues for Zara.

Likes	Negative	Positive	Comments	Negative	Positive	Shares	Negative	Positive
PEOPLE	42.71	68.23	lookbook	12.43	36.55	PEOPLE	36.87	70.45
editorial	3.23	33.63	PEOPLE	47.19	31.69	lookbook	7.81	35.21
http	−6.68	30.75	capsule	12.09	21.88	http	2.69	21.92
capsule	27.1	28.3	zaradaily	33.31	21.07	ZARA	−13.29	18.26
lookbook	17.38	25.55	http	3.02	17.62	tuesday	6.16	14.47
ZARA	−17.52	24.95	all	0.7	16.65	capsule	14.02	14.42
sale	−19.29	21.3	new	−6.91	16.44	zaradaily	11.67	13.83
zaranewin	−14.91	20.75	selected	10.6	15.68	sale	−3.79	12.23
start	−0.67	17.69	editorial	1.75	13.59	all	−1.68	11.35
selected	−3.34	17.31	store	−2.75	13.08	online	−2.36	10.36
tienda	7.76	16	online	1.3	12.86	new	1.76	10.04
online	−3.22	15.83	ZARA	−7.9	11.09	summer	−5.13	9.88
jacket	11.26	13.38	sale	5.25	10.69	in.store	1.59	9.55
store	−6.26	12.62	woman	4.92	10.46	woman	3.15	9.51
zarasale	−10.93	12.01	season	−3.55	10.35	editorial	2.11	9.28
all	−0.9	11.17	week	2.99	9.87	now	13.82	9.08
now	1.94	10.43	kids	−0.85	9.05	look	−2.06	9.06
zaradaily	34.43	9.95	zarasale	3.63	8.29	monday	−2.52	8.77
woman	13.44	8.6	denim	−3.48	7.99	store	0.56	8.57
look	−3.34	7.01	look	−3.25	7.8	season	−4.95	8.57
week	3.79	6.43	now	9.96	7.57	zarasale	−1.65	8.52
new	−3.91	5.21	in.store	−0.12	6.87	kids	0.31	8.42
recycle	4.64	4.13	zaranewin	−0.76	6.63	selected	−4.85	8.36
REBAJAS	5.39	3.53	start	0.05	6.59	week	−6.25	8.34
shirt	11.12	3.37	recycle	−3.34	5.7	outerwear	0.39	8.21

Table A4. *Cont.*

Likes	Negative	Positive	Comments	Negative	Positive	Shares	Negative	Positive
newthisweek	11.72	3.11	summer	−6.3	5.02	weekend	−4.65	6.83
in.store	−0.34	2.66	print	−1.85	3.7	more	−5.2	6.34
more	6.73	2.14	newthisweek	10.86	3.13	campaign	−5.07	6.16
kids	9.34	1.51	weekend	3.94	3.08	print	−4.33	5.92
campaign	−3.86	1.43	zaraeditorial-	4.66	2.8	bag	−1.44	5.89
summer	3.68	1.01	shirt	3.25	2.59	knitwear	−7.16	5.1
bag	3.63	0.85	monday	2.5	2.22	zaranewin	1.42	4.58
season	−3.02	0.06	campaign	−2.13	1.64	newthisweek	4.69	1.94
outerwear	7.89	−0.2	man	11.1	1.07	start	−5.11	0.87
monday	3.46	−0.73	jacket	−6.55	0.63	zaraeditorial	−4.87	0.49
weekend	5.9	−1.22	more	−1.79	−0.84	coat	9.36	−0.04
Dear	3.81	−1.4	bag	−3.91	−0.94	baby	−0.64	−0.2
knitwear	2.91	−1.84	available	24.09	−1.14	shirt	5.49	−0.26

Table A5. Negative and positive cues for Nike.

Likes	Negative	Positive	Comments	Negative	Positive	Shares	Negative	Positive
findgreatness	6.44	21.96	women	5.58	11.25	basketball	4.84	7.62
justdoit	0.77	8.91	more	1.08	10.89	free	−7.16	6.27
great	−1.61	8	here	−0.08	10.06	never	−1.1	6.03
free	−6.15	6.65	count	16.55	9.9	collection	2.81	5.73
life	0.01	4.99	now	4.09	8.56	run	−5.06	4.72
here	−4.15	4.89	basketball	5.44	7.86	justdoit	0.7	4.47
women	−3.72	4.77	life	0.83	7.48	great	0.75	4.22
more	−2.94	3.91	team	4.22	7.12	time	−1.68	3.44
new	−2.35	3.64	never	0.31	5.15	first	5.14	3.08
now	0.14	3.59	justdoit	4.3	4.79	game	1.35	2.86
conditions	−2.28	3.02	weather	0.37	4.02	women	2.23	2.85
weather	−0.04	2.92	sport	0.57	3.21	here	−4.3	2.83
control	1.49	2.52	Vapor	8.27	3.19	http	1.57	1.94
game	3.35	2.4	conditions	0.02	3.02	count	4.66	1.74
basketball	5.74	2.18	great	3.3	2.74	today	4.78	1.42
court	2.36	2.14	football	0.72	2.64	conditions	−1.41	1.42
team	−3.32	2.07	collection	7.26	2.45	control	2.32	1.4
athlete	0.6	1.43	free	−1.83	2.35	Vapor	3.82	1.32
know	3.8	1.16	today	3.32	1.67	athlete	2.95	0.97
never	−1.23	0.77	first	6.63	1.19	Hyperdunk	2.67	0.82
count	5.98	0.75	time	−1.22	0.86	air	0.53	0.78
collection	2.85	0.66	know	2.86	0.42	team	−0.68	0.35
Hyperdunk	−0.11	0.09	findgreatness	3.42	−0.22	fit	6.06	0.21
best	8.12	−0.01	Hyperdunk	1.35	−0.23	show	0.53	−0.38
design	0.07	−0.07	just	6.75	−0.29	know	2.66	−0.57
time	1.28	−0.08	train	5.67	−0.9	weather	−1.15	−0.74
run	2.61	−0.27	shoe	−0.76	−0.96	Nike	5.4	−0.84
cover	2.41	−0.41	cover	2.49	−1.18	more	−3.44	−0.97
show	−2.02	−0.59	photo	3.08	−1.25	best	5.37	−1
world	5.57	−0.69	design	−0.19	−1.33	new	3.28	−1.04
football	2.1	−0.94	best	−0.71	−1.61	court	2.72	−1.16
photo	2.13	−1.4	keep	6.68	−1.62	now	1.22	−1.24
fit	6.27	−1.69	show	−1.74	−1.67	keep	3.18	−1.31
feature	4.26	−1.74	game	6.52	−1.98	life	−3.39	−1.34
train	−2.42	−2.04	world	8.8	−2.2	shoe	−4.86	−1.54
speed	5.61	−2.12	athlete	0.86	−2.32	speed	−0.21	−1.63
just	3.87	−2.38	http	6.41	−2.37	findgreatness	3.09	−1.92

Table A6. Negative and positive cues for Adidas.

Likes	Negative	Positive	Comments	Negative	Positive	Shares	Negative	Positive
adidas	14.24	29.78	shoe	29.18	22.69	allin	18.23	24.39
train	12.01	26	adidas	24.23	22.17	like	20.36	20.45
now	16.01	19.25	allin	5.56	21.9	shoe	11.1	20.37
team	12.41	19.17	like	30.21	19.09	team	11.64	20.22
shoe	12.62	17.23	boost	−1.15	17.42	football	12.69	19.21
allin	5.86	16.14	football	28.29	16.76	adidas	11.99	16.23
http	11.57	15.51	go	15.25	16.72	here	14.12	15.7
game	1.35	14.38	now	25.97	15.97	go	5.57	15.03
me	16.24	12.05	team	14.99	15.93	me	16.01	14.54
win	15.24	12	new	18.56	12.71	game	4.35	14.47
Tsonga	−9.41	11.73	run	2.79	12.57	sport	9.92	14.38
football	6.25	11.72	win	20.42	12.37	http	9.57	14.12
sport	7.45	11.62	France	2.44	11.74	boost	−1	12.72
France	0.05	11.46	FindFocus	−2.62	11.05	now	12.76	12.71
final	0.49	11.44	olympique	0.29	10.76	first	9.81	12.29
world	6.59	9.5	video	−0.33	9.61	France	2.84	12.29
go	5.07	9.15	creatividad	2.7	8.53	new	10	12.06
chance	4.37	8.92	http	19.57	8.44	today	10.62	11.91
creatividad	8.73	8.41	para	1.64	8.23	creatividad	8.39	10.47
time	1.57	8.3	look	10.4	7.98	final	8.66	10.23
para	0.64	8.22	make	14.66	7.31	stage	13.79	10.07
boost	−5.38	7.75	game	15.94	6.84	time	−3.98	10.03
video	1.93	7.68	time	2.49	6.05	run	2.14	9.97
run	9.66	7.66	train	5.38	5.56	video	0.57	9.76
first	16.18	7.39	here	21.49	5.28	FindFocus	−5.56	9.34
speedtakes	11.12	7.33	first	13.58	5.11	Tsonga	0.42	8.79
make	−0.23	7.14	sport	11.76	5.1	photo	7.78	8.16
like	11.25	6.64	final	13.22	4.94	world	2.07	8.08
olympique	−5.5	5.98	today	10.69	4.49	chance	3.96	7.66
look	1.25	5.58	stage	17.56	3.47	look	5.39	6.39
here	8.53	4.62	challenge	5.05	3.28	origin	1.83	6.01
stage	18.03	4.41	speedtakes	10.95	3.22	ready	11.2	5.78
new	14.03	4.21	chance	7.64	3.16	make	1.56	5.55
today	9.19	3.97	me	14.2	2.71	train	2.11	4.02
find	8.49	1.76	Tsonga	9.93	2.08	win	7.56	3.44
challenge	6.67	1.28	heretocreate	4.44	0.4	para	−0.62	2.11
store	8.79	−1.28	cover	14.63	−0.95	store	9.44	1.55
heretocreate	4	−1.57	world	13.42	−1.11	olympique	−4.55	1.17

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