Insights from Twitter Analytics: Modeling Social Media Personality Dimensions and Impact of Breakthrough Events

Akshat Lakhiwal(✉) and Arpan Kumar Kar

Department of Management Studies, IIT Delhi, IV Floor, Vishwakarma Bhavan, Hauz Khas, New Delhi 110016, India
akshatlakhiwal@gmail.com, arpan_kar@yahoo.co.in

Abstract. Social media and big data have been in high focus due to their potentially huge impact on business, society and polity. This research contributes to the same domain and peruses the twitter community before and after an event which is a major breakthrough for an economy. Here, the event being monitored is the Union Budget-2016 in India. The research taps the occasion to understand the various groups which participate in the online discussion amongst 43,924 tweets from 22,896 users and the pre and post budget twitter metrics are analyzed, deducing the sensitivity of the groups to the day of proposal of the budget. The research framework incorporates twitter analytics and relies on visual and quantitative data, drawing inferences from the intelligence. How the personality dimensions change before and after the event, is also analyzed. This change in dimensions can directly account for the influencing nature of the social media group.

Keywords: Twitter analytics · Social media · Big data · Network analytics · Content analytics · Sentiment analytics · Brand personality · Dimensions

1 Introduction

The emergence of big data has created a new awakening in the business and research community. Such a large pool of data, being incremented every single second presents tremendous opportunity to analyze and reasonably pre-empt certain trends with a fair amount of certainty. Social Media [1, 17], out of all has been one of the main sources of generating data and has drawn interest of businesses for marketing purposes, which includes product development, service promotion, customer engagement as well as brand promotion. Research groups from diverse areas have been involved in observing and utilizing the opportunities presented by social media analytics to a great effect. Significant amount of work has been done in collecting and processing data through various portals to gain insights into several areas such as stock price prediction, Relief measures, Crisis Management, early event prediction, election prediction, public relations and public opinion [2, 3]. However, the analysis of the data presents its challenges due to its high variety, veracity, volume and velocity with which it is created and generated.

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Twitter [38–40], in particular, has been actively leveraged in facilitating social media analytics. Users active on twitter and interested in certain topics can easily communicate with one another using rapid and ad hoc establishment of shared 'hashtags' [33–35] which integrates the users even if they are not following each other. These hashtags along with the other metadata forms a basis for data extraction and analysis. Due to its open [3] architecture, twitter allows researchers to integrate smoothly to its API [4] and search for the desired content by using keywords such as the hashtags. A key aspect of twitter's persona is its real time nature [5, 40]. Research has shown that the reactionary nature of twitter is highly sensitive and the twitter posts can promptly reflect the occurrence of an event through generation of hashtags, formation of opinion based clusters and intermittent mentions to a certain group of twitter users. Tweets comprising of such content and sentiments [6] hold significant gravity as it can rapidly divide the social front into opinion groups like the political community, business groups, economists or individual users.

This social media segregation is the cornerstone of this research and puts forward the possibility of a relative sensitivity in several social media dimensions by analyzing 43,924 tweets from 22,896 users. The objectives of this paper are as follows: In the first step, we shall find observe how the social media community is split based on their opinion. Further, we shall assess the brand's social personality dimensions which can be associated with a twitter handle and consequently the sensitivity of the opinion group to the occurrence of the event.

2 Literature Review

The literature review has been organized into three subcategories beginning with the identification of the dimensions associated with a brand and its personality, studying social media and social media analytics.

2.1 Dimensions of Brand Personality

Considerable amount of work has been done in past in analyzing the consumer behavior, particularly to the association of human like attributes to a brand, referred to as brand personality [7, 15]. This personality of the brand allows the consumer to express him or his personality dimension through the use of the brand. The extensive study done in the past suggests that there are five characteristic personality attributes most commonly associated with a brand. These five personality dimensions [7, 16] viz. Sincerity, Excitement, Competence, Sophistication and Ruggedness can be understood by fifteen distinct dimensions (Fig. 1).

The possibility of dispersing a personality into several dimensions is crucial for our research as it allows deeper understanding [19] of the defining elements of the personality. With such an understanding, penetrating the consumer mind and adapting as per its need becomes a relatively simpler proposition. This framework has been extensively utilized by marketing researchers and business groups in the past to define the personality of a brand and align it with that of the target consumer group.

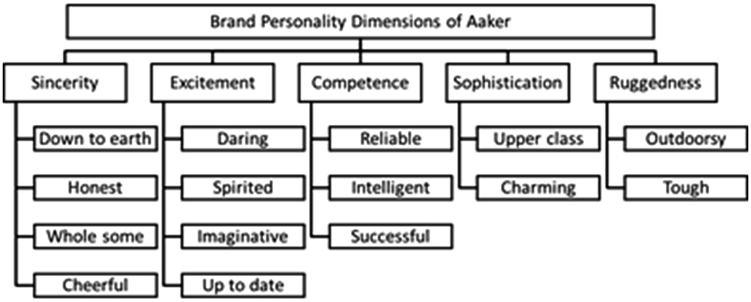

Fig. 1. The personality dimensions which constitute a brand's personality [7, 16].

This research aims at drawing coherence of the dimensions of brand personality with those of a social media entity and that of the defining facets with metrics [18] of web analytics.

2.2 Social Media and Its Classification

Social media in many capacities can be deemed as layer of functionality over Web 2.0 [8] sites. Web 2.0 facilitates greater and dynamic commotion of information through a greater collaboration among internet users, content providers and enterprises. Through this unique integration it truly allows the interfacing of different platforms of information, services and products through integration. Heavily reliant on user-generated and user-controlled content, it condones the use of any heavyweight infrastructure to access and use services, thereby empowering users and promoting larger collaboration. This strong support to information sharing and open expression has drawn significant attention on getting this data collected to uncover hidden patterns. Innovative business models are leveraging this strong social media layer to track and discover gaps in the real world. There can be numerous social media website categories [9, 36]: social networking sites, creativity sharing sites, intellectual property sites, user sponsored sites, company sponsored causes, company sponsored support sites, business networking sites, collaborative web, e-commerce sites, podcasts, news sites, educational sharing sites, open source communities, and social bookmarking websites. These platforms based on the functional blocks [9] facilitate management of identity, presence, relationships, reputation, groups, conversation and sharing, and thus project discrete utility to its users. Therefore, based on these blocks of functionality, present a different unique opportunity for greater exploration for researchers, since factors of brand personality would vary.

2.3 Social Media Analytics

Every social media entity has six broad functionalities [10] associated with it which serve as the building blocks for social media analytics. Figure 2 [9, 10] shows these user controlled functionalities. Based on these functionalities, the user's social media identity finds a unique spot in the social media topography. The progression of these over time eventually aids in settling the metrics [11] for analysis. In this context we will pay attention to one social media platform, Twitter [38–40]. We have chosen twitter because it is the fastest growing social platform, ahead of Facebook and Google+ [12] and unlike Facebook data, twitter data is considered to be 'open' [13]. It thus provides opportunity to the research and business groups by swiftly integrate with its API. This understanding of social media and social media data shall be leveraged to perform Twitter Analytics (TA) [12] on the twitter data. Twitter Analytics can broadly be categorized into three types of analytics – Descriptive Analytics (DA), Content Analytics (CA) and Network Analytics (NA). Each of these focuses on different dimensions of the data. Descriptive Analytics focuses on descriptive statistics [21, 22] such as number of tweets, distribution of different types of tweets and the number of hashtags. Such statistics are gateways to other metrics [12] like user activity and visibility [12]. Content analysis [23, 24] employs text mining and machine learning algorithms to perform word, hashtag and sentiment analysis [26]. Content analysis enables extraction of intelligence from Web2.0 [25], which must be preceded by meticulous text cleaning and processing. Network Analysis [27] leverages the network of @replies and re-tweets existing on twitter to perform topological [37] or community analysis. This network topology refers to a layout of nodes and edges based on the information of reply and re-tweet in Twitter. Network Analysis is useful in drawing significant number of community specific metrics [28] from the data.

3 Proposition

In the light of the above discussion, we can clearly identify the five personality dimensions which are associated with a brand and also observe that social media identities have a certain set of user controlled functionalities which define the extent of depth and breadth of the identity on the social media network. Taking twitter as the medium, every twitter identity has an alphanumeric nomenclature known as the twitter handle. The twitter handle is the unique name of the identity on the twitter network. Every time a user tweets, content is generated. This content comprises of a textual tweet which is upto 140 characters long, along with other data points such as the geo-location information, sending user's ID, time of posting, number of replies received, number of re-tweets and so on. These data points are known as metadata [11] and hold tremendous significance in establishing the social media functionality of the twitter identity. This research begins with identifying standard metrics prevalent over the twitter network which defines the functionality of a unique twitter handle. On identifying these metrics, an analogy can be drawn between them and the brand personality framework to obtain the personality dimensions of a unique twitter handle. Every dimension of the twitter personality can be aligned to a unique twitter metric which would serve as a facet to the dimensions, analogous to the brand personality framework. Consequently, the research proposes analytics as a tool to observe the sensitivity of these dimensions on the online forefront due to the occurrence of a major breakthrough event in the social arena. These metrics are the number of original tweets per total tweets, re-tweets received per total tweets tweeted, mentions received per total tweets tweeted, average favorite count received per tweet, visibility [12] of the twitter handle and the average sentiment [3] of the twitter handle.

Figure 2 shows one of the ways by which these social media metrics can be categorized by mapping them with the brand personality framework suggested above. Only the 5 most suitable of these metrics has been used in this study. By using this framework, we have mapped some of the social metrics with the five dimensions. This mapping was obtained as a result of a Delphi study [29–31] yielding a consensus amongst 12 social media experts in 3 iterations. By observing the percentage change (sensitivity) in the value of these metrics to the breakthrough event, the sensitivity of the dimensions of a twitter handle or a larger social media group can be obtained. In order to facilitate the clearer observation of any transition, the research looks at a large pool of twitter handles, and divides them into broader social media groups. This segregation is done on the basis of the nature of tweets tweeted by the twitter handle as well as the real life manifestos `which the account holder carries.

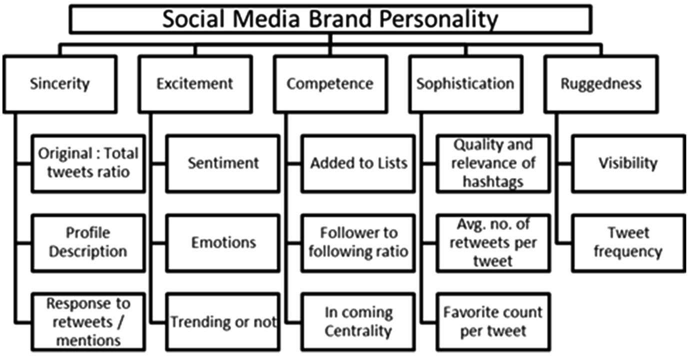

Fig. 2. Indicative social media metrics relevant to brand personality dimensions

For example, the twitter handle of a consultancy company offering an unbiased view forms the part of a different social media group as compared to the twitter handle of an individual affiliated with a particular political community. Similar analogy can be drawn for the twitter handles of a business group and an independent social media influencer or a Media Network such as a News Agency. Such twitter identities with similar real life affiliations can be clubbed together and hence an observation of the transition of the personality dimensions of a larger social group due to the occurrence of a major breakthrough event can be observed. Statistical tools are used to determine a change in the means of these dimensions due to the occurrence of the event at different confidence levels. This kind of clubbing was done to divide twitter users into broader groups.

Table 1. Example of a data sample along with metadata

Tweet	#Budget2016- 88% the survey respondents hope to see #tax reforms for minimisation of litigation. Our report: https://t.co/FYef8tewBz		
Metadata	**Value**	**Metadata**	**Value**
favorited	FALSE	replyToUID	NA
favoriteCount	0	statusSource	<a href="http://..
replyToSN	NA	screenName	GrantThorntonIN
created	2/28/2016 23:46	retweetCount	1
truncated	FALSE	isRetweet	FALSE
replyToSID	NA	retweeted	FALSE
id	7.04E+17	longitude	NA
		latitude	NA

4 Research Methodology

The process of calculating a change in the personality dimensions of social media groups begins with collecting twitter data (tweets and metadata) by identifying the topics or the area of interest. The acquisition of twitter data requires the use of API [12] which allows acquiring of up to 1 % of publically available data on twitter. The data thus obtained is less structured and more enriched in content thereby posing numerous challenges. For the purpose of research, the topic is a breakthrough event for the Indian social fabric, which is the day of proposal of the annual budget for the calendar year 2016-2017. The keyword used was '#Budget2016' [33–35]. Data collection was done for a period of 20 days, comprising of equal periods before and after occurrence of the event. Through analytical algorithms, every sample of data can be divided into a tweet and sixteen distinct metadata points. Table 1 shows the example of such a sample. The next step is to separate the data samples of those twitter handles which have been tweeting consistently before and after the occurrence of the event from the rest. This step becomes imperative because the transition of personality dimensions of a twitter handle can only be gauged if it continues to stay active on twitter after the occurrence of the event. Those twitter handles which are active for only one half (either pre or post occurrence) of the research are hence of little importance. These consistent twitter handles are then divided into well identifiable and distinct groups based on several factors like their real life manifestations, nature of tweets, relation with the event or their span of social influence. Once the data samples are consistent and divided, the six key metrics are calculated for every twitter handle for before and after the occurrence of the event. The visibility of the twitter handle can be calculated by adding the number of @replies received and the number of re-tweets received by it. The sentiment for a tweet can be calculated using several natural language algorithms [26] such as 'Sentistrength' [14]. Through these metrics, we can now transitively gather a fair idea of the personality dimensions of each of the social groups both before and after the event. By a comparison of these values, we can compare the sensitivity in the form of percentage change in every dimension of each social media group. This change in personality dimensions can also be tested using statistical tools like paired T-test on the means of the data corresponding to each social group identified. Let us assume that there are n social groups identified in the data set comprising of consistent twitter handles.

For each of these social groups there would be 5 personality dimensions. Each of these dimensions will have a mean value both before and after the event. Let us denote this mean by μ (before the event) and μ' (after the event). Thus, to check the difference in means occurring due to the event, paired T-test can be conducted as follows:

$$H_0 : \mu^{ij} = \mu'^{ij} \tag{1}$$

and

$$H_1 : \mu^{ij} \neq \mu'^{ij} \tag{2}$$

Here, H_0 refers to the null hypothesis, i.e., the means of the dimensions remain unchanged due to the occurrence of the event; while H_1 refers to the alternate hypothesis 'i' refers to the i^{th} personality dimension ranging from 1 to 5 and 'j' refers to the j^{th} social media group ranging from 1 to n. μ^{ij} = mean value of i^{th} dimension corresponding to j^{th} social media group before the occurrence of the event. μ'^{ij} = mean value of i^{th} dimension corresponding to j^{th} social media group after the event occurs.

5 Findings

A corpus of **43,924 twitter data** was extracted with the keyword '#Budget2016'. This comprised of tweets both before and after the occurrence of the event, separated by date. The data comprised of **22,896 distinct users**, out of which **1,534 users** were consistent in their activity and held relevance for the research. These tweets were further scanned and the tweets which were either not relevant to the research or were outliers were removed from the corpus. For example, tweets pertaining to the budget announcements in countries other than India were irrelevant to the research and were removed. Eventually, **10,231** tweets from the **1,534 unique users** were found to be relevant to the research and were used for the analysis. The final data set comprised of **6,050 (~59 %)** re-tweets. The unique users corresponding to the set of tweets were further classified into 11 distinct social groups as shown in Table 2. This categorization of the data set was developed as a result of the consensus obtained during the Delphi study [30–32] conducted amongst 12 social media experts in three rounds of iterations. The data samples which constituted each of these groups were used to calculate the personality dimensions for these groups before and after the event.

These dimensions were compared and the absolute percentage change in their values implied the sensitivity of these groups to the breakthrough event. Table 3 shows the transition in these personality dimensions for the social media groups.

It can be observed that the discrete social media groups which were identified have different sensitivities, showcased by the sensitivity of the social media metrics for different dimensions of the framework. This sensitivity enables us to break down and identify the susceptible regions in the social media fabric which are most impacted by any breakthrough event on the social media forefront. Statistical analysis using paired T test shows a significant change in means of dimensions corresponding to social groups as shown in Table 4.

Table 2. The consistent twitter handles were classified into 11 distinct social media groups

Social Media Group	Description
Business Group	Real life Business Groups and Profitable Organizations. Eg: 99acres, indiamart
Consultancy / Advisory	Consultancy firms across domains (Taxation, IT/ITeS, Financial services, etc). Eg: KPMG
Entrepreneural Community	Individuals or groups affiliated with the Entrepreneural Community. Eg: Startup India
Financial / Economic research	Individuals or group affiliated with the Financial research community. Eg: CRISIL India
Financial Markets	Individuals or group providing news and views of the financial markets. Eg: BSE India
Government Agency	Groups and Organizations endorsed by the Govt. of India. Eg: NITI Ayog
Social Influencers	Individuals, bloggers or groups, with high social influence. Eg: WeAllareIndians
Individual User	Twitter handle of an independent individual user.
Political Community	Individual or group, affiliated with a Political community or agenda. Eg: ModiforIndia
Industrial Community	Groups for Industrial Affiliations. Eg: CII India, Indiaretailbiz
Media Network	Individual or groups, affiliated with the Mass News Media. Eg: ETIndia, Forbes

Table 3. Changes in the Sensitivity of the Social Media Personality Dimensions after the event

	Excitement	Sincerety	Influence	Susceptibility	Reliability	Ruggedness
Business Group	36.78%	2.85%	7.65%	86.22%	5.72%	17.50%
Consultancy / Analysis	0.82%	6.11%	15.37%	25.77%	12.46%	69.30%
Entrepreneural Community	6.67%	1.82%	70.04%	22.73%	0.45%	23.45%
Financial / Economic research Community	19.44%	10.10%	25.68%	51.98%	0.00%	5.39%
Financial Markets	71.69%	5.32%	12.83%	59.75%	5.27%	14.80%
Government Agency	62.81%	10.46%	13.41%	50.87%	14.91%	82.72%
Independent Social Influencers	9.83%	12.50%	100.02%	15.64%	6.49%	114.60%
Individual User	5.21%	5.12%	69.59%	27.49%	3.66%	80.57%
Political Community	15.58%	0.71%	53.90%	9.20%	1.93%	72.40%
Industrial Community	8.67%	24.52%	12.26%	1.02%	3.96%	42.46%
Media Network	78.51%	2.94%	64.74%	38.28%	4.44%	56.05%

In the Table 4, S denotes a significant change, while NS denotes an insignificant change in means with 95 % confidence level. Major differences are perceived in excitement, sophistication and ruggedness of the brand personality through the Twitter profiles across user categories or groups. However, the context specificity (i.e. type of event being studied) of this outcome may not be ignored.

Table 4. Results of the paired T-test performed on the means corresponding to the dimensions.

	Excitement	Sincerety	Competence	Sophistication	Ruggedness
Business Groups	*S (0.033)*	*NS*	*NS*	*NS*	*NS*
Consultancy Groups	*NS*	*NS*	*NS*	*NS*	*NS*
Entrepreneural Community	*NS*	*NS*	*NS*	*NS*	*NS*
Financial / Economic research Community	*NS*	*NS*	*NS*	*NS*	*NS*
Financial Markets	*S(0.044)*	*NS*	*NS*	*NS*	*NS*
Government Agency	*NS*	*NS*	*NS*	*S(0.044)*	*NS*
Independent Social Influencer	*NS*	*NS*	*NS*	*NS*	*NS*
Individual Users	*S(0.004)*	*NS*	*NS*	*S(0.000002)*	*S(3.25E-11)*
Iindustrial Community	*NS*	*NS*	*NS*	*NS*	*NS*
Media Network	*S(2.254E-07)*	*NS*	*S(0.0029)*	*NS*	*S(0.002)*
Political Community	*NS*	*NS*	*NS*	*S(0.005)*	*S(0.064)*

Table 5. Most sensitive social groups based on overall change in personality dimensions

DIMENSION	MOST SENSITIVE AND SIGNIFICANT SOCIAL GROUPS IN THE DATA SET	TOTAL TWEETS
Sincerity	Industrial Community, Independent Social Influencers	495
Excitement	Business Groups#, Media Networks*, Financial Markets*, Individual users#	8763
Competence	Independent Social Influencers, Entrepreneurial Community, Media Network#	1643
Sophistication	Business Groups, Financial Markets, Government Agency#, Individual Users#, Political Community#	7940
Visibility	Independent Social Influencers, Government Agencies, Individual Users#, Media Network#, Political Community#	7579

A closer investigation highlights that majorly the individual users show a change of personality after breakthrough events, followed by media networks. Financial markets and business groups also highlight some statistically significant changes in personality in terms of their excitement.

6 Concluding Discussion

The research successfully manages to observe that the Social media universe can be judiciously divided into opinion groups. These groups comprise of entities which can exist in the form of twitter handles, Facebook groups or profiles. By identifying social media metrics which are coherent with the distinct facets of the brand personality framework, the five personality dimensions have been success fully associated with each of the opinion groups identified in the data.

In Table 5, asterisk (*) represents groups depicting both a high sensitivity and a significant change in mean. Hash (#) represents groups depicting a significant change in mean but with a low sensitivity. The framework brings out the most and least sensitive or rather susceptible social groups based on the percentage change in the values of the metrics mapped to these dimensions, due to the occurrence of the breakthrough event. The results of the analysis can be seen in Table 3. This framework of social media analytics is particularly useful in identifying the dimensions which are most susceptible intrinsically to these groups due to the occurrence of major events. Both the research and business community can gain significant insight into the Social media behavior of these groups by tracing the sensitivity of these frameworks. For people working in public policy, insights are provided on who are the most sensitive groups whose social discussion may polarize sentiments of an economy. How communities may interact may also be understood by NA.

In conclusion, this framework is a novel road-step in penetrating deeper into the social media fabric and dismantling the intricacies of social media analytics. The brand personality framework is one of the many methods which can be used to map the different social media metrics with the personality dimensions of a social media entity and remains one of the limitations of the research. However which parameters of brand personality get affected and among which user group may be a factor of the type of break-through events being explored. Generalizing the nature of personality change over different types of events may be considered in future research directions. Other parameters of brand personality dimensions based on social media can be explored in future research. Also variations in outcome may be observed if a different platform of social media (e.g. Facebook) is used for such a study. However, despite these limitations, the intuitive association between brand and social media personalities reveals an intriguing exploration which can be taken forward in future research.

References

1. Aral, S., Dellarocas, C., Godes, D.: Social media and business transformation: a framework for research. Inf. Syst. Res. **24**, 3–13 (2013)
2. Ranco, G., Aleksovski, D., Caldarelli, G., Grčar, M., Mozetič, I.: The effects of Twitter sentiment on stock price returns. PLoS ONE **10**(9), e0138441 (2015)
3. Bruns, A., Liang, Y.E.: Tools and methods for capturing Twitter data during natural disasters. First Monday **17**(4), 1–8 (2012)
4. Makice, K.: Twitter API: Up and Running: Learn How to Build Applications with the Twitter API. O'Reilly Media, Inc., Sebastopol (2009)
5. Sakaki, T., Okazaki, M., Matsuo, Y.: Earthquake shakes Twitter users: real-time event detection by social sensors. In: Proceedings of the 19th International Conference on World Wide Web. ACM (2010)
6. Kouloumpis, E., Wilson, T., Moore, T.D.: Twitter sentiment analysis: the good the bad and the OMG!. In: ICWSM 2011, pp. 538–541 (2011)
7. Aaker, J.L.: Dimensions of brand personality. J. Market. Res. **34**, 347–356 (1997)
8. O'reilly, T.: What is Web 2.0: design patterns and business models for the next generation of software. Commun. Strat. **1**, 17 (2007)
9. Kaplan, A.M., Haenlein, M.: Users of the world, unite! The challenges and opportunities of social media. Bus. Horiz. **53**(1), 59–68 (2010)
10. Kietzmann, J.H., et al.: Social media? Get serious! Understanding the functional building blocks of social media. Bus. Horiz. **54**(3), 241–251 (2011)
11. Bruns, A., Stieglitz, S.: Towards more systematic Twitter analysis: metrics for tweeting activities. Int. J. Soc. Res. Methodol. **16**(2), 91–108 (2013)
12. Chae, B.K.: Insights from hashtag# supplychain and Twitter analytics: considering Twitter and Twitter data for supply chain practice and research. Int. J. Prod. Econ. **165**, 247–259 (2015)
13. Gurstein, M.B.: Open data: empowering the empowered or effective data use for everyone? FirstMonday **16**(2) (2011)
14. Thelwall, M.: Heart and soul: sentiment strength detection in the social web with SentiStrength. In: Proceedings of the CyberEmotions, pp. 1–14 (2013)
15. Caprara, G.V., Barbaranelli, C., Guido, G.: Brand personality: how to make the metaphor fit? J. Econ. Psychol. **22**(3), 377–395 (2001)
16. Geuens, M., Weijters, B., De Wulf, K.: A new measure of brand personality. Int. J. Res. Market. **26**(2), 97–107 (2009)

17. Glynn, M.W., Faulds, D.J.: Social media: the new hybrid element of the promotion mix. Bus. Horiz. **52**(4), 357–365 (2009)
18. Clifton, B.: Advanced web metrics with Google Analytics. Wiley, New York (2012)
19. Ekinci, Y., Hosany, S.: Destination personality: an application of brand personality to tourism destinations. J. Travel Res. **45**(2), 127–139 (2006)
20. Kar, A.K.: A group decision support system for selecting an open source tool for social media integration. In: Sengupta, S., Das, K., Khan, G. (eds.) Emerging Trends in Computing and Communication. Lecture Notes in Electrical Engineering, vol. 298, pp. 407–413. Springer, India (2014)
21. Bruns, A., Highfield, T.: Political networks on Twitter: tweeting the Queensland state election. Inf. Commun. Soc. **16**(5), 667–691 (2013)
22. Xiang, Z., Gretzel, U.: Role of social media in online travel information search. Tourism Manag. **31**(2), 179–188 (2010)
23. Holsti, O.R.: Content Analysis for the Social Sciences and Humanities, pp. 602–611. Addison-Wesley, Reading (1969)
24. Riff, D., Lacy, S., Fico, F.: Analyzing Media Messages: Using Quantitative Content Analysis in Research. Routledge, New York (2014)
25. Chau, M., Jennifer, X.: Business intelligence in blogs: understanding consumer interactions and communities. MIS Q. **36**(4), 1189–1216 (2012)
26. Pang, B., Lee, L.: Opinion mining and sentiment analysis. Found. Trends Inf. Retr. **2**(1–2), 1–135 (2008)
27. Burt, R.S., Kilduff, M., Tasselli, S.: Social network analysis: foundations and frontiers on advantage. Ann. Rev. Psychol. **64**, 527–547 (2013)
28. Scott, P.J., Wasserman, S. (eds.): Models and Methods in Social Network Analysis, vol. 28. Cambridge University Press, Cambridge (2005)
29. Schmidt, R., Lyytinen, K., Keil, P.C.M.: Identifying software project risks: an international Delphi study. J. Manag. Inf. Syst. **17**(4), 5–36 (2001)
30. Osborne, J., et al.: What ideas-about-science should be taught in school science? A Delphi study of the expert community. J. Res. Sci. Teach. **40**(7), 692–720 (2003)
31. Gokhale, A.A.: Offshore outsourcing: a Delphi study. J. Inf. Technol. Case Appl. Res. **9**(2), 6–18 (2007)
32. Dyer, L., Blancero, D.: Workplace 2000: A Delphi-Study (1992)
33. Wang, X., et al.: Topic sentiment analysis in Twitter: a graph-based hashtag sentiment classification approach. In: Proceedings of the 20th ACM International Conference on Information and Knowledge Management. ACM (2011)
34. Small, T.A.: What the hashtag? A content analysis of Canadian politics on Twitter. Inf. Commun. Soc. **14**(6), 872–895 (2011)
35. Lau, J.H., Collier, N., Baldwin, T.: On-line trend analysis with topic models: \#Twitter trends detection topic model online. In: COLING (2012)
36. Hanna, R., Rohm, A., Crittenden, V.L.: We're all connected: the power of the social media ecosystem. Bus. Horiz. **54**(3), 265–273 (2011)
37. Jiang, B., Claramunt, C.: Topological analysis of urban street networks. Environ. Plann. B: Plann. Des. **31**(1), 151–162 (2004)
38. Kwak, H., et al.: What is Twitter, a social network or a news media? In: Proceedings of the 19th International Conference on World Wide Web. ACM (2010)
39. Java, Akshay, et al.: Why we Twitter: understanding microblogging usage and communities. In: Proceedings of the 9th WebKDD and 1st SNA-KDD 2007 Workshop on Web Mining and Social Network Analysis. ACM (2007)

40. Huberman, B.A., Romero, D.M., Wu, F.: Social networks that matter: Twitter under the microscope (2008)
41. Sakaki, T., Okazaki, M., Matsuo, Y.: Earthquake shakes Twitter users: real-time event detection by social sensors. In: Proceedings of the 19th International Conference on World Wide Web, pp. 851–860. ACM (2010)