



Article

Analysis of Community Interaction Modules of European and American Universities

Yulin Chen

Department of Mass Communication, Tamkang University, Tamsui District, New Taipei City 25137, Taiwan; 143530@mail.tku.edu.tw

Abstract: Purpose—Using a sample of universities from Europe and North America the research herein seeks to understand the content trends of university brand pages through an exploration of the social community and the measurement of user participation and behavior. The analysis relies on an artificial intelligence approach. Through the verification of interactions between users and content on the university brand pages, recommendations are made, which aim to ensure the pages meet the needs of users in the future. Design/methodology/approach—The study sample was drawn from six well-known universities in Europe and North America. The content of 23,158 posts made over the course of nine years between 1 January 2011 to 31 December 2019 was obtained by a web crawler. Concepts in the fields of computer science, data mining, big data and ensemble learning (Random Decision Forests, eXtreme Gradient Boosting and AdaBoost) were combined to analyze the results obtained from social media exploration. Findings—By exploring community content and using artificial intelligence analysis, the research identified key information on the university brand pages that significantly affected the cognition and behavior of users. The results suggest that distinct levels of user participation arise from the use of different key messages on the university fan page. The interactive characteristics identified within the study sample were classified as one of the following module-types: (a) information and entertainment satisfaction module, (b) compound identity verification module or (c) compound interactive satisfaction module. Research limitations/implications—The study makes a contribution to the literature by developing a university community information interaction model, which explains different user behaviors, and by examining the impact of common key (image) clues contained within community information. This work also confirms that the behavioral involvement of users on the university's brand page is closely related to the information present within the university community. A limitation of the study was the restriction of the sample to only European and North American cultural and economic backgrounds and the use of Facebook as the sole source of information about the university community. Practical implications—Practically, the research contributes to our understanding of how, in official community interactions, user interactions can be directed by features such as information stimuli and brand meanings. In addition, the work clarifies the relationship between information and user needs, explaining how the information characteristics and interaction rules particular to a given school can be strengthened in order to better manage the university brand page and increase both the attention and interaction of page users. Originality/value—This research provides an important explanation of the role of key information on the university fan pages and verifies the importance of establishing key (image) clues in the brand community, which in turn affect user cognition and interaction. Although related research exists on information manipulation and the importance of online communities, few studies have directly discussed the influence of key information on the fan pages of university brands. Therefore, this research will help to fill gaps in the literature and practice by examining a specific context, while at the same time providing a valuable and specific reference for the community operation and management of other related university brands.



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Keywords: university; brand page; key (image) clues; social media mining; ensemble learning

1. Research Background

It is estimated that there are approximately 2 billion people active on social media globally. Given such a huge potential audience, academic institutions have sought to use social media for messages about brand promotion, research successes and community development (Salomon 2013). Frequently, messages address topics of interest such as available courses and more general topics of interest (Hansen and Winter 2012). Moreover, in light of the competition among high-ranking universities across the world, brand building has become important for the image of high schools as well. Equally, university pages have also become an important tool of brand promotion (Opoku et al. 2006). Fan pages often supply unofficial lifestyle or study information, but may also serve as a reference for high school students seeking to choose a university (Rolfe 2003). Universities can conduct informal conversations through communities and use different social media platforms such as Facebook, Instagram, Snapchat, Twitter and LinkedIn to interact with a greater number of potential students (Camilleri 2019). Social media has also increased the brand awareness of universities (Constantinides and Stagno 2011; Kuzma and Wright 2013) while offering a valuable marketing tool. The effective use of social media can help students to identify suitable universities and establish a positive dialogue between both parties through continuous brand communication. Therefore, to be successful, the university must seek to use innovative methods to highlight the university's unique image.

In light of this, the construction of a community image is very important for any university (Abdelmaaboud et al. 2020; Kiang et al. 2000; Opoku et al. 2006). The combination of text and images contained on the fan page may serve as the basis for a user's general impression of the institution (Saichae and Morphew 2014). At present, most universities in the United States and the United Kingdom use Twitter for community conversations. Unfortunately, much of the literature on university social media sites focuses on the effectiveness of teaching and learning (Fikkers and Piotrowski 2020), seldom mentioning the value and significance of the page's content. This research aims to investigate how a university can successfully establish an interactive relationship with users through the analysis of university fan pages. The research examines the fan pages of six well-known universities in Europe and America, including the following UK universities: Imperial College London, University of Cambridge and University of Oxford; and the following US universities: California Institute of Technology, Massachusetts Institute of Technology and Stanford University. By analyzing the unconstructed text on the Facebook pages of the above universities, the study attempts to answer the following two questions:

- (a) Do posts on the fan pages of European and North American universities have specific "key (image) clues" to help build and promote the brand image of the university?
- (b) Using a machine learning, artificial intelligence approach, can the gratification of users, drawn from the information provided, be actively discovered based on interactive data, and is this amenable to behavioral analysis and prediction?

Previous related research on information management has shown that high-level visual information can successfully trigger positive emotional and behavioral responses from users (Foroudi et al. 2020; Foroudi et al. 2019). For example, stimuli such as gratification, trust and value recognition can help to promote the accuracy of a user's judgment of information, while at the same time also increasing the task value of information (Liu and Goodhue 2012; Wells et al. 2011). Furthermore, such stimuli can also increase brand trust and strengthen the link between the information and brand. However, within the field of community research, attention is generally limited to investigations of the behavior of users (Hashim et al. 2020; Parboteeah et al. 2009; Weng et al. 2010). To date, there are few discussions on the influence of social media content on behavioral interactions and even fewer that explore and analyze the content of the university social media pages.

Therefore, this study focuses specifically on: (a) examining a sample of well-known universities in Europe and North America; (b) understanding the content trends of university brand pages through community content exploration technology and using artificial intelligence calculation analysis to measure users' participation and behavior; (c) proposing

relevant verifications of the interactive benefits and making feasible suggestions for future analysis of the needs of users in university communities.

Overall, complete hypothesis verification and result analyses are constructed based on the open and transparent content and data available on the fan page, from which reviews are conducted and the social media operating characteristics of well-known European and North American universities are characterized. The second section of this paper briefly discusses the current literature on social media information, social media use and the theory of gratification. The third section of this paper suggests relevant hypotheses relating to university brand pages to evaluate the relationship between key information and user behavior. The fourth section of this paper focuses on the research methods. The fifth section contains data analysis and, finally, the sixth section discusses results, suggesting how the research model can be used to plan relevant university community information.

2. Literature Review

2.1. Community Information and Crowd Participation

Common Facebook fan-page information includes text, images, videos, URL links, votes, calls to action, etc. (De Vries et al. 2012). Pages users are able to like, share and comment by posting (Araujo and Neijens 2012; Curras-Perez et al. 2014). Facebook pages are widely used in political communication (Woolley et al. 2010), advertising (Chu 2011), demand gratification (Park et al. 2009), life consultation (Bender et al. 2011) and a range of other purposes including education (Meishar-Tal et al. 2012). In addition to regular brands, many non-profit organizations have also created fan pages, which serve as exclusive communication platforms (Cvijikj and Michahelles 2011; Fumasoli et al. 2020).

Facebook fan pages have settings for images, videos and links (De Vries et al. 2012). This diverse selection of media features produces rich online presentations (Coyle and Thorson 2001), stimulating user interaction based on different types of content (Liu and Shrum 2002). Furthermore, due to differences in brand positioning, content characteristics can be altered (De Vries et al. 2012; Lee et al. 2020). For example, posts that emphasize functional purposes are suitable for providing specific, practical information (Cvijikj and Michahelles 2011). On the other hand, entertaining posts can attract attention with humor and interesting content. If page managers were able to ensure that the information design of the fan page was appropriate, a better understanding of user gratification would develop and an overall improved user experience would become possible. (Liu et al. 2013). In addition, the issue of users rejecting information because of poor design and unattractiveness would become easier to avoid (Liu and Goodhue 2012; Pinar et al. 2020).

Since the importance of community participation continues to be valued, a greater number of studies have focused on observing the interaction between social media and its users. This includes studies on how brand messages may be effectively delivered to users, or how users may be stimulated to effectively and actively participate, thereby becoming active members of the brand community (Valenzuela et al. 2009). Behavioral responses have always been regarded as indicators of reference significance (Brodie et al. 2013; Schau et al. 2009). For example, online clicks and webpage views are used for multiple examinations and evaluations (Lehmann et al. 2012). Regarding the cognitive and behavioral responses of users, common drivers of responses include affection needs, tool needs, information needs and evaluation needs. Information needs and affection needs are necessary prerequisites for behavioral participation and are dependent on the extent of users' appetite for information or emotional stimuli (Liang et al. 2011). Information needs refer to the practical value and significance of the content and result in behaviors such as recommending, suggesting or sharing (Liang et al. 2011; Yousaf et al. 2020). Affection needs refer to the emotions that users invest in the process, such as care, understanding, anger, sadness and sympathy, which are often then expressed as likes or dislikes on posts.

The existing literature has found that different factors underlie public participation (Laroche et al. 2013). For example, participation is not only driven by the desire to obtain a product (Weinberg and Pehlivan 2011), a service or brand information (Bruhn et al. 2012).

Participation also allows users to build relationships with the community, which is frequently achieved through blogs, videos or images, sharing and recommendations (Schivinski and Dabrowski 2016). Such participation stimulates website traffic and increases brand discussions and popularity (Kim and Ko 2012; Lee et al. 2020). To exert a positive effect on user–brand interaction (Laroche et al. 2013), brands must constantly consider the impact of social media on the public (Bruhn et al. 2012). Only when the value of social media is better understood will brands be able to maximize the gratification benefits.

2.2. Uses and Gratifications

According to the different functions mentioned above, different forms of gratification exist (Horton and Richard Wohl 1956) and can be generated via the interaction of users with social media (Thorson and Rodgers 2006). This is particularly the case when communities offer unique interactivity. There exists a wide body of information-related research, including studies on information interaction and community association verification (Teo et al. 2003), information profitability, online participation characteristics and multiple other aspects. In relation to content, the context structure of traditional media newspapers (Robins et al. 2001), the characteristics of online content (Luo et al. 2011) and the information needs of mobile services have all been previously investigated (Lee et al. 2010).

Early research into use and gratification can be roughly divided into two categories (Katz et al. 1973): process gratification and content gratification (Raacke and Bonds-Raacke 2008; Stafford et al. 2004). In addition to exploring the reasons behind the choices made by users, research has sought to verify how users achieve self-gratification through experiences. As such, use and gratification theories are particularly relevant in explaining user decision-making motivations and the key drivers of choice (Luo et al. 2011; Xu et al. 2012).

“Process gratification” refers to the cognition, experience and evaluation of users (Weng et al. 2010). This includes participation, searching, dialogue and communication, especially in cases where a community provides a demand framework that can simultaneously meet pragmatic demands, social demands, available demands and enjoyment demands. Process gratification also explains the basic motivation of user participation in the community. A user may derive satisfaction in terms of cognition, interaction and enjoyment, which reflects the importance of pragmatic demands, social demands and enjoyment demands (Kohler et al. 2011).

On the other hand, the four keys to “content gratification” include information recognition gratification, emotional cognitive gratification, social gratification and entertainment gratification (Leung 2009). By enabling communication, entertainment, an escape from reality and the ability to maintain relationships, social media can meet the content demands of users. Therefore, young people frequently use social media to satisfy one or more of the following six items: amusement, affection, fashion, sharing, social interaction and social information (Dunne et al. 2010). In relation to content gratification, recognizing the reasons for the use of social media and strengthening the practical, social and enjoyment aspects should all be important objectives for social media information. The practical level refers to the feedback received by users in the information acquisition process (Kohler et al. 2011). In the process of receiving information, users may obtain brand-related knowledge, which contributes to the overall perceptions of the brand (Nambisan and Baron 2009). The community is the relationship between the brand and users, and the content is the basic element that affects community participation. Therefore, precise content serves to establish and enhance the physical participation of users, community identity and overall sense of community.

Users who share similar interests can recommend and comment (Pagani and Mirabello 2011) and, through such interactions, can establish their own social identity and build community support, friendship or intimacy (Dholakia et al. 2004). Furthermore, psychological support and attention can help users within the community to obtain inner gratification (Liang et al. 2011). Community experience may also prompt users to realize their own self-worth in the community. When the community environ-

ment reflects the personal values of users, more active participation in the community is engendered (Pagani and Mirabello 2011; Webster et al. 1993), mainly because users wish to present themselves through interaction (Liang et al. 2011).

According to social exchange theory, in addition to obtaining information value from community interaction, user interaction produces a sense of self-demand. Therefore, information content with a high degree of perception is more likely to produce self-expression, which in turn generates recognition and support for the community. Therefore, whether content perception is positive or not will further affect the perception of a brand (Fortin and Dholakia 2005; Wallace et al. 2014a). Efficient content and behavior complement each other, which in turn leads to positive communication effects (Rafaeli and Ariel 2007). In addition, interaction results in increased use of media (Thorson and Rodgers 2006); this is consistent with gratification theory, as users who identify with fan pages are more willing to interact in order to gain gratification. If a user's self-image can be displayed in the community (Animesh et al. 2011), their sense of imagination can be satisfied naturally. Through personal participation and self-image projection, a user's self-image may be transformed into a sense of belonging within the community. According to complementary needs theory, users are likely to choose multiple pieces of information drawn from the same category, which may elicit similar effects and convey a greater sense of practicality. In addition, multi-faceted information can help users obtain multiple pieces of information as well as gain multiple forms of gratification, such as interpersonal communication, self-expression, practicality and entertainment, as mentioned before. Therefore, in seeking a higher degree of complementary demands, users often actively seek information from different competing brands.

3. Research Hypotheses

After referring to the above literature, it is evident that information affects the cognitive state of users (Mehrabian and James 1974). For instance, in the example of e-commerce, it is clear that information exerts a positive impact on user perceptions (Parboteeah et al. 2009). Diversified information presentation may not only satisfy the multi-level curiosity of users regarding a given brand but may also induce users to experience a more complete entertainment effect (Muniz and O'Guinn 2001). Of course, it is assumed that the more frequently information is presented in alignment with a given task, the greater the possibility of task accomplishment (Nambisan and Baron 2009). This affirms the notion that information can help construct entertainment value and that well-positioned information is more likely to succeed in stimulating a pleasant experience among users (Animesh et al. 2011).

Therefore, we argue that the quality of information can be used to measure the accuracy and adequacy of a brand community's content positioning, and in order to improve information efficiency, the behavioral gratification stimulated by the information is a suitable benchmark with which to measure the gratification of users. Currently, brands tend to use social media to convey information, not only by simply delivering the information but also by providing interactive posts that will encourage users to participate (Nambisan and Baron 2009). Social interaction by users can help to build stronger connections with the brand and establish a consistent brand identity with other users. Therefore, information not only connects users but also promotes social integration among them (Muniz and O'Guinn 2001).

If the self-realization and existence value of users are to be enhanced through interaction with the information by users (Tsai and Pai 2012), we argue that the content of the social media post is a basic element that will directly affect community participation. This is because information can directly drive the cognitive and emotional response of users as well as affect user participation behavior (Zhang et al. 2014). Through the observation of the social media pages of most businesses, it is evident that key elements are frequently used to raise the emotional support of their audience and strengthen the information power of the community (Schau et al. 2009). Brand communities not only reflect the objective

attributes of users (Zhang et al. 2011) but also reflect the subjective demands of users (Weng et al. 2010).

In particular, the click-through rate is more often regarded as an effective measurement of participation behavior (Brodie et al. 2013) and can also be used as a quantitative indicator of online participation (Lehmann et al. 2012). Measurements on Facebook include clicks, likes, comments, sharing and other substantive behaviors (Wallace et al. 2014a). Frequent information sharing creates a supportive environment in which brand information, brand knowledge and relevant experience are shared within the community (Liang et al. 2011). Therefore, stronger social interaction is more likely to result in high-quality information being shared by others. In view of this, this research attempts to understand the so-called information value by examining key (image) clues as a means of evaluating user gratification with information, and based on the above concepts, two central hypotheses are proposed (Figure 1).

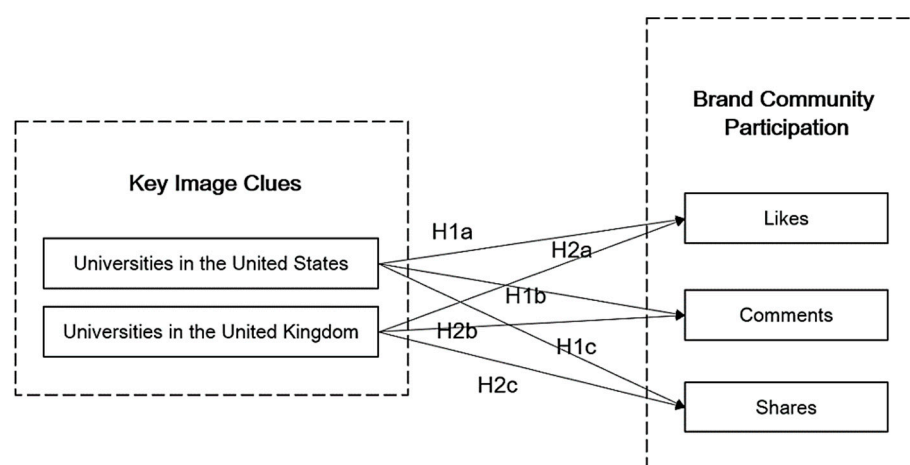


Figure 1. Extended research model.

Hypothesis 1a (H1a). *The university pages of universities in the United States possess “key (image) clues,” which have a significant influence on the “likes” of users.*

Hypothesis 1b (H1b). *The university pages of universities in the United States possess “key (image) clues,” which have a significant influence on the “comments” of users.*

Hypothesis 1c (H1c). *The university pages of universities in the United States possess “key (image) clues,” which have a significant influence on the “shares” of users.*

Hypothesis 2a (H2a). *The university pages of universities in the United Kingdom possess “key (image) clues,” which have a significant influence on the “likes” of users.*

Hypothesis 2b (H2b). *The university pages of universities in the United Kingdom possess “key (image) clues,” which have a significant influence on the “comments” of users.*

Hypothesis 2c (H2c). *The university pages of universities in the United Kingdom possess “key (image) clues,” which have a significant influence on the “shares” of users.*

4. Research Methodology

The study proceeded by conducting an empirical analysis of university brand pages to explore how key information contained within the post influences user participation. Facebook’s terms of service allow app designers to monitor interactions (Cvijikj and Michahelles 2011; Goorha and Ungar 2010). Most of the information on the Facebook fan pages is presented in four formats: text, photos, videos and links. The behavioral benchmark for measuring online participation includes three methods: clicking likes,

commenting and sharing information (Wallace et al. 2014b). Therefore, this research adhered to Facebook's terms of service, allowing app designers to participate in the relevant actions of interaction monitoring and in obtaining post data and content for the purpose of research (Cvijikj and Michahelles 2011; Goorha and Ungar 2010). Furthermore, to ensure the accuracy of the information, the Facebook Graph API was used to collect daily posts, including the content of each post, post type, posting time, post likes, post shares and post comments; this information was subsequently extracted and stored in the database for classification.

The samples of this study were taken from six well-known universities in Europe and America, including the following university fan pages: Imperial College London, University of Cambridge, University of Oxford, California Institute of Technology, Massachusetts Institute of Technology and Stanford University. Each fan page must meet the criteria of being stable and continuously updated, and the university must be among the top ten universities in North America and Europe. The content of posts from January 1, 2011 to December 31, 2019 was obtained through web crawlers, as well as the number and content of public responses to all corresponding articles. In total, 23,158 posts were received, of which 12,411 were posts from universities in the United Kingdom and 10,747 were posts from universities in the United States.

To ensure the validity of the content, the measurement items in this study directly adopted the functional classification set by Facebook and were appropriately divided into behavioral responses (like, comment, share). In addition, relevant research on visual perception was referred to (Loiacono et al. 2007), and the cognitive gratification and behavioral gratification of the crowd was measured (Nambisan and Baron 2009) in order to integrate relevant research theory. At the same time, concepts from the fields of computer science, data mining, big data and ensemble learning (Random Decision Forests, eXtreme Gradient Boosting and AdaBoost) were combined to discuss social media exploration.

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 universities in the United States had a total variance of 74.094% and a KMO value of 0.910. The factor characteristic value of universities in the United Kingdom had a total variance of 81.987% and a KMO value of 0.886. 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 0.898 for universities in the United States and 0.886 for universities in the United Kingdom. Each of these results shows good reliability (Figure 2).

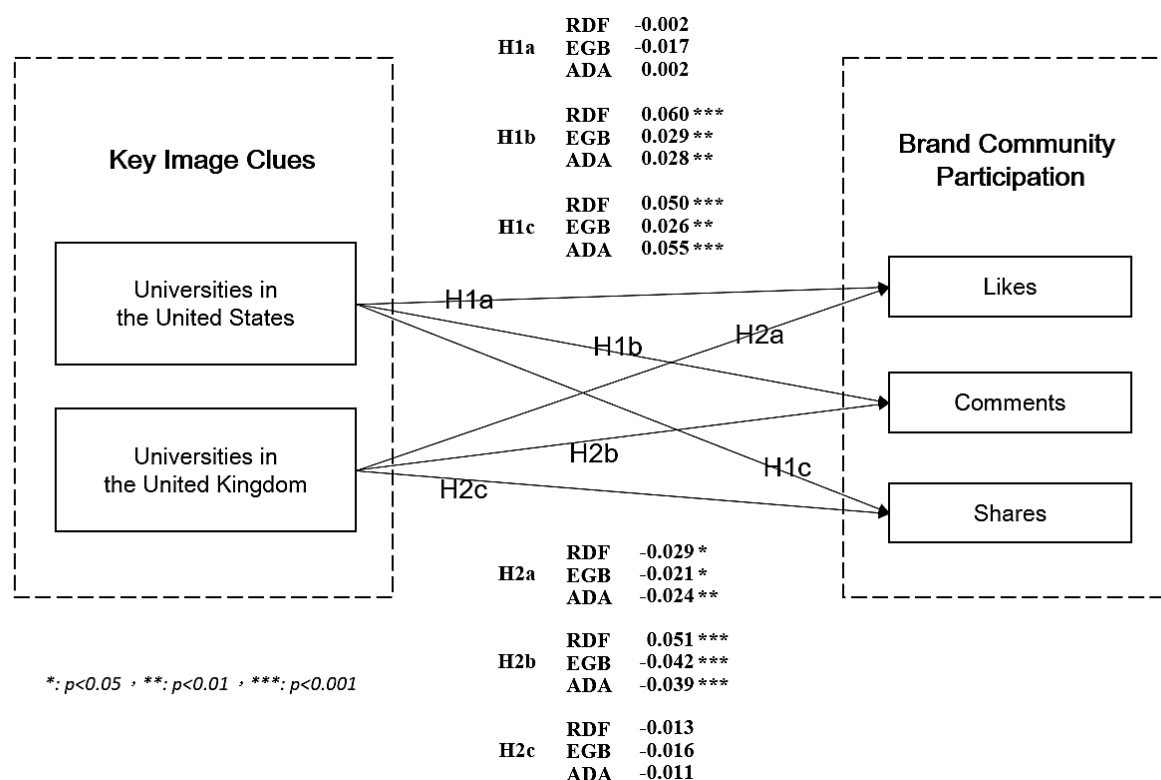


Figure 2. Model results. *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$

5.2. Hypothesis Testing

The results show that the university pages of universities in the United States possess “key (image) clues” and had a significant influence on the behavior of users (likes, comments, shares). Through ensemble learning, the following results were obtained: the key (image) clues provided by Random Decision Forests, AdaBoost and eXtreme Gradient Boosting were found to be significant predictors of comments and shares. The results show that the key predictions provided by Random Decision Forests, AdaBoost and eXtreme Gradient Boosting indicate that interaction via likes and comments were as predicted for the university pages of universities in the United Kingdom (Table 1).

Table 1. Summary of hypotheses.

ID	Hypothesis	Verdict
H1a	The university pages of universities in the United States possess “key (image) clues,” which have a significant influence on the “likes” of users.	Not established
H1b	The university pages of universities in the United States possess “key (image) clues,” which have a significant influence on the “comments” of users.	Established
H1c	The university pages of universities in the United States possess “key (image) clues,” which have a significant influence on the “shares” of users.	Established
H2a	The university pages of universities in the United Kingdom possess “key (image) clues,” which have a significant influence on the “likes” of users.	Established
H2b	The university pages of universities in the United Kingdom possess “key (image) clues,” which have a significant influence on the “comments” of users.	Established
H2c	The university pages of universities in the United Kingdom possess “key (image) clues,” which have a significant influence on the “shares” of users.	Not established

5.3. Data Verification

The results show that the key clues of social media significantly affected the public's response to content and behavior. The hypotheses on information among universities in the United States are supported. The behavior of users (comments) was found to have a significant impact on Random Decision Forests ($\beta = 0.060, p < 0.000$), eXtreme Gradient Boosting ($\beta = 0.029, p < 0.002$) and AdaBoost ($\beta = 0.028, p < 0.003$) made by users. Shares were found to have a significant impact on Random Decision Forests ($\beta = 0.050, p < 0.000$), eXtreme Gradient Boosting ($\beta = 0.026, p < 0.007$) and AdaBoost ($\beta = 0.055, p < 0.000$) (Table 2). Furthermore, the hypotheses on information among universities in the United Kingdom are supported. The behavior of users (likes) was found to have a significant impact on Random Decision Forests ($\beta = -0.029, p < 0.001$), eXtreme Gradient Boosting ($\beta = -0.021, p < 0.018$) and AdaBoost ($\beta = -0.024, p < 0.008$) made by users. Comments were found to have a significant impact on Random Decision Forests ($\beta = 0.051, p < 0.000$), eXtreme Gradient Boosting ($\beta = -0.042, p < 0.000$) and AdaBoost ($\beta = -0.039, p < 0.000$) (Table 3).

Table 2. Linear regression coefficient of determination and beta (universities in the United States).

Universities in the United States		R	R ²	Adjusted R ²	F-Change	ΔF	Durbin-Watson	B	Standard Error	Beta	T	Sig.
Likes	Random Decision Forests	0.002	0.000	0.000	0.000	0.044	1.639	-0.955	4.576	-0.002	-0.209	0.835
	eXtreme Gradient Boosting	0.017	0.000	0.000	0.000	3.023	1.637	-7.011	4.033	-0.017	-1.739	0.082
	AdaBoost	0.002	0.000	0.000	0.000	0.027	1.640	0.981	6.016	0.002	0.163	0.870
Comments	Random Decision Forests	0.060	0.004	0.004	0.004	39.129	1.701	1.325	0.212	0.060	6.255	0.000
	eXtreme Gradient Boosting	0.029	0.001	0.001	0.001	9.313	1.692	0.582	0.191	0.029	3.052	0.002
	AdaBoost	0.028	0.001	0.001	0.001	8.658	1.692	0.742	0.252	0.028	2.942	0.003
Shares	Random Decision Forests	0.050	0.003	0.002	0.003	27.111	1.876	7.756	1.490	0.050	5.207	0.000
	eXtreme Gradient Boosting	0.026	0.001	0.001	0.001	7.326	1.873	3.550	1.312	0.026	2.707	0.007
	AdaBoost	0.055	0.003	0.003	0.003	32.043	1.876	10.848	1.916	0.055	5.661	0.000

Table 3. Linear regression coefficient of determination and beta (universities in the United Kingdom).

Universities in the United Kingdom		R	R ²	Adjusted R ²	F-Change	ΔF	Durbin-Watson	B	Standard Error	Beta	T	Sig.
Likes	Random Decision Forests	0.029	0.001	0.001	0.001	10.152	1.881	-49.326	15.481	-0.029	-3.186	0.001
	eXtreme Gradient Boosting	0.021	0.000	0.000	0.000	5.638	1.879	-31.632	13.322	-0.021	-2.374	0.018
	AdaBoost	0.024	0.001	0.000	0.001	7.088	1.880	-38.524	14.471	-0.024	-2.662	0.008
Comments	Random Decision Forests	0.051	0.003	0.003	0.003	32.271	1.800	2.902	0.511	0.051	5.681	0.000
	eXtreme Gradient Boosting	0.042	0.002	0.002	0.002	22.344	1.788	-1.919	0.406	-0.042	-4.727	0.000
	AdaBoost	0.039	0.002	0.001	0.002	18.672	1.790	-2.068	0.479	-0.039	-4.321	0.000
Shares	Random Decision Forests	0.013	0.000	0.000	0.000	2.150	1.993	-24.569	16.755	-0.013	-1.466	0.143
	eXtreme Gradient Boosting	0.016	0.000	0.000	0.000	3.289	1.993	-26.942	14.857	-0.016	-1.813	0.070
	AdaBoost	0.011 a	0.000	0.000	0.000	1.518	1.993	-20.533	16.664	-0.011	-1.232	0.218

5.4. Data Findings

Ensembled learning was used to recommend key clues and organize the key (image) clues to achieve the significant impacts shown in Figure 3. This study uses three integrated analyses to compare each university page's posts with their higher-than-average interactions through positive clues (red) and negative clues (blue). It was found that there are some similarities and differences in the operation of key clues of each brand. The main characteristics of the clues after comparison are as follows.

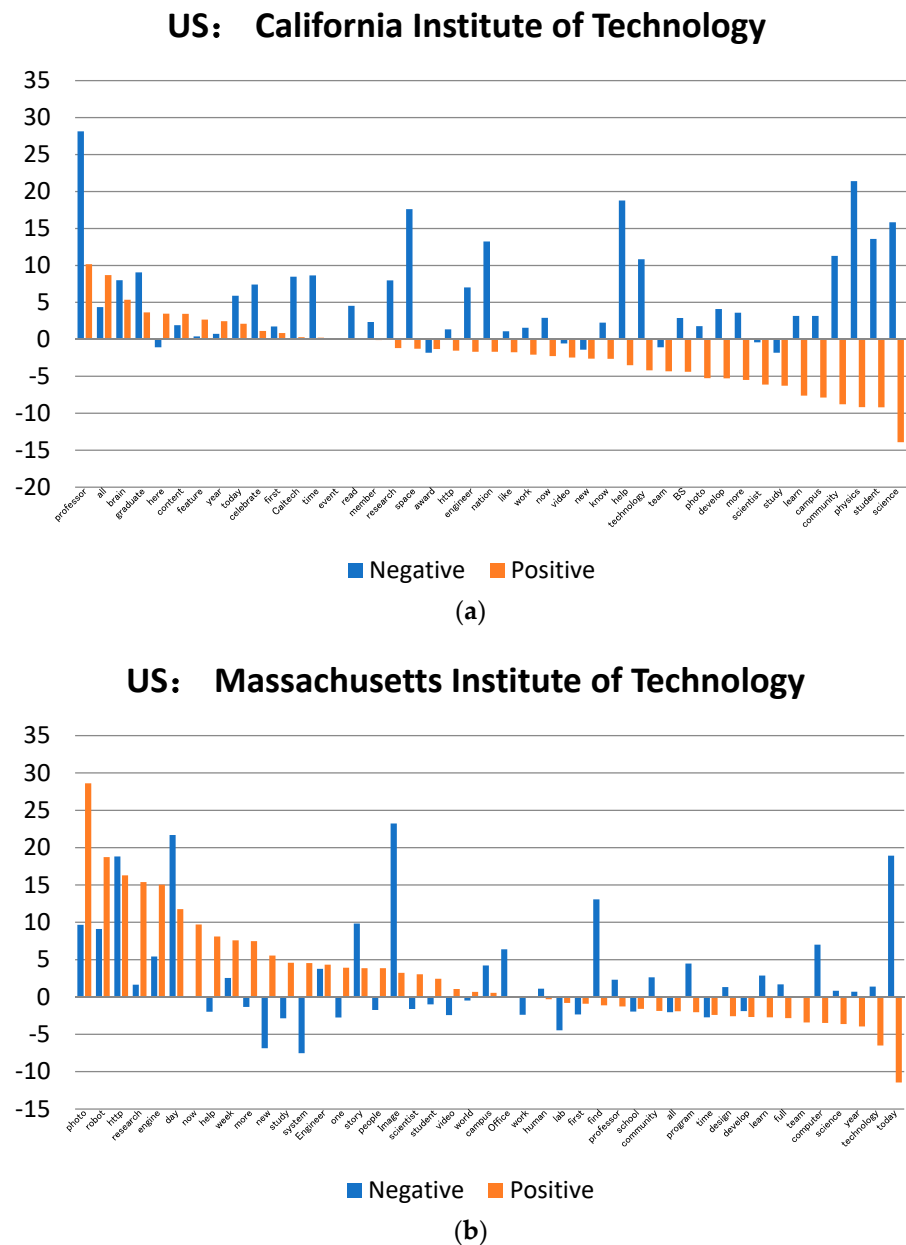


Figure 3. Cont.

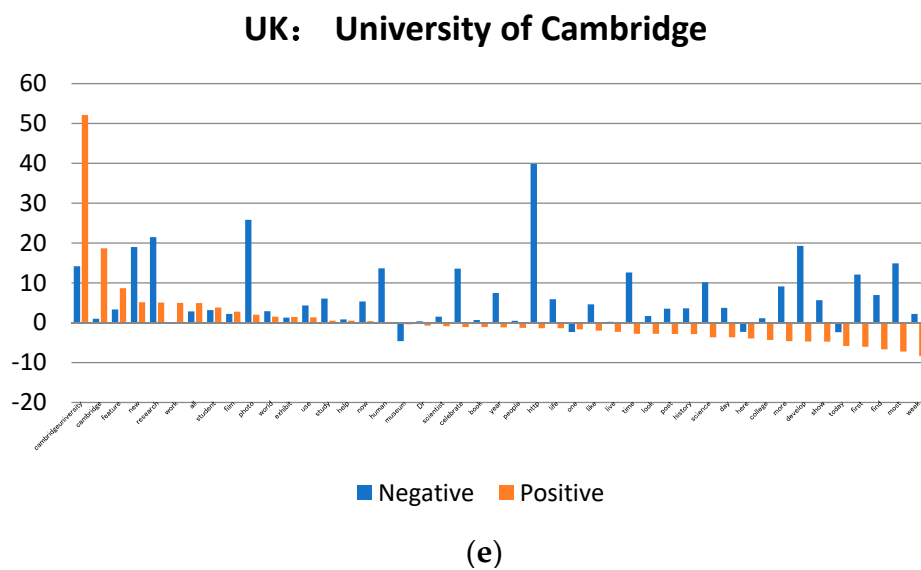
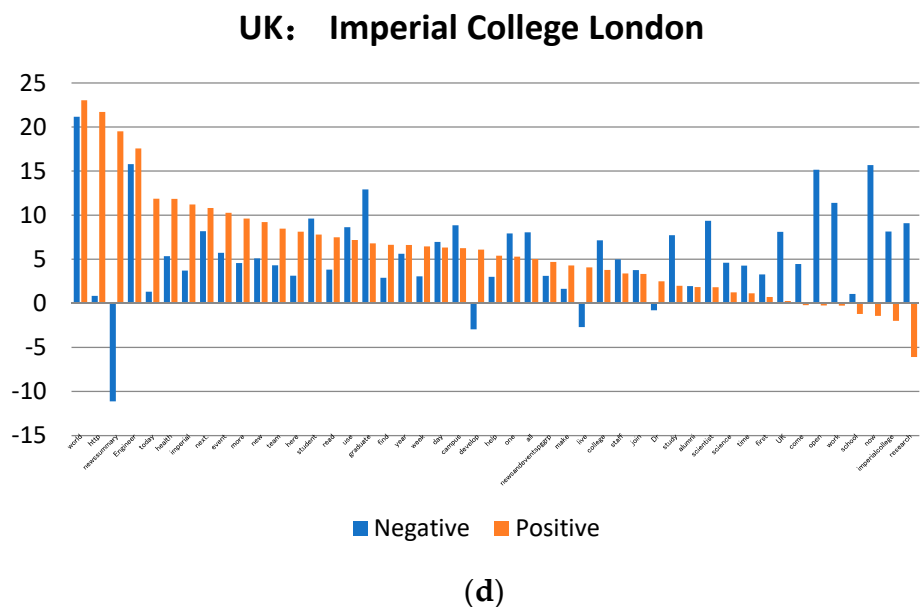
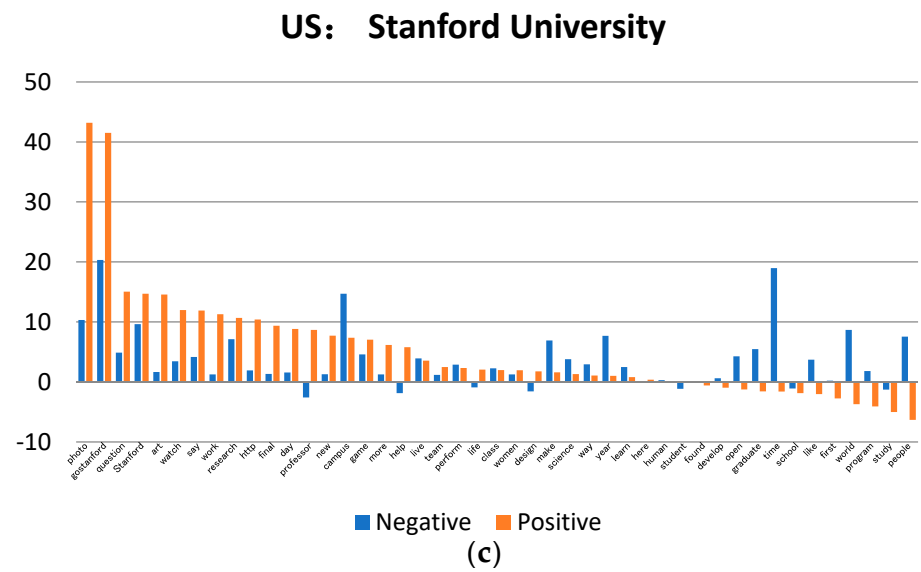


Figure 3. Cont.

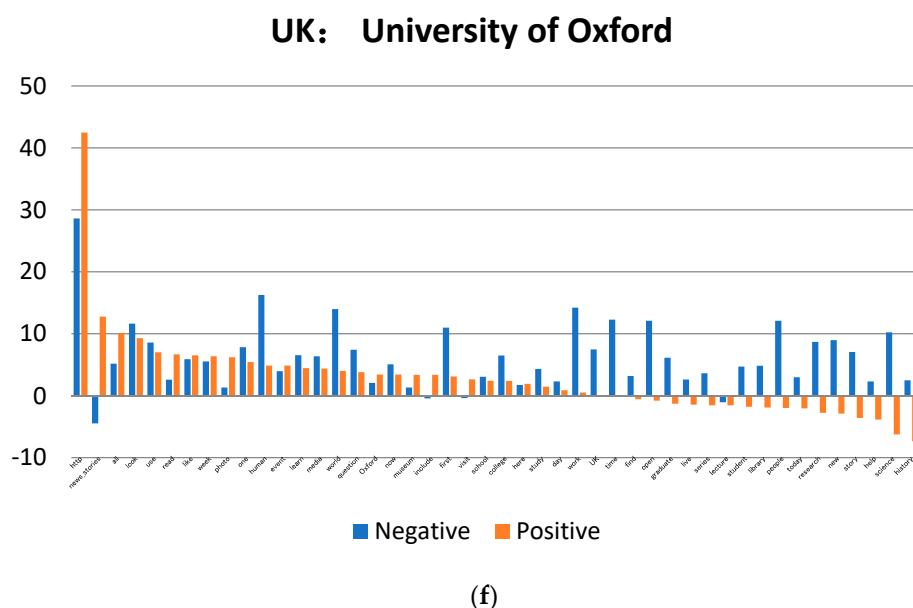


Figure 3. (a) Clues of California Institute of Technology; (b) clues of Massachusetts Institute of Technology; (c) clues of Stanford University; (d) clues of Imperial College London; (e) clues of University of Cambridge; (f) clues of University of Oxford.

(A) University in the United States: Stanford University

The key (image) clues provided by Random Decision Forests for likes included “photo,” “gostanford,” “question,” “Stanford” and “art”; the clues for comments included “gostanford,” “photo,” “http,” “watch” and “game”; the clues provided by eXtreme Gradient Boosting for likes included “Stanford,” “art,” “http,” “day” and “campus”; and the clues provided by AdaBoost for likes included “open,” “science,” “like,” “make” and “world” (Table A1, Appendix A).

Random Decision Forests and eXtreme Gradient Boosting jointly recommended “Stanford,” “art” and “campus”. These constituted recommendations for image construction, such as “Stanford” or “campus,” which received a high level of attention in terms of likes and comments. AdaBoost, on the other hand, returned “open,” “program,” “science” and “world.” These are keyword feature that, after the initial image construction is completed, are packaged into popular user topics such as, for example, course-related information, such as “open” and “program,” or representative research achievements, such as “science” and “world.” These then serve to successfully stimulate the cognition and intentions of the audience.

(B) University in the United States: Massachusetts Institute of Technology

The key (image) clues provided by Random Decision Forests for comments included “campus,” “http,” “engine,” “research” and “robot”; the clues for shares included “more,” “engine,” “research,” “http” and “scientist”; the clues provided by eXtreme Gradient Boosting for comments included “http,” “research,” “now,” “new” and “more”; and the clues for shares included “http,” “Office,” “all,” “new” and “more.” The key (image) clues provided by AdaBoost for shares included “study,” “today,” “school,” “Office” and “scientist” (Table A2).

Random Decision Forests and eXtreme Gradient Boosting jointly recommended “research,” “http” and “new.” AdaBoost suggested “study,” “today,” “school,” “Office” and “scientist,” and it found that the use of advanced recommended keywords obtained excellent interactive results in terms of comments and shares. In addition, it was also found that the information in which users were most interested included two key themes, “Office” and “today,” which reflected the most up-to-date information on the school, and research-related terms including “scientist” and “research.”

(C) University in the United States: California Institute of Technology

The key (image) clues provided by Random Decision Forests for likes included “professor,” “all,” “brain,” “graduate” and “here”; the clues provided by eXtreme Gradient Boosting for likes included “Caltech,” “professor,” “all,” “new” and “http”; and the clues provided by AdaBoost for likes included “physics,” “content,” “like,” “brain” and “know” (Table A3).

Random Decision Forests and eXtreme Gradient Boosting jointly recommended “Caltech,” “professor,” “new” and “research.” As such, the university’s brand image construction could be better focused by incorporating the terms “Caltech,” “professor” and “research” to reflect a professional image. Through AdaBoost, “physics,” “brain,” “space,” “engineer” and “award” were obtained, indicating that the school’s unique specialized achievements may be further utilized by words such as “physics,” “brain” and “award” to strengthen the connection and impression of themes and information.

(D) University in the United Kingdom: University of Oxford

The key (image) clues provided by Random Decision Forests for comments included “http,” “photo,” “college,” “event” and “media”; the clues provided by eXtreme Gradient Boosting for comments included “http,” “college,” “all,” “day” and “here”; and the clues provided by AdaBoost for comments included “media,” “news_stories,” “include,” “new” and “question” (Table A4).

Random Decision Forests and eXtreme Gradient Boosting jointly recommended “http,” “photo” and “college.” The key clues recommended by AdaBoost included “media,” “news_stories,” “new” and “question.” In addition to providing general information, users were more likely to leave messages on special topics such as “news_stories” and “question,” owing to user interests and demands.

(E) University in the United Kingdom: University of Cambridge

The key (image) clues provided by Random Decision Forests for likes included “cambridgeuniversity,” “cambridge,” “feature,” “new,” and “research.” The key (image) clues provided by eXtreme Gradient Boosting for likes included “http,” “cambridgeuniversity,” “photo,” “research” and “new”; the clues for comments included “http,” “cambridgeuniversity,” “year,” “student” and “all.” The key (image) clues provided by AdaBoost for likes included “feature,” “cambridge,” “more,” “new” and “research,” and the clues for comments included “cambridge,” “new,” “feature,” “more” and “research” (Table A5).

Random Decision Forests and eXtreme Gradient Boosting jointly recommended “cambridgeuniversity,” “http,” and “year.” AdaBoost, on the other hand, recommended “cambridge,” “new,” “feature,” “more,” “research” and “college.” According to the verification result of the integrated analysis, the brand is heavily focused on the content of the image type, such as “cambridgeuniversity,” “cambridge” and “college”. Therefore, the interactive stimulation is principally based on the results of likes and comments, and it is difficult to measure the value of the active sharing of information.

(F) University in the United Kingdom: Imperial College London

The key (image) clues provided by Random Decision Forests for likes included “world,” “http,” “newssummary,” “Engineer” and “today”; the clues provided by eXtreme Gradient Boosting for likes included “http,” “student,” “day,” “more” and “research.” The key (image) clues provided by AdaBoost for likes included “newsandeventspggrp,” “imperialcollege,” “newssummary,” “today” and “staff” (Table A6).

Random Decision Forests and eXtreme Gradient Boosting jointly recommended “http,” “student,” “world,” and “research.” AdaBoost recommended “newsandeventspggrp,” “imperialcollege,” “newssummary” and “today.” However, if pure image promotion or informative information were to be selected as the main theme, such as “newsandeventspggrp,” “imperialcollege” and “newssummary,” it may be impossible to generate further comments and shares due to a lack of entertainment or interactive value in the information.

6. Contributions and Suggestions

6.1. Research Module Inference

The study found that, through social context exploration combined with artificial intelligence analysis, key information on the university brand page did indeed affect the perception and behavior of users. Well-known university pages not only make effective use of their reputation but also place focus on the quality and quantity of posts. Aside from focusing on appropriate key information, the range of themes is diverse.

On the other hand, based on the above verification results, it is found that users intend to interact with multiple university fan pages simultaneously. Based on the theory of use and gratification, users' choice of content inevitably complements their behavior. Due to differences in demands and personalities, different demands may be fulfilled through the choice of information. This includes the first level, involving information gratification, which is the most basic purpose of information acquisition, fulfilling demands for music, fashion, culture and the other current and relevant information. The second level, which includes entertainment gratification, is the main motivation for reading or participating on account of the interesting nature of the content. The third level, interactive gratification, is established to satisfy users' desires to establish interactive relationships with friends or acquaintances through the community. The fourth level, identity verification gratification, allows particularity and distinction of individuals to be showcased, including interpersonal relationships, self-expression and social status (Choi et al. 2013).

In alignment with the above four major gratification characteristics, the information obtained in the study can be classified into three categories: (a) information and entertainment gratification module, (b) composite identity verification gratification module, and (c) composite interactive gratification module.

(a) Information and entertainment gratification module.

The first type of module tends to use simple "like" interactions as the desired response to a post, and, through information gratification and entertainment gratification, the behavioral purpose of the module can be achieved. This module is present on the pages of Imperial College London and California Institute of Technology. Information gratification and entertainment gratification are subjective characteristics of user experience. Based on artificial intelligence analysis of users' behavioral responses after receiving information, it was found that practical information is one of the most critical factors affecting this type of module (Animesh et al. 2011; Sledgianowski and Kulviwat 2009).

(b) Composite identity verification gratification module.

This module is designed to offer multiple stimuli, including information gratification, entertainment gratification and identity verification gratification, by operating comments or by combining behavioral modes such as likes and comments. The university brands that meet the characteristics of this module include the University of Oxford, University of Cambridge and Stanford University. After further observation, it is found that most of the information that successfully achieved the promotion effect was applied or adjusted based on content positioning, rather than the repeated information for publicity and notifications so that the basic demands of the users were met. When users experience social media, they immediately respond to gratification via emotional and behavioral responses (Weng et al. 2010). Information with information gratification, entertainment gratification and identity verification gratification can thus be transformed into likes and comments by the higher user brand cognition.

(c) Composite interactive gratification module.

The third type of module is the most diverse. By combining the above-mentioned information relating to gratification, entertainment gratification, interaction gratification and identity verification gratification, active participation in comments and shares is promoted. The most obvious case of implementation is by the Massachusetts Institute of Technology. The brand is particularly good at enabling users to obtain easy-to-use information and successfully avoids excessive image packaging, which may result in content being ineffectively communicated to users. In addition, more complete information can

be delivered directly via videos or website links. The purpose is to help users understand more detailed university information through simple operations, thereby increasing users' willingness to like and share information. Therefore, in addition to the text, the adequate use of links and the comment and share functions in brand posts is very important (Fortin and Dholakia 2005). This is supported by Social exchange theory, whereby, in addition to allowing gratification of users following social interaction, there is value in allowing users to generate positive emotions such as self-expression, contribution or support (Crocker and Amy 2008). Social interaction can enhance communication, encouraging sharing and allow a university community to create an overall positive communication environment (Liang et al. 2011).

6.2. Theoretical Contributions

Based on the research results and findings, the following three academic contributions are listed systematically.

- (A) This research verifies a university communication information interaction model, showing how users participate in different behaviors, and successfully examines the impact of common key (image) clues in community information. The research model explains the key information benefits of the fan pages of university brands and verifies the importance of establishing key (image) clues in the brand community through diverse levels of cognition and interaction. Although previous research exists on the topics of information operation (De Vries et al. 2012) and community importance (Fikkers and Piotrowski 2020; Zarrella 2009), few studies directly explore the impact of key information characteristics on the fan pages of university brands. Therefore, this research has the potential to fill a gap in the literature and practice within this area of study and may also be used as a specific reference for the operation and management of other relevant brands (Schmitt et al. 2011).
- (B) This research sets out to verify the influence of key (image) clues on several types of interactions by analyzing university brand communities. By publishing specific content to promote continuous online communication among users via various forms of information, key information corresponding to brand image may successfully attract user attention and recognition (Fumasoli et al. 2020). For example, when a user visits a fan page, to what key information will they pay most attention? This research uses artificial intelligence and machine learning to perform calculations, which may be used to aid in the administration of a fan page, successfully identify key pieces of influential information and clues, and better understand the impact of this information on different types of interactions (Gensler et al. 2013).
- (C) Verifying that the involvement of users on the university's brand page has an inseparable relationship with the image of the university community. With respect to the availability of information, it is important to focus on the practical aspects that determine user participation. In other words, it is important to consider the experience and tangible benefits of participation received by users while obtaining information (Yousaf et al. 2020). It is also important to convey relevant brand knowledge through the process, such as brand culture, brand strategy and brand information. (Laroche et al. 2013). Furthermore, through interaction on social media, users develop higher loyalty and trust for a given brand (Valerio-Ureña et al. 2020). Therefore, this research analyzes the behavioral involvement of users on university brand pages and considers the possible impact of key information. Effort is made to explore the relationship between users' cognitive involvement and behavioral support while also analyzing the lack of response to content from different competing brands (Fikkers and Piotrowski 2020).

6.3. Practical Implications

The contribution at the practical level includes the following three points.

(A) This research focuses on disentangling the relationship between information and the demands of users. This is achieved by investigating how information characteristics and interaction rules exclusive to a given school may be strengthened by a successfully designed university brand page and by examining how the attention and participation of users can be promoted.

By exploring the relationship between key information and community behavior, this research explains the complementary relationship between content positioning and experience gratification in university brand pages. The demand for information by users in terms of community content is examined, and through artificial analysis, the content may be curated to better meet the expectations of users in terms of achieving more positive social interactions and more effective click performance. Moreover, it is believed that this framework provides a method to effectively examine the content and interaction of multiple university fan pages.

(B) This research module helps improve the understanding, in the context of official community interactions, of how to stimulate users' recognition of a brand and generate interactive intentions.

For example, because the majority of users are likely to be students or alumni of the school, they would naturally respond to participation under a high degree of brand recognition and would therefore be willing to share any posts that are pleasant or joyful. Moreover, they might actively invite the participation of friends or family, thus achieving the rolling value of spreading information continuously. In addition, research confirms that users' acceptance of information availability is of great benefit to content interaction (Campbell et al. 2013). Therefore, it can be inferred that the behavior of users and the information presentation on social media are complementary. When the crowd perceives specific information, regardless of whether the information successfully meets the demands, it may still exert a strong impact on the behavior of users.

(C) The study examines how the university brand page uses content, communication and traffic guidance to create a better brand interaction mechanism.

With the widespread use of social media, the media landscape has undergone major changes (Bruhn et al. 2012). Social media generates communication through collaboration and content sharing (Kaplan and Haenlein 2010). Social media today is all-embracing, including blogs, Weibo, Wiki, live streaming, photos and video sharing (Laroche et al. 2013). Social media continues to replace traditional media, gaining greater popularity among the public (Bruhn et al. 2012). Therefore, an increasing number of brands are focusing on enhancing the promotion of products and services through social media platforms (Weinberg and Pehlivan 2011). Much of these efforts are focused on content, communication and traffic guidance in order to create a more complete brand interaction mechanism (Kim and Ko 2012). Therefore, this research confirms the impact of social media on users and universities, and by understanding the role that social media can play, reveals the mechanisms underlying the successful construction of key (image) clues (Schultz and Peltier 2013).

6.4. Research Recommendations and Limitations

Despite many clear contributions, the study has several limitations. For example, the sample is limited to the European and North American cultural and economic backgrounds; therefore, cross-cultural research and comparison with user participation beyond this background is not analyzed. It is suggested that, in the future, a broader analysis of multinational university brands is conducted to better identify the relevant factors of information construction based on cultural or economic characteristics (Viswanathan et al. 2017; Yousaf et al. 2020). Furthermore, this research is limited to Facebook's brand community, so the observation of other social networking sites is not included. In the future, investigations should be conducted on different social media platforms, and customized

content planning should be implemented according to the platform for different types of information presentation (Fikkers and Piotrowski 2020).

After multiple analyses of the brand pages of six European and American universities, this research proposes three suggestions for the content management and brand planning of the university pages.

(A) Page administrators should show initiative when thinking about the content of the information and should adapt to more appropriate means of presentation.

Of the samples selected in this study, the universities have strong reputations, and the types of community content on which they rely are diverse. By sharing the research results of the university through the fan page and its exceptional performance in international competition, the page can inspire a sense of pride in users, and they may be willing to share this information through interaction. Even users who are not members of the school, provided that the published research is deemed to contribute broadly to the users' interests, may still share and like content due to recognition of the value of the school's achievement (Abdelmaaboud et al. 2020). Therefore, whether a post is a simple school celebration video with campus photos or a professional-led research report, a simple and understandable presentation method should be chosen to reduce the barriers to the reception of information for the public (Hashim et al. 2020).

(B) The traditional use of university fan pages and official bulletin boards for information dissemination should be avoided.

After examining posts to which the response was poor, it was found that most fan pages still remain in the information and entertainment gratification module, focusing solely on university publicity or official bulletin boards, which leads to a sense of distance from or difficulty in interacting with the content. This greatly reduces any sense of shared identity and the willingness of users to share. This again emphasizes how effectively responding to the needs of users is the primary task that all community managers must not ignore (Fikkers and Piotrowski 2020; Zhang et al. 2012).

(C) Universities should seek to use different methods for releasing brand information, guiding users to interact with the brand, so the amount of brand attention can be increased.

The most important objectives are to avoid unnecessary duplication of information as much as possible, to strengthen user experiences with dialogue and interaction functions, and to support the brand in launching content that meets the preferences of the audience through more precise key information operations, so as to reach a consensus on the demands of both parties. The administrators should therefore formulate a unified content strategy based on the brand's community positioning, and combine different types of information (such as photos and videos) and interactions (such as user-generated content, fan feedbacks and KOL effects) and images (such as campus information and university-specific images). This can be achieved through regular publicity, activities that aim to create relevant content, and by striving to create a strong connection effect through information and brand image.

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Appendix A. Measurement and Items

Table A1. Negative and positive clues (Stanford University).

Likes	Negative	Positive	Comments	Negative	Positive	Shares	Negative	Positive
photo	10.31	43.19	gostanford	17.42	35.19	gostanford	0.67	12.32
gostanford	20.33	41.5	photo	−10.9	17.84	question	3.81	7.53
question	4.89	15.04	http	−1.38	13.58	human	3.51	7.28
Stanford	9.63	14.71	watch	15.73	9.21	game	2.01	6.47
art	1.64	14.56	game	4.26	6.75	time	14.93	6.25
watch	3.45	11.98	Stanford	4.09	5.65	design	2.84	5.86
say	4.15	11.9	day	6.88	5.5	develop	−1.58	5.6
work	1.25	11.27	work	1.63	5.36	photo	−2.15	4.99
research	7.11	10.67	help	0.37	4.18	school	3.23	4.45
http	1.92	10.41	team	−0.22	4.16	help	−1.89	4.21
final	1.33	9.36	make	8.23	4.13	team	−4.68	3.77
day	1.58	8.82	like	−0.37	3.76	campus	0.1	3.62
professor	−2.58	8.67	student	0	3.59	found	−0.59	3.12
new	1.28	7.72	research	−1.07	3.54	art	1.84	3.05
campus	14.7	7.36	professor	1.36	3.3	Stanford	0.56	3.01
game	4.6	7.03	art	5.14	3	http	−1.81	2.24
more	1.24	6.15	develop	−6.17	2.93	more	0.21	1.88
help	−1.88	5.78	way	1.61	2.73	class	4.73	1.53
live	3.92	3.56	question	6.22	2.68	new	−1.84	1.35
team	1.17	2.49	more	−0.79	2.02	watch	6.05	1.3
perform	2.87	2.33	year	5.83	1.77	live	1.16	1.14
life	−0.92	2.06	say	1.34	1.73	people	−0.15	1.02
class	2.26	1.98	final	−1.03	1.37	year	1.49	0.92
women	1.26	1.95	open	4.86	1.34	student	1.03	0.87
design	−1.58	1.77	campus	13.8	1.25	life	−2.88	0.55
make	6.9	1.6	time	17.85	0.81	like	1.2	0.21
science	3.79	1.3	program	3	0.42	day	−1.12	−0.02
way	2.93	1.06	visit	0.77	0.24	here	2.41	−0.34
year	7.69	1.01	found	−5.64	0.17	perform	1.38	−0.59
learn	2.47	0.81	live	3.97	−0.01	world	4.62	−0.76
here	−0.02	0.36	perform	3.52	−0.07	work	−3.25	−1.02
human	0.28	0.03	life	−2.82	−0.22	way	−4.76	−1.04
student	−1.14	0.01	class	0.44	−0.28	program	−0.84	−1.41
found	−0.03	−0.6	people	0.88	−0.29	research	2.17	−2.12
develop	0.62	−0.95	first	−3.81	−0.67	say	1.91	−2.21
open	4.27	−1.25	here	7.76	−1.43	first	−3.64	−2.24
graduate	5.47	−1.58	new	3.81	−1.52	make	2.41	−2.3
time	18.97	−1.61	design	4.72	−2.62	professor	−1.62	−2.39
school	−1.1	−1.88	science	11.3	−2.64	open	2.96	−2.56
like	3.72	−2.04	human	2.65	−3.2	women	4.07	−2.67
first	0.21	−2.75	women	6.22	−3.56	study	2.98	−2.69
world	8.66	−3.71	learn	3.6	−3.66	learn	1.8	−2.7
program	1.8	−4.09	graduate	4.52	−3.67	graduate	1.43	−2.96
study	−1.28	−5.02	world	6.1	−4.17	final	−3.85	−3.12
people	7.56	−6.33	study	3.03	−6.04	visit	7.98	−4.03
visit	14.47	−9.31	school	7.09	−6.8	science	10.3	−6.75

Table A2. Negative and positive clues (Massachusetts Institute of Technology).

Likes	Negative	Positive	Comments	Negative	Positive	Shares	Negative	Positive
photo	9.66	28.62	campus	17.42	25.25	more	0.2	19.08
robot	9.1	18.74	http	10.23	24.29	engine	3.64	16.44
http	18.82	16.28	engine	0.29	15.84	research	5.42	16.38
research	1.64	15.4	research	1.13	15.1	http	12.2	16.32
engine	5.42	15.04	robot	6.75	13.73	scientist	11.59	15.96
day	21.69	11.77	week	10.77	12.41	new	−4.2	15.5
now	−0.11	9.7	more	1.09	10.86	human	12.21	8.65
help	−1.98	8.1	study	−4.31	10.05	Engineer	7.42	7.82
week	2.54	7.59	system	−4.9	8.76	system	5.76	7.53
more	−1.32	7.47	now	1.16	8.56	campus	4.78	6.21
new	−6.87	5.56	new	−4.15	7.93	robot	9.55	6.13
study	−2.85	4.58	science	−1.97	6.58	school	4.07	6.1
system	−7.52	4.55	one	−1.14	4.26	world	4.46	5.05
Engineer	3.77	4.32	photo	−2.45	4.22	people	−0.87	4.14
one	−2.74	3.93	year	2.96	4.12	week	6.14	3.85
story	9.84	3.86	help	1.7	3.75	develop	9.81	3.62
people	−1.74	3.86	Image	12.71	3.51	all	−0.9	3.01
Image	23.24	3.24	Office	−1.12	3.3	student	2.17	2.36
scientist	−1.6	3.04	Engineer	1.6	2.87	design	−1.52	2.22
student	−0.98	2.45	design	−2.22	2.76	study	−5.1	2.18
video	−2.43	1.07	develop	3.64	1.88	one	−0.8	2.02
world	−0.47	0.69	day	5.12	1.83	work	7.84	1.91
campus	4.23	0.56	full	0.75	1.51	Office	6.8	1.7
Office	6.38	0.07	human	4.98	1.08	first	−7.21	0.87
work	−2.37	−0.1	video	−2.57	1.04	story	7.86	0.52
human	1.11	−0.3	learn	11.83	0.92	time	−0.02	0.51
lab	−4.46	−0.79	all	−0.87	0.75	program	4.7	0.34
first	−2.34	−0.9	work	8.3	0.67	computer	12.16	0.25
find	13.08	−1.11	student	0.06	0.64	find	6.9	−0.03
professor	2.32	−1.27	time	2.39	0.24	video	3.99	−0.47
school	−1.96	−1.58	lab	−0.73	−0.07	full	−2.94	−0.85
community	2.63	−1.87	community	−6.14	−0.84	learn	4.85	−1.42
all	−2.03	−1.9	team	1.46	−0.98	day	9.23	−1.45
program	4.47	−2.03	first	3.82	−1.18	team	3.01	−1.54
time	−2.73	−2.4	computer	2.99	−1.79	year	−0.48	−1.66
design	1.33	−2.58	people	0.73	−1.8	community	2.24	−1.8
develop	−1.89	−2.69	today	7.24	−2	professor	0.82	−1.83
learn	2.87	−2.72	world	1.4	−2.07	photo	4.71	−2.15
full	1.7	−2.83	professor	−1.91	−2.4	now	−2.88	−2.31
team	−0.06	−3.4	program	5.55	−2.85	today	5.05	−2.44
computer	7.01	−3.47	school	−1.99	−2.88	Image	7.97	−2.91
science	0.84	−3.63	story	5.23	−2.91	science	−0.15	−3.39
year	0.71	−3.95	technology	5.84	−3.77	lab	2.94	−4.12
technology	1.39	−6.49	scientist	3.58	−3.99	help	−0.16	−4.81
today	18.92	−11.44	find	10.65	−5.44	technology	0.32	−9.52

Table A3. Negative and positive clues (California Institute of Technology).

Likes	Negative	Positive	Comments	Negative	Positive	Shares	Negative	Positive
professor	28.13	10.16	graduate	5.1	20.62	content	−2.53	20.91
all	4.37	8.69	content	1.58	14.04	http	−6.85	17.93
brain	8	5.35	year	−3.83	10.27	professor	21.31	17.8
graduate	9.05	3.64	like	−0.62	10.09	scientist	11.04	10.97
here	−1.07	3.48	space	10.91	9.37	first	5.9	9.97
content	1.92	3.46	know	6.9	9.02	graduate	−1.94	7.92
feature	0.39	2.68	all	−6.76	7.97	today	−6.93	6.87
year	0.74	2.45	http	3.77	6.68	video	−4.71	5.8
today	5.9	2.12	more	−3.75	6.63	new	1.59	5.18
celebrate	7.41	1.13	nation	4.93	4.87	space	2.17	4.99
first	1.75	0.85	photo	9.09	4.42	event	−0.93	4.12
Caltech	8.48	0.3	now	0.59	4.28	engineer	4.69	3.82
time	8.64	0.23	first	0.42	3.55	time	2.09	3.71
event	0	0.02	brain	2.33	1.84	physics	2.2	3.68
read	4.53	−0.01	member	1.34	1.66	BS	1.66	3.39
member	2.35	−0.1	campus	8.69	1.64	member	4.15	3.33
research	7.97	−1.17	video	−4.49	1.27	team	−4.01	3.27
space	17.61	−1.26	award	−0.22	0.81	campus	6.61	2.87
award	−1.8	−1.3	develop	1.68	0.8	year	−6.74	2.79
http	1.36	−1.53	BS	−0.43	0.57	all	−1.93	2.75
engineer	7.03	−1.67	technology	−1.32	0.33	like	2.05	2.65
nation	13.24	−1.68	research	−1.8	−0.45	more	0.32	2.38
like	1.09	−1.75	help	−0.89	−0.49	student	0.86	2.27
work	1.56	−2.07	time	2.28	−0.59	read	−8.13	1.55
now	2.91	−2.26	new	0.61	−0.76	know	0.92	1.54
video	−0.55	−2.45	feature	0.25	−0.88	Caltech	7.14	0.83
new	−1.4	−2.61	team	−1.4	−1.67	science	4.68	0.33
know	2.27	−2.62	Caltech	3.54	−2.19	brain	0.34	−0.1
help	18.77	−3.49	scientist	3.7	−2.51	feature	−0.94	−0.31
technology	10.83	−4.2	physics	9.46	−2.76	develop	15.41	−0.62
team	−1.07	−4.31	celebrate	2.65	−2.86	help	11.85	−1.74
BS	2.88	−4.39	work	4.12	−3.18	award	−2.89	−1.74
photo	1.78	−5.24	read	−8.02	−3.6	nation	0.14	−2.25
develop	4.11	−5.27	learn	10.71	−3.64	technology	3.7	−2.51
more	3.61	−5.48	here	−6.98	−4.02	work	−1.12	−2.61
scientist	−0.41	−6.12	student	8.65	−4.29	now	−0.86	−2.95
study	−1.8	−6.26	professor	11.63	−4.3	research	8.68	−2.99
learn	3.17	−7.62	today	0.74	−4.81	community	7.83	−3.09
campus	3.16	−7.88	science	8.26	−6.04	here	−3.87	−3.26
community	11.28	−8.78	study	0.85	−6.18	celebrate	7.34	−4.44
physics	21.39	−9.17	engineer	7.87	−6.53	learn	3.49	−5.04
student	13.58	−9.18	event	−0.55	−8.94	photo	0.81	−5.21
science	15.83	−13.91	community	15.17	−11.39	study	−0.23	−8.14

Table A4. Negative and positive clues (University of Oxford).

Likes	Negative	Positive	Comments	Negative	Positive	Shares	Negative	Positive
http	28.61	42.47	http	43.67	79.3	http	27.71	61.03
news_stories	−4.46	12.76	photo	23.63	43.74	photo	10.22	32.19
all	5.18	10.11	college	38.54	27.23	college	30.61	23.61
look	11.64	9.29	event	1.31	20.59	media	−7.4	12.76
use	8.58	7	media	−13.98	18.53	new	−1.21	12.46
read	2.6	6.67	new	−2.14	16.4	event	2.5	11.5
like	5.89	6.53	today	10.9	15.22	now	3.8	11.33
week	5.54	6.37	Oxford	8.45	14.82	here	8.35	11.19
photo	1.34	6.21	study	3.55	13.6	look	5.14	10.77
one	7.83	5.44	research	5.75	12.49	study	0.27	10.23
human	16.25	4.86	news_stories	−4.53	10.64	Oxford	2.16	9.54
event	3.96	4.86	day	15.65	10.43	include	11.4	9.27
learn	6.55	4.45	all	16.76	9.58	news_stories	−7.84	8.61
media	6.36	4.38	like	7.78	8.56	week	−1.53	8.6
world	13.98	4.01	week	5.71	8.45	like	1.23	8.07
question	7.42	3.82	graduate	11.91	7.95	human	10.75	7.84
Oxford	2.08	3.43	first	−3.13	7.52	all	0.39	7.69
now	5.08	3.41	work	9.16	7.15	school	4.63	7.06
museum	1.32	3.36	question	4.46	7.05	museum	5.42	6.85
include	−0.44	3.36	look	10.42	6.73	work	9.4	5.86
first	11	3.1	open	17.31	6.58	one	2.95	5.42
visit	−0.39	2.65	now	21.53	6.28	read	3.59	5.41
school	3.06	2.41	series	6.22	6.19	visit	6.47	5.4
college	6.49	2.39	school	10.96	6.13	world	11.75	4.6
here	1.73	1.91	lecture	2.59	6.02	day	1.94	4.24
study	4.33	1.46	library	9.95	5.29	find	6.4	4.08
day	2.31	0.89	history	2.73	5.15	library	7.06	3.72
work	14.21	0.53	learn	−1.03	4.8	research	1.96	3.5
UK	7.48	−0.14	use	5.32	4.52	UK	6.98	3.17
time	12.29	−0.19	human	8.28	4.22	learn	5.53	3.13
find	3.19	−0.55	read	0.06	4.07	time	6.51	3
open	12.11	−0.79	visit	4.05	3.96	today	−0.46	2.71
graduate	6.12	−1.28	include	13.4	3.74	first	−0.03	2.27
live	2.63	−1.44	live	10.02	3.73	help	11.2	1.34
series	3.63	−1.53	here	10.15	3.2	question	0.98	1.2
lecture	−1.05	−1.53	story	9.39	2.72	use	5.59	1.09
student	4.7	−1.77	time	8.08	2.4	open	14.94	1.02
library	4.83	−1.9	student	6.65	2.3	live	9.19	0.46
people	12.09	−1.99	UK	6.8	1.78	series	2.4	0.3
today	2.97	−2.02	science	6.07	1.73	graduate	10.58	−0.03
research	8.7	−2.76	museum	−1.42	1	lecture	3.31	−0.09
new	8.97	−2.89	world	3.46	0.5	student	7.87	−1.91
story	7.05	−3.58	one	13.06	0.22	story	7.83	−2.03
help	2.32	−3.83	help	4.13	−0.85	people	9.55	−3.35
science	10.25	−6.23	find	1.83	−1.47	history	1.75	−4.64
history	2.49	−7.35	people	10.37	−2.9	science	10.42	−5.89

Table A5. Negative and positive clues (University of Cambridge).

Likes	Negative	Positive	Comments	Negative	Positive	Shares	Negative	Positive
cambridgeuniversity	14.15	52.13	cambridgeuniversity	6.61	42.6	cambridgeuniversity	−4.98	10.19
cambridge	1	18.67	cambridge	−3.77	13.95	cambridge	−5.92	4.75
feature	3.34	8.65	student	3.65	9.8	celebrate	0.73	3.92
new	19	5.12	year	−0.04	3.56	day	2	3.9
research	21.49	5.07	use	2.92	3.5	first	3.57	3.38
work	0	4.97	world	2.45	2.68	post	−4.51	3.33
all	2.83	4.93	all	−2.99	2.35	human	6.94	2.88
student	3.17	3.81	museum	−4.04	2.08	work	−4.66	2.55
film	2.21	2.78	first	6.32	0.13	like	3.44	1.62
photo	25.8	2.02	life	−2.99	−0.21	help	0.85	1.53
world	2.89	1.52	celebrate	11.28	−0.42	exhibit	−2.38	1.52
exhibit	1.27	1.46	work	−2.88	−0.56	book	−4.5	1.25
use	4.33	1.37	one	−1.07	−0.57	museum	1.42	1
study	6.04	0.53	like	0.21	−0.68	find	2.57	0.68
help	0.84	0.53	week	2.95	−0.72	develop	4.57	0.43
now	5.32	0.4	human	6.88	−1.22	world	−3.49	0.38
human	13.65	0.21	history	3.5	−1.57	now	0.45	0.34
museum	−4.64	−0.41	college	1.55	−1.57	show	−0.36	0.2
Dr	0.35	−0.72	here	1.77	−2.1	college	−5.53	0.03
scientist	1.54	−0.9	now	2.81	−2.16	science	0.59	−0.23
celebrate	13.58	−1.1	new	16.11	−2.38	here	1.01	−0.4
book	0.67	−1.11	film	−0.45	−2.6	Dr	1.06	−0.59
year	7.48	−1.19	day	10.22	−2.74	research	11.33	−0.8
people	0.48	−1.3	help	−1.09	−2.79	people	3.97	−0.93
http	39.85	−1.36	book	0.6	−2.88	year	−2.3	−1.11
life	5.88	−1.38	look	5.45	−2.99	most	2.09	−1.13
one	−2.34	−1.66	people	0.56	−3.31	life	−1.58	−1.5
like	4.61	−1.98	science	−0.93	−3.89	time	3.23	−1.91
live	0.22	−2.3	time	1.66	−3.97	http	16.13	−1.95
time	12.61	−2.77	exhibit	1.59	−4.01	film	−2.4	−1.99
look	1.69	−2.79	research	17.54	−4.6	feature	10.17	−2
post	3.53	−2.81	live	4.04	−4.64	one	−2.88	−2.19
history	3.62	−2.85	show	−1.49	−4.8	history	−2.31	−2.26
science	10.17	−3.64	scientist	5.06	−4.98	all	−0.11	−2.62
day	3.71	−3.65	find	3.42	−5.17	live	0.54	−2.87
here	−2.3	−3.94	study	2.54	−5.51	new	7.98	−3.57
college	1.1	−4.36	most	3.39	−5.68	study	5.01	−3.62
more	9.1	−4.64	Dr	3.65	−6.22	scientist	2.83	−3.63
develop	19.26	−4.71	develop	0.93	−6.45	use	0.08	−3.74
show	5.66	−4.75	more	10.97	−6.93	today	0.17	−4.13
today	−2.36	−5.82	post	8.38	−7.11	student	4.35	−4.27
first	12.1	−6.02	today	2.99	−8.48	photo	7.7	−4.99
find	6.93	−6.69	photo	26.68	−8.52	week	−1.34	−5.04
most	14.88	−7.22	feature	23.64	−16.13	more	3.49	−5.05
week	2.21	−8.39	http	34.68	−17.85	look	1.11	−6.29

Table A6. Negative and positive clues (Imperial College London).

Likes	Negative	Positive	Comments	Negative	Positive	Shares	Negative	Positive
world	21.16	23.03	live	−3.38	53.74	world	16.66	26.52
http	0.84	21.71	newssummary	−2.91	28.85	newssummary	−13.71	23.13
newssummary	−11.12	19.5	UK	−2.64	27.46	http	0.39	19.56
Engineer	15.78	17.56	use	−2.4	26.97	imperial	3.4	16.08
today	1.31	11.87	world	−1.69	26.54	study	3.98	15.95
health	5.34	11.84	year	−1.65	23.44	more	4.89	15.85
imperial	3.72	11.22	develop	−1.62	21.28	today	7.64	15.22
next.	8.18	10.82	read	−1.42	20.09	here	3.39	13.99
event	5.72	10.26	campus	−1.12	19.63	scientist	6.38	13.08
more	4.57	9.61	week	−1	18.94	Engineer	7.8	12.75
new	5.09	9.22	science	−0.6	17.77	next.	2.96	12.47
team	4.32	8.47	next	−0.58	16.48	develop	−0.26	12.19
here	3.14	8.12	new	−0.58	16.14	live	−0.13	11.15
student	9.61	7.8	make	−0.33	16.12	all	11.92	10.83
read	3.82	7.49	Dr	−0.26	15.66	day	5.24	10.71
use	8.63	7.18	school	0	15.53	now	6.48	9.92
graduate	12.92	6.8	health	0	15.17	help	−0.4	9.9
find	2.89	6.63	now	0	14.59	one	6.52	9.73
year	5.62	6.61	newsandeventspggrp	0.6	14.19	event	10.56	9.04
week	3.06	6.45	alumni	0.71	13.88	week	3.3	9.04
day	6.96	6.33	Engineer	0.9	13.01	newsandeventspggrp	−2.1	9.02
campus	8.85	6.26	come	0.95	12.76	graduate	11.84	8.48
develop	−2.95	6.09	scientist	1.11	11.98	year	13.3	8.04
help	3	5.41	one	1.12	11.59	campus	7.33	8.02
one	7.93	5.29	find	1.61	11.16	student	11.06	7.97
all	8.05	5.02	staff	1.64	10.74	science	5.42	7.42
newsandeventspggrp	3.12	4.69	research	1.87	10.4	new	7.77	6.79
make	1.65	4.3	open	1.99	10.39	health	2.7	6.02
live	−2.69	4.08	imperialcollege	2.05	9.53	work	12.22	5.98
college	7.14	3.78	more	2.11	8.85	alumni	−0.46	5.85
staff	4.98	3.38	here	2.24	8.69	team	3.58	5.65
join	3.77	3.33	college	2.55	8.41	first	0.05	5.57
Dr	−0.79	2.5	graduate	2.77	8.04	staff	6.12	5.43
study	7.72	1.99	team	2.92	7.98	use	4.73	4.9
alumni	1.95	1.84	all	3	7.22	read	0.46	4.76
scientist	9.36	1.82	http	3.15	7.09	time	8.03	4.72
science	4.61	1.24	today	3.19	7.07	come	4.85	4.68
time	4.28	1.14	event	3.42	6.78	UK	9.65	4.18
first	3.27	0.71	work	3.57	6.7	Dr	−1.05	3.8
UK	8.1	0.27	time	3.57	6.49	open	13.47	3.48
come	4.45	−0.21	student	3.69	6.44	find	2.48	3.17
open	15.15	−0.25	study	3.87	6.35	school	5.3	2.47
work	11.39	−0.27	first	4.07	5.33	imperialcollege	7.02	2.33
school	1.07	−1.21	day	4.11	4.37	join	9.63	1.89
now	15.68	−1.43	help	4.25	3.04	research	10.43	0.68
imperialcollege	8.14	−1.98	imperial	5.57	0.06	make	−1.84	−0.45
research	9.09	−6.1	join	6.89	−5.62	college	16.94	−7.18

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