ROI of social media: Investigating Measurement of Message Intentions used by B2B firms

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ABSTRACT

Social media has revolutionized customer business communication and established a new marketing communication channel. Marketers worldwide need to understand the mechanisms involved in social media marketing to implement a successful strategy. Various platforms such as Facebook, Linkedin and Twitter offer organizations chances to reach customers and increase brand awareness. This study is going to concentrate on one of the most popular social media platform, namely Twitter. Little is known about the effectiveness of Twitter activities and even less is known about the Return on Investments (ROI) for B2B firms. Therefore this study concentrates on Twitter activities of B2B firms. Relevant variables in the context for effective Twitter messages will be discussed. A framework to classify message intentions of Tweets is established, which can be used for future studies on B2B micro-blogging message intentions.

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1. INTRODUCTION

Competition has risen immensely over the past years. Globalization, technological innovations and the rise of Web 2.0 have created new opportunities for companies' operations. Social media has become a trend, inevitable for businesses to ignore (Kietzmann, Hermkens, McCarthy & Silvestre, 2011). Social media has been proven not be a platform where users generate content, but to be a medium where users seek for two-sided communication and wish to connect with other (Chen, 2011). The intention to connect with others on a social media platform discloses a new channel for marketers. These channels give firms the opportunity to engage in timely and direct consumer contact at lower costs and with better results compared to traditional communication tools (Kaplan & Haenlein, 2010). The question rises to what extent investments in social media marketing are really worthwhile. Marketing budgets are limited and management has to make decision where to put their focus on. The use of social media is cost free, but employees have to invest working hours, which result in costs. The popularity of the micro blogging platform Twitter, with more than 500 Million users worldwide (O`Carroll, 2012), has been recognized by the industry and is used by firms worldwide to communicate with customers, partners and shareholders. The social interaction on Twitter results in benefits such as establishing and maintaining connections (Riedl, Koebler, Goswami & Krcmar, 2013). A special feature of Twitter is its power to influence followers by pushing information and therefore creating awareness for products and services (Rui, Liu & Whinston, 2013). The effectiveness of using social media and best practices in this field was still not established by literature (Riedl et al., 2013). A study by Rodriguez, Peterson and Krishnan (2012) found empirical evidence that social media have a positive affect on sales performance for Business-to-Business (B2B) organizations. However, little attention is paid on measurement for using Twitter in a Business-to-Business (B2B) context yet. The Model by Favier (2012) attempts to estimate the Return on Investments (ROI) for companies using social media activities. Favier (2012) established time, trust, sentiment and income as the dependent variables of the effectiveness of Twitter messages, so-called Tweets. Income is a fixed variable, measured by the average income per second of the user. Time accounts for the number of seconds the reader spends on a Tweet. Sentiment measures the likelihood that the user is positive about a brand, whereas trust refers to the closeness of the relationship (Favier, 2012). From a marketer's point of view it is important to know how these three variables can be influenced to achieve the highest possible ROI. Jansen, Zhang, Sobel and Chowdury (2009) suggest that in a B2C context, word-of-mouth (WOM) branding via Twitter have a substantial impact on the company-customer relationship. So WOM influences the trust level and the related online-word-of-mouth (OWOM) concept can be conceptualized with the underlying intention of a comment (Jansen et al., 2009). Consequently, the underlying message intention of a Tweet should have an influence on the trust level. However, Twitter messages can have different intentions and the goal of this study is to give an overview of potential and relevant Twitter message intention codes for B2B firms. For the purpose of exploring the variable message intention a factor analysis of chosen Tweets will be conducted. The investigation of this variable is of importance for marketers as the message intention can be influenced to increase the ROI of social media.

Literature is mainly concerned with B2C Twitter marketing effectiveness, but B2B companies, such as the multinational companies Intel and Oracle have also embedded Twitter to their social media strategy as well. The problem remains to which extent their Twitter activities reach their intended goal. This study is going to add some insight into the measurement of Twitter message intentions of B2B firms, which can serve as a conceptualization for future research. The research question is formulated as: What are relevant message intentions to analyze the Tweets of B2B firms? The paper is structured as follows. In the next section the model and the theoretical framework will be developed. Afterwards information about the method will be presented. This research will conclude with an appropriate test and the results will be discussed accordingly.

2. THEORY

2.1 Trust

Marketers recognize trust as a key success factor for customer relationship management (Benedicktus, & Andrews, 2006; Corbitt, Thanasankit & Han, 2003). Therefore, investments that lead to an increase of the trust level should result in more effective marketing performance. In a social media setting, the trust level increases for example because companies can directly confront negative feedback (Singh, Veron-Jackson & Cullinane, 2008). In addition, especially Twitter was found to be an effective communication channel because it allows marketers to build trust in a way that is rather nonintrusive and deviates from a selling point of view (Andzulis, Panagopoulos & Rapp, 2012). Singh et al. (2008) suggest that blogging itself creates awareness and loyalty because the customer co-creates the experience and expectations with a brand or firm. Especially the open dialogue is likely to increase loyalty (Singh et al., 2008). Another important aspect of trust in the social media context is that it also occurs in a setting where the sender and receiver are not familiar, for example in the case of reviews (Duana, Gub & Whinston, 2008). Notwithstanding, it is more likely that friends have a closer relationship and consequently a higher trust level. According to Favier (2012), people that are close friends mimic each other's behaviors and trust each other's judgments. Close friends, which are close colleagues in the B2B context, will also spend more time on each other's Tweets and will trust in recommendations or criticism (Favier, 2012). In addition, Favier (2012) proposed a measurement for the degree of trust which is based on Dan Zarrella`s (2009) Retweetability metric: (Retweets per day/ Tweets per day) / Followers. Basically, this metric suggests, that sharing a Tweet that was initially published by someone else shows trust. This measurement is justified by the following argumentation: The interested receiver will spent more time, for example by reading a posted link or comment on a Tweet. The more time is spend, the more likely it is that the receiver trusts that Tweet and will be more likely to retweet it (Favier, 2012).

In literature the importance of Tweets and trust can be also found by the following argumentation. Tweets can be treated as a new type of WOM, and WOM is usually seen as a credible and trusted source from a consumer's point of view when it comes to buying decisions (Rui, Liu & Whinston, 2013). Jansen at al. (2009) refer to this form of trust as online Word-of-Mouth (OWOM). OWOM, which occurs in Twitter, is a powerful marketing tool because it is immediate and has a significant reach.

In the Twitter context, trust is therefore defined as a variable that forms brand relationship and leads to brand attachment and to future purchases (Jansen et al., 2009). Consequently, using Twitter for OWOM branding is a powerful tool, as it is perceived as a trusted source. Based on this argumentation, it is important to find out what factors will influence, or more specifically, will increase the trust level.

2.2 Message Intention

In order for a message to be retweeted by the reader and thereby showing trust in a message, many factors are important. The research group, with whom the data collection was conducted, studied the relationships of the effectiveness of Twitter messages and assumed that the message intention is one variable of these factors (Klaver, 2013 & Naumann, 2013). It is important as it shapes the message and intents to deliver information in an innovative and interesting way (Singh et al., 2008). As any other marketing practice, the message intention should be strategic and aligned with the marketing objectives (Kaplan & Haenlein, 2010; Singh et al., 2008). Ho and Dempsey (2010) suggest that a message should not be formulated just to attract attention, it should also give the follower a reason to want to share the piece of information with others. Douglas and Sutton (2003) found evidence that the language does not form the message intention but that the message intention rather influences the language. Furthermore, it is stated that the message intention contains and is aimed at delivering a certain emotion (Douglas & Sutton, 2003). The concept of Word-of-mouth marketing defined as the "intentional influencing of consumer-to-consumer communications by professional marketing techniques" (Kozinets, De Valck, Wojnicki, Wilner, 2010, p.7) accounts also for formulating a Tweet. As interaction on Twitter, WOM communications are coproduced in consumer networks (Kozinets et al., 2010). In their Network Coproduction Model, message intention is the link between consumers. The marketer is able to influence the marketing message and meaning (Kozinets et al., 2010).

Furthermore it is argued that the content of a message is an important indicator of the effect of a marketing strategy and even more important than for example communication frequency (Kozinets et al., 2010). In a Twitter context we assume that certain types of message intentions have a higher potential to influence a follower or to put it more specifically increase the level of trust. Furthermore, the assumption is made that message intentions of Tweets can be classified by different categories. Jansen et al. (2009) proposed a framework for categorizing Tweets into 23 different categories. Tweets can be classified for example as a comment, notification or suggestion. Klaver (2013) classified these 23 different message intentions into five-message intention. The five message intention codes were grounded on the six-intention framework to novel writing proposed by Jakobson (1960). The application of reduction by Klaver (2013) was done subjectively. The first message intention was called expressive message intentions. It was characterized as a sender-centered message in which the sender expresses strong feelings or ideas and does not consider the reader when formulating the text. Klaver (2013) assumed that the following message intentions, initially proposed by Jansen et al. (2008), can be classified as expressive: announcement, consuming, expecting, maintenance, missing and research. The same procedure was applied to the other four classifications. Considering the expressive message definition, it is arguable whether in a strategic B2B Twitter setting a Tweet is sent out without considering the receiver.

Other authors have also designed coding frameworks to categorize Tweets (Naaman, Boase, & Lai, 2010; Honeycutt & Herring, 2009; Java, Song, Finin, & Tseng, 2007). But their categories were mainly based on Tweets made by individuals towards individuals grounded on subjective impressions and were not published in a scientific paper.

2.3 Theoretical Framework

Based on the 23 classifications of Jansen et al. (2009), this research is going to elaborate further on categorizing Tweets into different message intentions. The assumption this study makes is that in a B2B context Twitter intentions can be classified in different categories. As mentioned earlier, Klaver (2013) assumed that the message intentions of B2B Twitter activities could be categorized into five message intentions (expressive, conative, informative, phatic and meta-linguistic). Based on this assumption, five hypotheses were tested about the relationship of trust and message intention. The expressive message intention and meta-linguistic intention had a negative correlation coefficient on trust, whereas conative, informative and phatic Tweets had a positive relationship on trust (Klaver, 2013). However, none of the relationships were significant for any type of message intention on trust. Table 1 provides an overview of the coding schemes of Jansen et al. (2009) and of the corresponding classification made by Klaver (2013). Some of the action codes were used in two classifications and marked with a star in Table 1. This classification implies that certain message intentions are related and can be measured by underlying factors. The research in question is going to investigate whether the classification of Klaver (2013) holds by conducting an exploratory factor analysis on the 23 message intentions of Jansen et al. (2009). In the next step, this research will draw conclusions for further research based on the outcome of the analysis and indicate implications of the findings.

3. METHOD

3.1 Twitter

The micro-blogging platform Twitter was launched in March 2006. It allows users to share messages of maximum 140 characters and to track other messages of users, leave comments and share them (Westermann, Spence, & Van Der Heide, 2012). These users are called followers and information shared by someone's followers will be displayed on one's own start page. The short messages are called Tweets and can also include links, pictures or videos. If a user decides to share a Tweet that was initially published by another user, the frequency will be displayed and is called a Retweet. A cost- free registration is necessary to use the platform. The importance of Twitter is justified by its fast-growing popularity. From June 2008 to June 2009 Twitter registrations increased from 1 million to 21 Million (Chen, 2011). Besides private individuals, Twitter gained also popularity as many celebrities and companies have a Twitter account. The profiles of famous people, such as Barack Obama, are officially verified by Twitter and signaled by a check mark. Twitter was initially developed as an alternative to mobile text messages and mobile Twitter users are still nowadays more active (Schreiner, 2013).

Another unique feature of Twitter is the usage of the character @. Some short messages are followed or include a reference to another Twitter account. These tweets include the character @. With that reference included, a specific audience, individual or organization will be notified and sees that the Tweet was composed specifically for the account.

The use of hash tags is an often-used method on Twitter to suggest a specific mood or put a message into a specific context. In Twitter the same hash tags are linked automatically to the same hash tags used by other Twitter accounts. In that way, Twitter users can use the search option on Twitter to look for specific phrased hash tags and read Tweets that suit their search input. Hash tags are therefore an important tool to target a specific audience.

Notwithstanding, one might distinguish between registrations and active users. 40% of users do not tweet themselves, but is just reading the Tweets sent out by others (Huffington Post, 2013). Favier (2013) claims that only about 10% of users have more than 15 followers and use the platform to link. Furthermore, he argues that Twitter users with more than 500 followers, many of them are celebrities or corporations, use twitter to broadcast and have rarely reciprocal relationships with its followers.

3.2 Study Subjects

The research is going to concentrate on the Twitter activities of Oracle and Intel. These firms were chosen due to similarities of their operations and due to the fact that their customers are mainly other corporations. Although analyzing all the different accounts of one company might result in a clearer picture of the overall effectiveness of the Twitter strategy, this study is going to compare the Twitter activities and effectiveness of two B2B firms. The comparison was chosen to assure external validity.

3.2.1 Oracle

Starting with few facts, Oracle is a software and hardware company, which was found in the United States of America in 1977. It has about 390.000 customers and 115.000 employees worldwide. Oracle offers the world´s biggest database, which is providing higher scalability and accelerated performances. They operate in 145 countries and their revenue was 37.1 billion US dollar in 2012. The main profession of this company is information technology (IT) and their products can be incorporated to Windows and Linux systems. Notwithstanding, Oracle is having customers in many industries such as airlines and automotive companies. Regarding this research topic, it has to be stated that Oracle is active in social media platforms such as Twitter. This company is using Twitter for publishing information as well as news. Moreover, by having several accounts for different departments, many relevant information regarding Oracle and its products can be found on this side.

3.2.2 Intel

Intel is one of the biggest competitors of Oracle. Similar to Oracle, Intel was founded in the United States of America in 1968. Intel has currently 82.500 employees worldwide and its revenue was about 53.3 billion US dollar in 2012. Compared to Oracle, Intel' s revenue was higher. Intel´s portfolio is offering a wide range of products which are divided into personal computers and devices, intelligent systems, enterprise systems, storage solutions, and education products. Additionally, Intel is trying to be innovative and recently entered the smartphone and tablet market. Intel is having customers in different industries such as automotive, energy, healthcare and communication. Similarly to Oracle, Intel is using the social media platform such as Twitter to post news as well as information of the company and its products. Additionally, it is also having different accounts for all the different departments. Therefore, this company is providing good basis for this research topic.

3.3 Measurement

To measure message intention, a content analysis will be conducted. A research team will code 159 collected Tweets according to the intention framework of Jansen et al. (2009). In case that Tweets have no intention, they will be excluded from the analysis.

The definitions for possible different message intention are shown in Table 1. At the same time, it shows the classification done by Klaver (2013).

Table 1. Message intention action codes and categories (Klaver, 2013)

1. Expressive	
Announcement	Declaring the upcoming objects
Consuming	Drinking or eating objects
Expecting	Looking forward to objects from a company
Maintenance	Managing objects
Missing	Feeling from the lack of objects and expecting to have them back
Research	Examining objects
2. Conative	
Confirmation	Giving assurance or validation regarding objects
Negative comment	Critiquing, complaining
Order via Twitter Twitter	Attempting to place order on
Patronizing going to	Physically being in objects or objects frequently
Positive comment	Complimenting, praising
Question	Expressing confusions or doubts toward objects
Recommendation request	Seeking advice regarding objects
Request	Asking for objects
Response	Giving unnecessary feedback
3. Informative	
Forwarding	Pointing to potential useful objects
Notification	Letting one know on objects
Recommendation	Providing positive advice regarding objects
Suggestion*	
Supplement	
Research*	
4. Phatic	
Answer	Handling questions
Chitchat	Casual conversation
Question*	
Response*	
5. Meta-linguistic	
Answering*	
Comment feelings	Expressing mixed or neutral regarding objects
Negative comment*	
Positive comment*	
Supplementing*	

The Tweets can be coded with multiple intentions. A Tweet about a new product, praising some new feature, is coded as a notification (12) and as a positive comment (15) at the same time. No limit is set for the maximum intentions of one Tweet.

3.4 Data Collection

The data consist of published Tweets of certain Oracle and Intel Twitter accounts. The published short messages will be analyzed by an elaborated coding scheme. The time period from February 1 until February 28, 2013 was chosen due to a business event that was held in this month and could have resulted in higher Twitter activities.

Besides their corporate accounts, each firm has more than 20 accounts that are targeted at specific countries, regions or interest fields. As this research is conducted to investigate ROI measurement of Twitter activities of B2B firms, four Twitter accounts were chosen that made the impression of targeting B2B followers. The first Twitter page is named Intel Inside (@IntelInside). 21 Tweets were published by this Profile in February. The B2B character is justified as 17 Tweets contained some kind of information about a product that was launched by one of Intel´s business partners. The second Twitter account is named Intel Intelligence Systems (@IntelSys). It is the most active account with 70 Tweets made in February. Only half as

Intel Inside. Although some of the Tweets contain general information, the B2B context is also justified as the major number of Tweets is directly targeted at a business partner, i.e. @Philips. Likewise from Oracle two accounts were chosen. Oracle Commerce (@OracleCommerce) tweeted 44 times in February, of which 37 Tweets were published on the same day. The high activity on this day is explained by an event that was held during that date. The event was targeted towards other businesses and titled 'B2B Oracle Commerce Summit'. The last account Oracle Profit Online (@OracleProfit) is the Twitter page of its corresponding quarterly published online journal. The 24 published Tweets during the time period have all included a link to a B2B related article.

Due to this segmentation, it is reasonable to assume that the following analysis and the corresponding conclusion can be referred to B2B Twitter activities

3.5 Type of Analysis

Due to the qualitative data of this study and to ensure reliability of the findings, the first analysis that will be conducted is the calculation of the Cohen´s Kappa coefficient. The research team will be divided and through a sample of codes made by different teams, the strength of the inter-rater agreement will be calculated. A Kappa coefficient over 0.8 will lead to the conclusion of a high inter-reliability agreement between the research teams.

To explore possible categories of the variable message intention, a factor analysis will be conducted. Before the factor analysis, assumptions will be tested based on the Kaiser-Meyer-Olkin (KMO) criteria, sample size, communalities and anti-image result. After that, the correlation coefficients for 159 coded Tweets will be calculated for each pair of message intention and will be displayed in an R- matrix. Afterwards Factor Rotation will be applied to obtain optimal results considering the data values.

Additionally, this research will propose new message intention labels based on the factor analysis outcome. In the case that message intentions show significant correlations with multiple factors, the highest correlation coefficient will be considered.

4. RESULTS

4.1 Data Results

4.1.1 Sample Size and Communalities

As mentioned earlier, the data collection was conducted in a research group and includes more information than just message intention. Due to this fact the sample size is rather low for this type of analysis and could have been more adequate if it was collected just for this research purpose. Different authors suggest different guidelines for an appropriate size of the sample for a factor analysis. A sample size of minimum 300 is suggested (Comrey & Lee, 1992; Tabachnick and Fidell, 2012; Field, 2013). Thus, the sample size of 159 is rather low for a factor analysis. Besides, the number of collected cases the sample size condition can be also checked by considering the communality outcome (Field, 2013). If the communality values have values above 0.5 the sample size of 159 would be sufficient (Field, 2013). But the communality outcomes ranges from 0,11 to 0.984 (see Appendix, Table 4). More precisely, 9 communality values below 0.5 are identified and are problematic for the factor analysis and for the upcoming extraction criteria of factors.

4.1.2 Preliminary Analysis

Firstly, the Cohen´s Kappa results show high inter-reliability agreement with a value of 0.86 for the first research team and a value of 0.94 for the second research team. This outcome indicates a high level of inter-coder reliability.

According to the Kaiser-Meyer-Olkin (KMO) value criteria, the value of 0.51 fulfills the condition as it is above the minimum criteria of 0.5 (Field, 2013). The sampling adequacy patterns of correlations are moderately compacted, and this study proceeds with the Factor Analysis as it is reasonable to assume that the outcome should yield distinct and reliable factors (see Appendix, Table 5).

The values of the Anti-image outcome are concerning. Eleven variables are not above the suggested limit of 0.5, namely answer, maintenance, request, recommendation request, question, response, research, patronizing, recommendation, positive comment and negative comment (see Appendix, Table 6). Therefore, it is advised to conduct two tests: one in which the alarming variables are included and one in which the variables are excluded. But in this case it is not recommendable to exclude 11 out of 21 variables. A factor analysis will be executed anyway because it is the best option available at the moment. The results of the Factor analysis should be treated with attention.

4.1.3 Factor Extraction

In the first step linear components within the data set are determined. The SPSS output displays the eigenvalues associated with each factor (see Appendix, Table 7). Factor 1 has an eigenvalue of 2.63 and explains 12.52% of total variance. In general, 11 out of 21 possible factors have a bigger value than 1. According to Kaiser (1979), these 11 factors should be retained because they explain a substantial amount of variation. Another rule by Jolliffe (1972) suggests retaining all factors that have a minimum value of 0.7. This would result in the extraction of 13 Factors. Field (2013) argues that the Kaiser criterion is appropriate whenever the variable size is below 30 and when the communalities after extraction are greater than 0.7. Although the number of values criterion is fulfilled, the communalities after extraction do not show all values above 0.7. Likewise, a factor extraction based on the outcome of the scree plot suggests the extraction of 11 factors but this conclusion is also rather unreliable as a minimum sample size of 200 is suggested to draw conclusion from it (Field, 2013). In conclusion, the factor extraction could be done differently in this case. However, for this study Kaiser´s criterion will be applied and therefore 11 factors are extracted. The scree plot supports the extraction of 11 factors as well (see Appendix, Table 8). The 11^{th} factor has an eigenvalue of 1.01 and explains 4.82% of the total variance. Before extraction, 77% of total variance can be explained by the first 11 factors. After extraction this number decreases to 55% of total variance.

Table 2 shows the loadings of each variable on each factor.

Table 2. Factor Matrix[a]

	Factor										
	1	2	3	4	5	6	7	8	9	10	11
Expecting	.879		-.215		.265						
Consuming	.800		-.204		.256						
Suggestion	.560			.361	-.386	-.255	.337				
Forwarding	.473	.321			-.399						
Notification	-.429						.245		-.211		
Announcement	.400						-.358	-.328			
Response		.809			.429						
Chitchat		.583				.233	-.240	.214			
OrderviaTwitter		-.212	.841								
Confirmation		-.221	.759								
Patronizing				.776	.502						
NegativeComment				.363	.237						
Question				.249				.231			
PositiveComment				-.201		-.487		.334	.253		
Research				-.226		.455	.370		.422		
Request						-.301					
Answer							-.396		.218		.331
Comment									-.345		
Recommendation											
RecommendationRequest		.465								-.496	
Maintenance		.354			.217					.390	

Extraction Method: Principal Axis Factoring.

a. Attempted to extract 11 factors. More than 25 iterations required. (Convergence=,011). Extraction was terminated.

The highest correlation between a variable and factor 1 has the message intention expecting (0.88). Consuming shows also a high correlation of 0.8. Furthermore, announcement suggestion, forwarding and notification have a relative high correlation with factor 1. Factor 2 has a high correlation with response (0.81) and chitchat (0.58). Confirmation and order via Twitter are the main factor loadings for the third factor. Patronizing has a high correlation with factor 4 and a moderate correlation with the message intention negative comment.

4.1.4 Factor Rotation

In the next step, it was tried to maximize the variance of each factor. Therefore, factor rotation was applied. The total explain variance remains the same but the eigenvalues of the first four factors decrease, whereas the eigenvalues of the other factors increase.

Table 3. Rotated Factor Matrix[a]

	Factor										
	1	2	3	4	5	6	7	8	9	10	11
Expecting	.974										
Consuming	.905										
OrderviaTwitter		.892									
Confirmation		.801									
Patronizing			.935								
NegativeComment			.443								
Response				.808			.536				
Maintenance				.588							
Suggestion					.835						
Request					.402						
Forwarding					.338	.561					
Chitchat				.259		.541					.412
Question						.434					
RecommendationRequest							.745				
Announcement								.657			
Notification	-.214				-.224			-.483			
Research									.797		
PositiveComment										-.702	
Comment						-.262			-.202	.280	
Recommendation											
Answer											.566

Extraction Method: Principal Axis Factoring.

Table 3 shows this Rotated Factor Matrix. Factor 1 correlation with expecting (0.97) and consuming (0.91) increased and notification decreased. Based on the rotated correlations, the following factors with the corresponding message intentions can be classified:

Factor 1: Expecting, consuming

Factor 2: Order via Twitter, confirmation

Factor 3: Patronizing, negative comment

Factor 4: Response, maintenance

Factor 5: Suggestion, request

Factor 6: Forwarding, chitchat, question

Factor 7: Recommendation request

Factor 8: Announcement, notification

Factor 9: Research

Factor 10: Positive or general comment

Factor 11: Answer

5. CONCLUSION

5.1 Discussion

With the rise of Web 2.0 and the resulting social media platforms, companies can nowadays improve communication with customers and simultaneously lowering costs of marketing communication. However, firms need to know how effective their investments are in social media platform to be able to make improvements. This research concentrated on the most popular micro-blogging platform Twitter. Favier (2012) developed a model to estimate the effectiveness of Tweets published by B2C firms. He also customized the algorithms for B2B firms. Four variables were established and this research attempted to establish a measurement for message intention as it is believed that the message intention influences one of the four variables proposed in Favier´s model, namely trust. Klaver (2013) tested the proposed relationship but failed to show a significant relationship. However, Klaver’s (2013) categorization of message intention was done subjectively and this research conducted a factor analysis to test how message intentions of Tweets could be classified. Jansen et al. (2009) gave the basis for message intentions coding. In a sample of 159 B2B Tweets, Tweets were first distinguished by the proposed framework and afterwards a factor analysis was used to see possible patterns in the classification of message intentions.

First, two message intentions, supplement and missing, could be eliminated as no Tweet was identified to have this intention. It can be argued that supplement and missing are no relevant message intentions in a B2B context. It could be also interpreted that these two attributes rarely occur and that this sample size failed to catch Tweets with this message intention. In Jansen et al. (2009) these message intentions were also just found in 0.9% and 0.6% of cases.

Consequently, the factor analysis was conducted with 21 message intentions. The resulting factor extraction reduced the variable message intention to 11 Factors. The first factor correlates highly with expecting and consuming. Both variables include either the wish or the actual consumption of a product. Hence, the underlying intention is called: Product usage. The second factor is related to buying procedures as it explains the variability for order via Twitter and confirmation. If someone wants to place an order via Twitter, he or she is likely to get a summarized by a factor labeled: Order process. The third factor correlates with patronizing and negative comment. Both message intentions can have a persuasive effect on the reader. Sending out a negative comment about a product will most likely lead to a negative buying decision. Both message intentions have persuasive power. Therefore this factor can be summarized by: Persuasion/ Influence. The fourth factor correlates with response and maintenance. Tweets that are responding and aimed at maintenance are essential for customer relationship management (CRM). Suggestion and request are mainly explained by the next factor. In both of these message intentions the publisher reveals his opinion about a topic, brand or other objects. A Tweet that suggests something represents some kind of option and proposes some idea to the reader, whereas a request is more direct. Both message intentions exhibit a subjective opinion but differ in the degree of straightforwardness. In such a short message of 140 characters, the line between suggestion and request is rather blurred. So one might consider that the underlying intention is to try to make someone do something actively. The factor will be therefore labeled leading. Forwarding, chitchat and question do all provoke interactions. Consequently, the sixth factor is named interaction. The next factor is mainly correlated with recommendation request. Hence, this factor keeps its label. Tweets that were classified as notifications or announcements are mainly explained by factor eight. These attributes have in common that the sender wants to inform the receiver. Accordingly, the factor is labeled information. The next factor correlates highly with research. It is noteworthy, that in this sample 8.8% of Tweets were classified with a research message intention, whereas the sample of Jansen et al. (2009) contained just 0.1% research Tweets. It seems to be logical that in a B2B setting findings from scientific studies play a major role. Therefore, it seems to be legitimate to leave this factor with a single variable. Factor ten correlates with the message intentions positive comment and comment. The outcome of the last factor is surprising. Factor eleven correlates with answer. Logically one might assume that answering should also correlate with the same factor as response, so with Factor four (CRM). But the results do not support this assumption. One explanation could be that Jansen et al. (2009) categorized answer and response into different categories. In common language these words are synonyms but in this case responses and answers were distinguished. Responses are defined by giving unnecessary feedback and answers were defined as handling questions (Jansen et al., 2009). Given the Twitter environment the difference between unnecessary feedback and handling questions might have been difficult to distinguish. Especially in a B2B setting the raters might have not been able to distinguish correctly between a response and an answer. Concluding, Twitter message intentions can be classified according to the following framework:

Factor 1	Product usage
Factor 2:	Order process
Factor 3:	Persuasion/ Influence
Factor 4:	CRM
Factor 5:	Leading
Factor 6:	Interaction
Factor 7:	Recommendation request
Factor 8:	Information
Factor 9:	Research
Factor 10:	Positive or general comment

5.2 Implication

The results of this factor analysis and resulting interpretation of the factors implicates that Tweets published by B2B firms can be classified by 11 message intentions. These 11 factors explain 55% of total message intention variation. The first factor, product usage, has a factor loading of 1.9 and explains 9.2% total variance. This implies that the largest part of B2B Twitter marketing deals with specific products. Marketing managers of Intel and Oracle seem to primarily aim at developing brand awareness and increasing the demand for the product. This goal also holds for the next two factors, order process and persuasion/influence. Especially order process relates to specific products and persuasion/ influence aims at influencing buying decisions. The primary goal for the two factors is to influence or manage purchase decisions. In summary, it seems that the first three factors with the highest loadings, in total 27.1% aim at enhancing buying decision. It can be stated that 16.3% of Twitter messages are explained by the factors CRM, interaction, positive comment and answer. These four factors have in common that they integrate some kind of sender-receiver communication. Recalling the findings of Chen (2011) that Twitter users primarily seek for two-sided conversations, one could have expected that interactive communication, basically the four mentioned factors, would account for the largest share.

The reason that Oracle's and Intel's Tweets are focused on products could be that both companies are mainly operating in a B2B environment. As the primary customers are business partners, product related Tweets are more suitable to communicate a professional impression, whereas Tweets about random day-to-day activities are less of interest for the business partner or could even damage a brand's reputation. 27. 1 % of Tweets being related to products, CRM and persuasion is probably a strategic choice and pursued to meet overall marketing objectives as suggested by Kaplan and Haenlein (2010) and Singh et al. (2008).

In addition, this research implies that in a B2B setting fewer categories are necessary to classify message intentions of a Tweet compared to classifications in a B2C context as proposed by Jansen et al. (2008). To show why this difference exists was not part of this study. It might be the case that fewer classifications are sufficient because B2B firms follow different overall marketing strategies aimed at segmented partners with similar characteristics.

Comparing the factor analysis outcome to the classification applied by Klaver (2013), it can be stated that her assumption that the message intentions can be reduced was correct. But the method was not suitable for this sample. It is not appropriate to combine the message intentions into the five categories proposed by Jakobson (1960). Hence, it was not accurate to conduct a multiple regression analysis of message intention and trust. The outcome of this multiple regression analysis was that the correlation between message intention and trust were not significant. Therefore, a relationship between message intention and trust was rejected. However, based on these research findings, the relationship was not tested appropriately; therefore, message intention might indeed have an effect on trust as proposed by theory. Yet, this has to be tested in further research.

5.3 Limitations

The results must be interpreted according to the limitations of this research. The outcome of this study might be biased due to the following reasons:

First, the theoretical framework, including the elaboration of the variable message intention, is mainly based on B2C marketing literature. The 23 message intentions by Jansen et al. (2009) for example were framed mainly for message intentions generated in B2C research. But we do not know whether other message intentions should have been included in the framework. It might be the case that an important attribute of message intention was not considered in the B2C context but should have been included in a B2B context. Furthermore, several assumptions are not fulfilled to allow an appropriate interpretation of the factor analysis outcome. The sample size is not large enough to allow for distinctive factor extraction and the anti-image correlations are weak and indicate that a factor analysis might have not been appropriate for this data set. The missing 45% variance indicates that there is space for improvement. A reason for this explanation power could be the small sample size. With a bigger sample size the correlations between variables and factors might have shown a more distinctive picture.

5.4 Future Research

Although these limitations weaken the accuracy of the interpretation, it points out that a B2B message intention measurement scheme has still not been objectively established. Marketers need to understand in-depth the implications and possibilities to transmit a certain intention via a Twitter message, to achieve the highest possible ROI. The research has managed to give a suggestion how Twitter messages can be distinguished based on their intentions. The message schemes used by literature so far were barely published in a scientific journal. This indicates that a model to categorize message intentions should be addressed by future research. Furthermore, it was highlighted that the former tested relationship of message intention and trust are not trustworthy as the measurement was not accurate and subjective. The relationship test should be redone as theory implies an existing relationship. Further research should test the relationship of different message intentions and their influence on the dependent variables trust, sentiment and target of Favier (2012). Another interesting research topic could be derived from the assumption that the message content is more important than communication frequency (Kozinets et al., 2010). Even this sample has shown that some accounts published more Tweets than others. Certain message intentions might lead to a higher ROI although the account is less active. Likewise, the outcome suggests that the bigger part of the message intention entailed not two-sided communication. Chen (2011) however showed that Twitter users mainly want to interact and connect with others. Therefore, future research could test whether Tweets that encourage communication are more effective than product-related Tweets for B2B firms.

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8. APPENDIX

Table 4. Communalities

	Initial	Extraction
Announcement	.243	.494
Chitchat	.322	.614
Answer	.125	.339
Comment	.146	.252
Confirmation	.531	.664
Maintenance	.298	.356
Forwarding	.450	.597
Request	.209	.206
RecommendationRequest	.299	.564
Suggestion	.429	.849
Question	.186	.221
Response	.470	.976
Research	.183	.666
Patronizing	.264	.917
Recommendation	.131	.106
PositiveComment	.210	.543
OrderviaTwitter	.543	.816
NegativeComment	.212	.222
Notification	.272	.401
Consuming	.829	.840
Expecting	.840	.984

Extraction Method: Principal Axis Factoring.

Table 5. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.510
Bartlett's Test of Sphericity	Approx. Chi-Square	793.323
	df	210
	Sig.	.000

Table 6. Anti-image Matrices

		announcement	chitchat	answer	comment	confirmation	maintenance	forwarding	request	recommendationrequest	suggestion	question	response	research	patronizing	recommendation	positivecomment	Orderviatwitter	negativecomment	notification	consuming	expecting
Anti-image Covariance	announcement	.757	.060	-.105	.056	.024	.016	-.092	.056	.037	.068	.026	-.011	-.006	.074	-.066	.094	-.072	-.080	.189	.011	-.035
	chitchat	.060	.678	-.199	.095	.001	-.122	-.151	-.042	-.088	.025	-.148	-.041	.082	.066	.062	.098	.001	-.033	-.014	-.003	.020
	answer	-.105	-.199	.875	.009	-.003	.022	.090	.015	.002	.021	.047	.048	.022	-.007	.051	.034	.027	.026	.121	-.003	.010
	comment	.056	.095	.009	.854	.005	.002	.063	.018	-.012	.046	.051	.034	.172	-.005	.060	.198	.010	-.085	-.033	.003	.004
	confirmation	.024	.001	-.003	.005	.469	.002	.003	.001	.001	.006	-.001	.000	-.144	.004	.009	.007	-.326	-.005	-.001	.001	-.002
	maintenance	.016	-.122	.022	.002	.002	.702	.060	.115	.199	-.023	.021	-.300	.001	-.004	-.003	-.018	-.006	-.002	-.064	.003	-.011
	forwarding	-.092	-.151	.090	.063	.003	.060	.550	.119	-.063	-.263	-.124	-.003	.074	.079	.118	.071	.058	.030	-.008	.003	-.017
	request	.056	-.042	.015	.018	.001	.115	.119	.791	.088	-.225	-.023	-.170	.010	.037	.060	-.061	.033	.016	.046	-.003	.014
	recommendationrequest	.037	-.088	.002	-.012	.001	.199	-.063	.088	.701	.036	.048	-.299	-.016	-.021	-.030	-.034	-.019	-.009	-.062	.002	-.008
	suggestion	.068	.025	.021	.046	.006	-.023	-.263	-.225	.036	.571	.113	.057	.050	-.045	-.045	.108	-.071	-.049	.090	.007	-.024
	question	.026	-.148	.047	.051	-.001	.021	-.124	-.023	.048	.113	.814	.034	.022	-.221	-.114	.028	-.015	.088	.006	.002	.002
	response	-.011	-.041	.048	.034	.000	-.300	-.003	-.170	-.299	.057	.034	.530	.036	.005	.046	.075	.010	.006	.098	-.002	.009
	research	-.006	.082	.022	.172	-.144	.001	.074	.010	-.016	.050	.022	.036	.817	.045	.128	.182	.117	-.008	-.034	.001	.005
	patronizing	.074	.066	-.007	-.005	.004	-.004	.079	.037	-.021	-.045	-.221	.005	.045	.736	.135	.065	.010	-.311	.042	-.001	.001
	recommendation	-.066	.062	.051	.060	.009	-.003	.118	.060	-.030	-.045	-.114	.046	.128	.135	.869	.156	.037	-.097	.028	-.015	.022
	positivecomment	.094	.098	.034	.198	.007	-.018	.071	-.061	-.034	.108	.028	.075	.182	.065	.156	.790	.013	-.017	.091	.001	.007
	Orderviatwitter	-.072	.001	.027	.010	-.326	-.006	.058	.033	-.019	-.071	-.015	.010	.117	.010	.037	.013	.457	.019	.049	-.003	.013
	negativecomment	-.080	-.033	.026	-.085	-.005	-.002	.030	.016	-.009	-.049	.088	.006	-.008	-.311	-.097	-.017	.019	.788	.034	-.001	.009
	notification	.189	-.014	.121	-.033	-.001	-.064	-.008	.046	-.062	.090	.006	.098	-.034	.042	.028	.091	.049	.034	.728	-.010	.042
	consuming	.011	-.003	-.003	.003	.001	.003	.003	-.003	.002	.007	.002	-.002	.001	-.001	-.015	.001	-.003	-.001	-.010	.171	-.148
	expecting	-.035	.020	.010	.004	-.002	-.011	-.017	.014	-.008	-.024	.002	.009	.005	.001	.022	.007	.013	.009	.042	-.148	.160
Anti-image Correlation	announcement	.653[a]	.083	-.129	.070	.041	.022	-.142	.073	.050	.103	.033	-.017	-.008	.100	-.082	.121	-.122	-.104	.255	.030	-.101
	chitchat	.083	.593[a]	-.258	.125	.002	-.177	-.247	-.057	-.128	.040	-.199	-.069	.110	.093	.081	.134	.001	-.046	-.021	-.008	.060
	answer	-.129	-.258	.404[a]	.010	-.005	.028	.130	.018	.003	.030	.056	.070	.025	-.009	.058	.041	.042	.032	.152	-.007	.026
	comment	.070	.125	.010	.503[a]	.008	.003	.092	.022	-.015	.066	.061	.051	.206	-.007	.070	.241	.016	-.103	-.042	.009	.010
	confirmation	.041	.002	-.005	.008	.500[a]	.004	.006	.001	.002	.011	-.001	-.001	-.233	.007	.014	.011	-.705	-.008	-.002	.002	-.008
	maintenance	.022	-.177	.028	.003	.004	.388[a]	.097	.154	.283	-.036	.027	-.491	.001	-.005	-.004	-.024	-.011	-.003	-.090	.007	-.034
	forwarding	-.142	-.247	.130	.092	.006	.097	.556[a]	.180	-.102	-.469	-.186	-.006	.111	.125	.171	.108	.117	.046	-.012	.011	-.056
	request	.073	-.057	.018	.022	.001	.154	.180	.357[a]	.118	-.335	-.029	-.262	.012	.048	.072	-.078	.055	.021	.060	-.009	.038
	recommendationrequest	.050	-.128	.003	-.015	.002	.283	-.102	.118	.409[a]	.057	.064	-.490	-.021	-.030	-.038	-.046	-.034	-.012	-.087	.005	-.023
	suggestion	.103	.040	.030	.066	.011	-.036	-.469	-.335	.057	.547[a]	.166	.104	.073	-.069	-.063	.161	-.139	-.073	.139	.024	-.080
	question	.033	-.199	.056	.061	-.001	.027	-.186	-.029	.064	.166	.401[a]	.052	.026	-.286	-.136	.035	-.025	.110	.008	.006	.006
	response	-.017	-.069	.070	.051	-.001	-.491	-.006	-.262	-.490	.104	.052	.461[a]	.054	.008	.067	.115	.021	.009	.157	-.006	.031
	research	-.008	.110	.025	.206	-.233	.001	.111	.012	-.021	.073	.026	.054	.379[a]	.058	.152	.226	.191	-.010	-.044	.003	.015
	patronizing	.100	.093	-.009	-.007	.007	-.005	.125	.048	-.030	-.069	-.286	.008	.058	.422[a]	.169	.085	.018	-.409	.058	-.003	.004
	recommendation	-.082	.081	.058	.070	.014	-.004	.171	.072	-.038	-.063	-.136	.067	.152	.169	.322[a]	.188	.059	-.117	.035	-.040	.058
	positivecomment	.121	.134	.041	.241	.011	-.024	.108	-.078	-.046	.161	.035	.115	.226	.085	.188	.429[a]	.022	-.021	.119	.004	.019
	Orderviatwitter	-.122	.001	.042	.016	-.705	-.011	.117	.055	-.034	-.139	-.025	.021	.191	.018	.059	.022	.484[a]	.031	.085	-.011	.049
	negativecomment	-.104	-.046	.032	-.103	-.008	-.003	.046	.021	-.012	-.073	.110	.009	-.010	-.409	-.117	-.021	.031	.478[a]	.045	-.002	.026
	notification	.255	-.021	.152	-.042	-.002	-.090	-.012	.060	-.087	.139	.008	.157	-.044	.058	.035	.119	.085	.045	.695[a]	-.027	.122
	consuming	.030	-.008	-.007	.009	.002	.007	.011	-.009	.005	.024	.006	-.006	.003	-.003	-.040	.004	-.011	-.002	-.027	.570[a]	-.893
	expecting	-.101	.060	.026	.010	-.008	-.034	-.056	.038	-.023	-.080	.006	.031	.015	.004	.058	.019	.049	.026	.122	-.893	.574[a]

a. Measures of Sampling Adequacy(MSA)

Table 7. Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.630	12.524	12.524	2.400	11.430	11.430	1.929	9.185	9.185
2	2.035	9.689	22.214	1.720	8.189	19.618	1.477	7.036	16.221
3	1.789	8.518	30.732	1.525	7.263	26.882	1.168	5.562	21.783
4	1.552	7.389	38.121	1.207	5.746	32.628	1.120	5.331	27.114
5	1.407	6.702	44.823	1.098	5.228	37.856	1.109	5.279	32.393
6	1.329	6.329	51.152	.817	3.893	41.749	.969	4.615	37.008
7	1.254	5.972	57.124	.752	3.582	45.331	.920	4.379	41.387
8	1.162	5.531	62.655	.646	3.074	48.405	.883	4.207	45.594
9	1.073	5.108	67.763	.603	2.872	51.277	.754	3.591	49.185
10	1.034	4.925	72.688	.505	2.405	53.682	.739	3.518	52.703
11	1.012	4.820	77.508	.354	1.687	55.369	.560	2.666	55.369
12	.867	4.127	81.635						
13	.769	3.662	85.297						
14	.609	2.900	88.197						
15	.572	2.723	90.920						
16	.503	2.393	93.313						
17	.419	1.996	95.309						
18	.346	1.647	96.956						
19	.296	1.411	98.367						
20	.256	1.218	99.585						
21	.087	.415	100.000						

Extraction Method: Principal Axis Factoring.

Table 8. Scree Plot