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Features of Marketer-Generated Content Tweets For Electronic Word of Mouth in Banking Context

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Abstract

This study aims to identify the features of Market-Generated Content (MGC) tweets that are posted with a purpose of initiating electronic word of mouth (known as eWOM). A successful tweet is a tweet that earns active participation from the customers, e.g. getting Retweeted (RT) or Favorited (FAV). The phenomenon of eWOM effectively helps to propagate marketing agendas in both short-term marketing campaigns and long-term brand awareness. In the analysis process, logistic regression and Association rule methods were applied to mine the significant features on the MGC posts which were collected from four selected banks in Thailand during a specific period of time. For results, logistic regression indicated a set of features that causes a substantial number of RT and FAV. Additionally, the Apriori algorithm of the Association rule further specified two key features for effective RT and FAV, and it also suggested how to combine other features with those two key features to enhance the gain of RT and FAV.

Keywords: electronic Word of Mouth, eWOM, Marketer-Generated Content, MGC, Logistic regression, Association rule, Social media, Twitter mining.

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1. Introduction

As social media becomes a norm for facilitating global connectivity in social and business concerns, people share information and express opinions through the social network which is available in various forms, e.g. Facebook, Twitter, and LinkedIn, to name a few. Many researchers [1–3] have reported about the phenomenon where businesses propagate marketing agendas to acquire competitiveness through the social network platform. This idea is supported by the marketing concept of "Word of Mouth" [4] that is assumed to work well in the virtual world in the same way as has been proved in the real world. At a later time, the concept that adapt Word of Mouth for use in the virtual world is called *electronic Word of Mouth* or *eWOM* [5–8].

In the cyberspace, the impacts on purchasing intention and brand awareness of customers from the information exchanged via social media like Twitter, one of the leading social networking platform, were studied and positively confirmed [9, 10]. In 2009, Jansen et al. [11] specified that there appeared a brand name of a product posted in every 5 posts in Twitter. Since Twitter provides a very convenient and popular platform for encouraging eWOM, many companies have created pages on the Twitter using official account. This enables the Marketer-Generated Content (MGC) to be easily disseminated. Up to 2013, there were more than 77% of 500 firms actively participating on Twitter [12]. The interesting issue on the eWOM based on the MGC is to understand the factors that influent the success of eWOM on the social media as indicated in [13].

Focusing on the MGC-based eWOM on Twitter, this paper studies the variables that are found on the tweets and proposes a set of specific variables that are presumable by determining power for encouraging eWOM in the context of Thai society. For the current stage of study, only the MGC tweets which are posted by four leading banks in Thailand were studied and only being retweeted (RT) and favorited (FAV) were determined as the resulting eWOM.

This paper is organized in the following manner: after the introduction, the literature review about eWOM characteristics and Twitter concepts is provided. The analytic techniques and the experiment design are discussed next. Then, the results and discussion will be given with insights. Finally, the conclusion and research direction are touched.

2. Literature review

2.1. Twitters as a platform for eWOM

Users on Twitter can post messages called tweets with the limitation of 140 characters including text messages and links. This limitation has been modulated since 2016 because Twitter will no longer count the enriched media, e.g. photos, videos, quoted tweet, GIFs, and polls, as part of the character limitation. Other users who see the tweet can forward the tweet by retweeting or give short comments on it. Also, they can express their impression on or 'favorite' a tweet by pressing a Like button. By default, tweets can be seen in public without having to log on. These strengths of Twitter enable people to rely on it in their daily life to share their experiences and their opinions in an almost real-time fashion. On the other hand, these properties make Twitter a good platform for eWOM, especially retweeting and liking (or getting favorited) which can help to spread messages and support interaction among customers. eWOM websites facilitate the exchange of information among users about a wide variety of products and services [14]. Therefore, marketers can use it as a tool to propagate news, product information, services, promotions or any messages lifting brand awareness.

Twitter also provides a set of indicators which represent events of eWOM, e.g. the number of retweets (RT) and favorites (FAV). RT which is shown on the tweet indicate the number of times the tweet has been shared. Many researchers use RT as a main indicator of eWOM [15, 16]. FAV is also shown on the tweet. It reflects the number of times that people express positive feelings or agreement on the post.

This research aims to find out which features make each MGC tweet gets different numbers of RT and FAV and analyze the results to represent effective eWOM.

2.2. Prospective features for effective MGC tweets.

MGC is a content published on the cyberspace by a person (e.g. marketer) officially representing his/her company to gain customer interaction. There have been some studies about MGC features in tweets, for examples [17, 18]. Lately, [13] categorized the features into 4 dimensions: contextual, entertainment, informational and brand related.

Contextual features: These show how the tweet is presented, included variables are whether the tweet includes a picture, video, hashtag (#), hyperlink, or mentions another twitter account (@), or if it is pure text.

Informational features: These represent the information offered by the tweet. We classify information into product and service information, information about the company, and promotion/discount information.

Entertainment features: These characteristics measure how much effort the tweet put into entertaining the audience, including interaction with customers, answering questions directly, announcing events or social actions, and celebration of holidays and other important dates.

Brand related features: These reflect how much the tweet is influenced by brand. Included variables are: brand centrality (if the brand is the focus of the tweet) and announcement of campaigns organized by the company.

3. Methods and Experimental Design

To find the important features and gain insights into their interaction in enhancing the eWOM for MGC activities on Twitter, we respectively applied logistic regression analysis [19] and the Association rule [20–22] to analyze the tweets gathered from four banks' official Twitter accounts. The first method is powerful in identifying all key features which highly correlate with the eWOM activities. In addition, the second one can pinpoint the relationship amongst them which can cause more effective eWOM.

For this study, we assume a tweet will have an effective eWOM when it can generate a satisfactory number of Retweet (RT) or Favorite (FAV): Gaining a number of RT or FAV greater than the median value of the sampled data. The justification is based on our empirical investigation indicating most of tweets had at least one or two RT or FAV no matter what features are employed. This gives no meaning for the analytical interpretation if defining only one RT or FAV as gaining eWOM as treated in [13].

Corresponding to the methodologies, the experiment in this study was conducted in the following three steps of procedure: (i) variables assignment, (ii) Tweets collection and variable coding, and (iii) the analysis by Logistic regression and the Association rule.

Firstly, the prospective features of eWOM tweets were identified as seen in Table 1. Among these 21 characteristics, seventeen of them were chosen from the existing literature as specified in Section 2. Four new variables were nominated as they were presumably effective for Thai culture or are characteristics of financial tweets: financial advice (informational dimension), social news update (separated from company's event news in entertaining dimension), foreign language (contextual dimension) and celebrity figures (brand related dimension).

Secondly, 809 tweets from four commercial banks were collected from the corresponding official Twitter accounts, namely Krung Thai Bank (@KTB_Care), Siam Commercial Bank (@scb_thailand), Kasikornbank (@KBank_Live), and Bangkok Bank (@BangkokBankNEWS). All tweets were posted between 1 January 2017 and 15 June 2017. The features of each tweet were coded manually according to the coding defined in Table 1.

Thirdly, based on the coded values obtained from the second step, used as the independent variables, Logistic regression and Association rule (Apriori algorithm) [23] analyses were computed to determine the dependent variables of effective eWOM (RT and FAV).

Table 1: Binary Coding Instruction for all variables: 1 indicates the presence of a characteristic and 0 indicates the absence.

Variables		*Coding*	
Dependent variables:			
1	Being retweeted	If the tweet is retweeted more than 3 times[1]: coded as 1	–If not: 0
2	Being favorited	If the tweet is favorited more than 3 times[2]: coded as 1	–If not: 0
Independent variables:			
Category 1: Contextual			
1	Pictured	If there is a picture in the tweet: coded as 1	–If not: 0
2	Video	If there is a video in the tweet: coded as 1	–If not: 0
3	Only text	If there is no picture or video in the tweet: coded as 1	–If not: 0
4	Hyperlink	If there is a link in the tweet: coded as 1	–If not: 0
5	Hashtag	If there is a '#' in the tweet: coded as 1	–If not: 0
6	Mention	If there is an '@' in the tweet: coded as 1	–If not: 0
7	Foreign Language	If a language other than Thai is used: coded as 1	–If not: 0
Category 2: Informational			
8	Product or service info.	If there is this information: coded as 1	–If not: 0
9	Company information	If there is this information: coded as 1	–If not: 0
10	Discount or promotion	If there is this information: coded as 1	–If not: 0
11	Financial advice	If there is financial advice in the tweet: coded as 1	–If not: 0
Category 3: Entertainment			
12	News Update	If there is up-to-date news in the tweet: coded as 1 (e.g., the volatility of oil prices)	–If not: 0
13	Being entertaining	If there is something entertaining: coded as 1	–If not: 0
14	Interaction with customers	If there is customer interaction: coded as 1	–If not: 0
15	Direct answer to customer	If there is a direct answer to a customer's question: coded as 1	–If not: 0
16	Event news	If there is company's event news: coded as 1	–If not: 0
17	Social actions	If there is a mention of a social action by company: coded as 1 (e.g., blood donation)	–If not: 0
18	Celebration of important dates	If there is an important date noted: coded as 1 (e.g., important religious date, national dates)	–If not: 0
Category 4: Brand related			
19	Celebrity figures	If there is a reference to celebrity figures: coded as 1 (e.g., picture of celebrity as a presenter of company)	–If not: 0
20	Brand centrality	If the brand is the focus of the tweet: coded as 1	–If not: 0
21	Campaigns	If there is news about a campaign: coded as 1	–If not: 0
[1]Median of the number of retweet, [2]Median of the number of favorite.			

Table 2: Coding frequencies.

Variables	*KTB*		*SCB*		*KBank*		*BangkokBank*		*Total*	
	235 tweets		*315 tweets*		*223 tweets*		*36 tweets*		*809 tweets*	
	Coded as 1	*Coded as 0*	*Code as 1*	*Code as 0*	*Code as 1*	*Code as 0*	*Code as 1*	*Code as 0*	*Code as 1*	*Code as 0*
Being retweeted	108	127	157	158	82	141	7	29	354	455
Being favorited	97	138	145	170	111	112	15	21	368	441
Pictured	225	10	235	80	217	6	0	36	677	132
Video	7	228	16	299	0	223	0	36	23	786
Only text	0	235	57	258	3	220	36	0	96	713
Hyperlink	108	127	162	153	190	33	36	0	496	313
Hashtag	85	150	129	186	101	122	0	36	315	494
Mention	23	212	1	314	1	222	0	36	25	784
Foreign Language	0	235	8	307	0	223	0	36	8	801
Product or service info.	109	126	56	259	65	158	28	8	258	551
Company information	1	234	2	313	2	221	1	35	6	803
Discount or promotion info.	33	202	36	279	47	176	7	29	123	686
Financial techniques	8	227	43	272	40	183	0	36	91	718
Social news	0	235	104	211	11	212	0	36	115	694
Being entertaining	28	207	36	279	29	194	0	36	93	716
Interaction with customers	8	227	5	310	4	219	0	36	17	792
Direct answer to customer	1	234	4	311	8	215	0	36	13	796
Event news	18	217	22	293	39	184	0	36	79	730
Social actions	3	232	20	295	2	221	0	36	25	784
Celebration of important dates	14	221	23	292	9	214	0	36	46	763
Celebrity figures	4	231	0	315	0	223	0	36	4	805
Brand centrality	27	208	23	292	23	200	0	36	73	736
Campaigns	24	211	25	290	20	203	1	35	70	739

4. Results and Discussion

Based on the data collected during the first half of 2017, as seen in Table 2, empirical observation shows that SCB seems to be the most effective in attracting overall eWOM activities with retweet and favorite rates at almost half of all tweets, that is 157 of 315 (or 49.8%) for retweeted, and 145 of 315 (or 46%) for favorited. KBank is also on par with SCB with the favorited tweets up to 49.7% of the 223 tweets. Bangkok Bank (BBL) comes with the lowest number of tweets (only 36 initiated tweets) and seems to be the most conservative player with rare use of extra features other than text and official information.

4.1. Logistic regression

Logistic regression was employed to understand the factors that cause customers to retweet and favorite the tweets. The study is divided into two parts according to the dependent variables; retweet and favorite models.

The results for retweet model (Table 3) show that there are nine predictors with significant contribution (p-value $<$ 0.05): Video, Hyperlink (-), Mention (-), Foreign Language (-), Discount or promotion information (-), social news update, Event news (-), Social actions, and Celebration of important dates. The sign (-) implies negative relation: the higher the number of appearance is, the less eWOM in terms of RT will be. Most of the results conform with the result found in [13] which examined the features of eWOM for six prominent pure-play e-commerce operated in tourism industry. The main differences are that Pictured and Brand centrality are found insignificant while social actions and social news update become positively relevant in our case. Tweets with Social action or Video seems to have the highest positive impact to the RT (estimates of coefficient = 2.6 and 1.8, respectively). Note that since the tourism is quite hedonic by nature, difference in factors are expectable. In addition, out of the four features which are newly introduced, only social news update and the avoidance of foreign language could effectively attract customers to make RT.

According to Table 4, there are six significant predictors in the favorite (FAV) model (p-value $<$ 0.05): Hyperlink (-), Discount or promotion info. (-), Interaction with customers, Event news (-), Social actions, and Celebration of important dates. Hyperlink again seems to be the most influential factor with the lowest p-value. In addition, the feature of Interaction with customer is also the most powerful (estimates = 1.90826) in attracting customers to give FAV.

In the overall picture, there are five common predictors that are significant in both models of RT and FAV: Hyperlink, Discount or promotion info., Event news, Social actions, and Celebration of important dates. This result suggests a strategic set of features for banks when they need to initiate a message for eWOM. Now, another

Table 3: Logistic regression results for the retweet model.

	Estimate	Std. Error	z value	*p*-value
Pictured	0.64333	0.62695	1.026	0.30483
Video	1.80441	0.82614	2.184	**0.02895**
Only text	1.34225	0.77187	1.739	0.08204
Hyperlink	-1.24815	0.20756	-6.013	**0.00000**
Hashtag	0.06959	0.18328	0.38	0.70419
Mention	-2.81384	0.64453	-4.366	**0.00001**
Foreign Language	-3.08033	1.22266	-2.519	**0.01175**
Product or service info.	-0.26465	0.27492	-0.963	0.33574
Company information	0.22244	0.96293	0.231	0.81731
Discount or promotion info.	-1.29801	0.36051	-3.6	**0.00032**
Financial techniques	-0.03848	0.32285	-0.119	0.90512
Social news update	0.88223	0.34036	2.592	**0.00954**
Being entertaining	-0.1175	0.28405	0.414	0.67912
Interaction with customers	0.1944	0.65707	0.296	0.76733
Direct answer to customer	-0.00892	0.6296	-0.014	0.98869
Event news	-0.94017	0.34327	-2.739	**0.00616**
Social actions	2.61091	1.04665	2.495	**0.01261**
Celebration of important dates	1.7691	0.64701	2.734	**0.00625**
Celebrity figures	1.41694	1.25066	1.133	0.25723
Brand centrality	0.27026	0.36508	0.74	0.45913
Campaigns	0.59327	0.41586	1.427	0.15369

Note: Bold figures: significant variables, $p < 0.05$

interesting question emerges: can they go together and synergistically provide a good support to eWOM activities? Association rule can help answer this question.

4.2. Association rules

The result obtained from the Logistic analysis can provide only a group of candidate features, but no relationship among them is validated for giving effective RT or FAV. Association rule can help to further mine the knowledge to suggest which ones should go together for effective eWOM.

Table 4: Logistic regression results for the favorite model.

	Estimate	Std. Error	z value	*p*-value
Pictured	0.8147	0.67918	1.2	0.23032
Video	1.30567	0.82618	1.58	0.11402
Only text	1.3141	0.76142	1.726	0.08437
Hyperlink	-0.78563	0.19912	-3.945	**0.00008**
Hashtag	-0.07592	0.17396	-0.436	0.66253
Mention	-16.95985	479.20435	-0.035	0.97177
Foreign Language	-1.30904	0.88013	-1.487	0.13693
Product or service info.	-0.45401	0.25956	-1.487	0.13693
Company information	1.22961	1.15216	1.067	0.28587
Discount or promotion info.	-0.45401	0.32798	-2.084	**0.03719**
Financial techniques	0.45188	0.31094	1.453	0.14615
Social news update	0.23001	0.31087	0.74	0.45937
Being entertaining	-0.07519	0.2735	-0.275	0.78337
Interaction with customers	1.90826	0.72409	2.635	**0.00840**
Direct answer to customer	0.4739	0.62136	0.763	0.44566
Event news	-0.72972	0.31878	-2.289	**0.02207**
Social actions	1.77103	0.64919	2.728	**0.00637**
Celebration of important dates	1.13153	0.4712	2.401	**0.01633**
Celebrity figures	0.27911	1.06507	0.262	0.79328
Brand centrality	-0.18809	0.35785	-0.526	0.59916
Campaigns	0.01333	0.39586	0.034	0.97313

Note: Bold figures: significant variables, p-value < 0.05.

To identify meaningful rules mined by the Apriori algorithm, only rules with Lift value higher than 1, Confidence value around 90% and Support value higher than 0.01 are considered. Based on the Apriori algorithm, we found that only the features of Social action and Celebration of important dates (both are in the category 3 entertainment of the eWOM features) are the important causes for both effective RT and FAV.

For RT:

{Social Action = 1} => {RT = 1}: Support = 0.3, Confidence = 0.96, Lift = 1.96

{Celebration = 1} => {RT = 1}: Support = 0.53, Confidence = 0.93, Lift = 1.9

For FAV:

{Social Action = 1} => {RT = 1}: Support = 0.03, Confidence = 0.88, Lift = 1.9

{Celebration = 1} => {RT = 1}: Support = 0.05, Confidence = 0.85, Lift = 1.83

To gain more insights, a mining for causality with more than one features were conducted for RT and FAV and the results are as shown in Table 5 and 6, in respective order.

Table 5: Association rule results for the retweet model.

Rules	1	2	3	4	5	6
Pictured		/		/	/	/
Hyperlink			/			
Hashtag						/
Product or service info.	/				/	
Social actions	/	/			/	
Celebration of important dates			/	/		/
Support	0.01	0.02	0.03	0.04	0.01	0.02
Confidence	1.00	1.00	0.95	0.95	1.00	0.95
Lift	2.04	2.04	1.95	1.93	2.04	1.94

According to the RT model, Social actions and Celebration of important dates are found to go together with some other factors and yield better results. Social actions can be supported by Pictured and Product or service information with Confidence = 1.0 and a very high Lift of 2.04. In the same fashion, Celebration of important dates which is supported by Pictured or Hyperlink can also encourage RT with a Confidence of 0.95 and a Lift higher than 1.9. Three factors in a go, which are Hashtag, Pictured, and Celebration, also give similar Confidence and Lift values. Note the supportive role of Hashtag, Pictured and Hyperlink which are suppressed in Logistic regression but can be revealed by Association rule.

For the Favorite model, as shown in Table 6, Social actions can go together very well with Product/Service information or Pictured. These are exactly the same rules as those found in RT model. Confidence value is around 0.9 and Lift value is around 1.9. Celebration will be good with the support of Pictured, Hashtag or both. However, the Confidence values are just around 0.85 which are not so strong as those found in the case of RT.

By the way, there is a special case when Financial advice is posted in an entertaining way (Being entertaining), the FAV can be raised up and come with higher Confidence (0.0.9) and Lift (1.91.95) than the usage of Celebration.

Table 6: Association rule results for the favorite model.

Rules	1	2	3	4	5	6
Pictured			/		/	/
Hashtag				/		/
Product or service info.	/					
Financial advice		/				
Up-to-date news						
Being entertaining		/				
Social actions	/		/			
Celebration of important dates				/	/	/
Support	0.01	0.01	0.02	0.02	0.04	0.02
Confidence	0.91	0.90	0.89	0.86	0.84	0.86
Lift	1.97	1.95	1.92	1.87	1.82	1.85

5. Conclusion

A mining of features of MGC posting on Twitter that impact the effectiveness of eWOM activities in terms of getting Retweets (RT) and Favorited (FAV) has been conducted using Logistic regression and Association rule algorithms. The model was experimented on the eBank domain focusing on the leading ones in Thailand: BBL, KBANK, KTB, and SCB. Original tweets initiated by these four banks were extracted and processed to measure the relationship between the usages of each features and the responses in terms of effective retweets and favorites.

Seventeen existing features as referred from the literature review process plus four new candidate features presumed to be valid for Thais' social context were experimented. By Logistic regression, five common features are found to be effective for managing RT and FAV: Hyperlink, Discount or promotion info., Event news, Social actions, and Celebration of important dates. Further analysis using Association rules algorithm discovered that only Social actions and Celebration of important dates can play as a sole factor to attract effective RT and FAV. Otherwise, mixed features should be designed to strengthen the tweet. Surprisingly, some suppressed features in the Logistic regression can associate with these two and synergistically enhance user involvement: Pictured, Product and Service info., and Hashtag which are in the Contextual and Informational categories. Among the new features proposed, only the Social news update and Avoidance of foreign language were found to be significant for RT in the Logit model. Apriori algorithm also discovered a surprising rule that the financial advice can be dependable for FAV only when appearing in an entertaining fashion. These discoveries from the mining process can be exemplars for help a bank in improving eWOM activities to get larger numbers of RT and FAV.

Direction of future research may be that of applying the model to explain the eWOM in other industries. Other dimensions of eWOM, e.g. number of Replies, number of unique individuals making RT or FAV can be of interest for mining, too. Last but not least, an AI algorithm that automatically determine the relationship between emotion and effectiveness of the eWOM maybe another dimension to study.

References

[1] Bickart, B. and Schindler, R.M. Internet forums as influential sources of consumer information. Journal of Interactive Marketing 2001; 15 (3): 31–40.

[2] Huang, L. Social contagion effects in experiential information exchange on bulletin board systems. Journal of Marketing Management 2010; 26 (3/4): 197–212.

[3] Kumar, N. and Benbasat, I. Research note: the influence of recommendations and consumer reviews on evaluations of websites. Information Systems Research 2006; 17 (4): 425–439.

[4] Arndt, J. Role of product-related conversations in the diffusion of a new product. Journal of Marketing Research 1967; 4 (3): 291–295.

[5] Hennig-Thurau, T., Gwinner, K.P., Walsh, G. and Gremler, D.D. Electronic word-of-mouth via consumer-opinion platforms: what motivates consumers to articulate themselves on the internet? Journal of Interactive Marketing 2004; 18 (1): 38–52.

[6] Kozinets, R., Wojnicki, A.C., Wilner, S.J. and De Valck, K. Networked narratives: understanding word-of-mouth marketing in online communities. Journal of Marketing March 2010; 74 (2): 71–89.

[7] Sookhyun, K., Jiyoung, P and Yuri, L. The E-Word-of-Mouth effect on consumers' Internet shopping behaviour: focus on apparel products. International Journal of Fashion Design, Technology and Education 2013; 6 (3): 160 -172.

[8] Wang, C., The Influence of Electronic Word-of-Mouth on the Decision-making of Online Travel Booking. International Symposium on Computer, Consumer and

Control 2016: 934 - 937

[9] Tsimonis, G. and Dimitriadis, S. Brand strategies in social media. Marketing Intelligence & Planning 2014; 32 (3): 328–344.

[10] Wang, X., Yu, C. and Wei, Y. Social media peer communication and impacts on purchase intentions: a consumer socialization framework. Journal of Interactive Marketing 2012; 26 (4): 198–208.

[11] Jansen, B.J., Zhang, M., Sobel, K. and Chowdury, A. (2009) 'Twitter power: Tweets as electronic word of mouth', Journal of the American Society for Information Science and Technology; 2009 60 (111): 2169–2188.

[12] Barnes, N.G., Lescault, A. and Wright, S. Fortune 500 are Bullish on Social Media: Big Companies Get Excited About Google, Instagram, Foursquare and Pinterest [online] https://www.umassd.edu/media/umassdartmouth/cmr/studiesandresearch /2013_Fortune_500.pdf [accessed 11 Oct 2017]

[13] Alboqami, H., Al-Karaghouli, W., Baeshen, Y., Erkan, I., Evans, C. and Ghoneim, A. Electronic word of mouth in social media: the common characteristics of retweeted and favourited marketer-generated content posted on Twitter. Int. J. Internet Marketing and Advertising 2015 9 (4): 338–358.

[14] Martinez-Torres, M. R., Toral, S., Olmedilla, M., Arenas-Marquez, F. J. Features of Reputed Users in eWOM Using Evolutionary Computation. 9th International Conference on Developments in eSystems Engineering 2016, p.223 - 227

[15] Hoffman, D.L. and Fodor, M. Can you measure the ROI of your social media marketing? Sloan Management Review 2010; 52 (1): 41–49.

[16] Wolny, J. and Mueller, C. Analysis of fashion consumers' motives to engage in electronic word-of-mouth communication through social media platforms. Journal of Marketing Management 2013; 29 (5/6): 562–583.

[17] Boyd, D., Golder, S. and Lotan, G. Tweet, tweet, retweet: conversational aspects of retweeting on Twitter. In: System Sciences (HICSS) 43rd Hawaii International Conference, IEEE; 2010. p.1–10. s

[18] De Vries, L., Gensler, S. and Leeflang, P.S. Popularity of brand posts on brand fan pages: an investigation of the effects of social media marketing. Journal of Interactive Marketing 2012; 26 (2): 83–91.

[19] Serkan, A., Erdener, K., Eda, A. and Aksoy, Ş. Where does the logistic regression analysis stand in marketing literature?: A comparison of the market positioning of prominent marketing journals. European Journal of Marketing; 2007; 41 (5/6): 537-567

[20] Agrawal, R., Imielienski, T. and Swami, A. Mining Association Rules between Sets of Items in Large Databases. In: Proc. Conf. on Management of Data. New York: ACM Press; 1993. p. 207-216

[21] Agrawal, A., Mannila, H., Srikant, R., Toivonen, H. and Verkamo, A. Fast Discovery of Association Rules. In: Fayyad et al; 1996. p. 307–328

[22] Rong, J., Vu, H. Q., Law, R., and Li, G. Behavioral analysis of web sharers and browsers in Hong Kong using targeted association rule mining. Tourism Management August 2012; 33 (4): 731-740

[23] Borgelt, C. and Kruse, R. Induction of Association Rules: Apriori Implementation. The 15th Conference on Computational Statistics (COMPSTAT); 2002. p. 395-400.