Exploring the effect of user engagement in online brand communities: Evidence from Twitter

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Abstract

Social media such as forums, blogs and microblogs has been increasingly used for public information sharing and opinions exchange nowadays. It has changed the way how online community interacts and somehow has led to a new trend of engagement for online retailers especially on microblogging websites such as Twitter. In this study, we investigated the impact of online retailers' engagement with the online brand communities on users' perception of brand image and service. Firstly, we analysed the overall sentiment trends of different brands and the patterns of engagement between companies and customers using the collected tweets posted on a popular social media platform, Twitter. Then, we studied how different types of engagements affect customer sentiments. Our analysis shows that engagement has an effect on sentiments that associate with brand image, perception and customer service of the online retailers. Our findings indicate that the level, length, type and attitude of retailers' engagement with social media users have a significant impact on their sentiments. Based on our results, we derived several important managerial and practical implications.

Keyword: social media, microblogging, engagement, online community, online retailing

1 Introduction

Social media is no longer trivial and optional. In recent years, social media has emerged into huge proliferation spurred by the growth of the Internet and mobile technologies. It has been making its way into corporations, media, education and other settings by providing a highly interactive platform where people can create, share, exchange information and engaging way of online interaction. Microblogging service such as Twitter is one of the most popular social media platforms that have become a rich source of information and an effective communication tool with hundred millions of users (Barnaghi, Breslin, & Ghaffari, 2016; Madani, Boussaid, & Zegour, 2015). Twitter enables users to create, send and read short messages called tweets with 140-characters and talk about everything and anything happening in their daily and work activities (Arakawa, Kameda, Aizawa, & Suzuki, 2014). It has been extensively used by companies such as Amazon to interact with customers and develop the corporate reputation and brand image. Leveraging of this new media requires companies to constantly monitor information related to their brands. To add on that, statistic shows that global retailers such as Amazon, Etsy and Nike were on the list of the most popular retail and consumer merchandise brands on Twitter as of May 2016 (see Figure 1).

In particular, a growing number of customers and businesses have engaged in social media on brand-related activities such as creating and spreading information and content about brands (Muntinga, Moorman, & Smit, 2011). At this time, an online community or what we referred as brand community in this study comes into existence. This community normally shares similar interests about brands, discusses and interacts with each other about brands that they are interested in (Jansen, Zhang, Sobel, & Chowdury, 2009). They can facilitate functions such as reply, retweet, like, and share information from others and spread directly with people within the community. According to a recent study by Nagy and Midha (2014), almost 80% of Twitter users were found habitually mentioned brands in their tweets. It indicates that companies could now start using Twitter to engage with public for numerous purposes including brands enhancement, product marketing and innovation. For the past years, 72% of large companies have already deployed social media based networks in their operations (Meske & Stieglitz, 2013). In principle, the emergence of microblogging platform has given opportunity to customers to engage and expressing their thoughts towards the brands. It is something that companies must pay more attention on online opinions about products and services as consumers' insights generated on social media can facilitate company in their marketing, brand positioning and product development (Zabin & Jefferies, 2008).

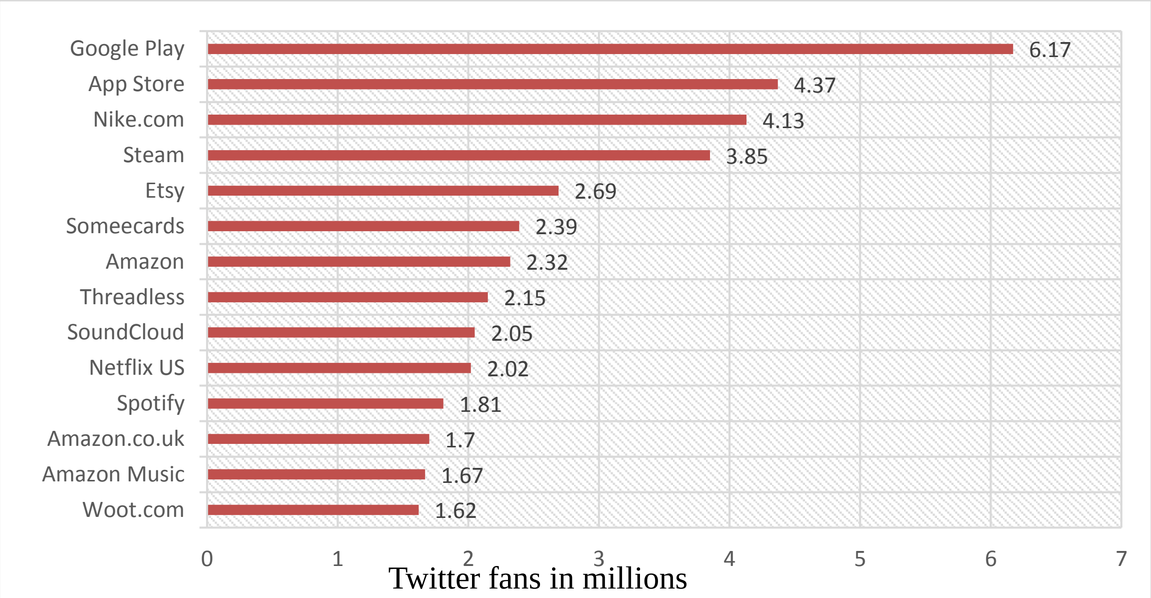


Figure 1. Leading retail and consumer merchandise brands on Twitter (Statista, 2016)

The key importance of Twitter is that it provides real-time data for public to express opinions and ideas as a well-suited source for opinion mining and sentiment popularity detection (Pang & Lee, 2008). The reason why companies should concern about social media is because tweets from the public would be a reflection of public sentiments towards their brands due to positive and negative influences on other customers as well as potential customers in particular. Tweets can significantly affect public perception of the brand image and how companies engage with the social media and handle customer's tweets could also influence public opinions. As we know, tweets, opinions, reviews and comments that have been published online could influence existing and new customers' decision making (Stieglitz & Dang-Xuan, 2013; Zeng, Chen, Lusch, & Li, 2010). The contents of the tweets has become vital for global brands for their branding strategy (Okazaki, Díaz-Martín, Rozano, & Menéndez-Benito, 2015). Global brands like Tesco, Starbucks and Apple require insights and interactions with their customers on the Internet to keep up the evolving consumer behaviour facilitated by the technological advancement. However, customer engagement on online platform has been relatively understudied (Okazaki et al., 2015) in contrast to rich studies on customer interactions on traditional platforms. In fact, there are only few literature on customer engagement of online retailing since most of prior studies focused on related topics such as online brand community on webpages and brands participation on social networking sites (Okazaki et al., 2015). Therefore, this study attempts to fulfil this gap by exploring how the engagement with the brand community (e.g. Twitter) affects online retail brands.

Engagement does not only influence customers but also has implications for companies in consideration of their brand building and product development. It should be considered as a necessity since customers are now increasingly publishing their opinions and experiences on digital platforms and that, will accumulate a huge amount of customer reviews and perceptions of products or service online (Horrigan, 2008). Customers' opinions and comments on social media is one of the powerful sources that can facilitate companies to improve their brands image and increase user satisfaction, in return for an improvement in reputation and overall customer satisfaction over time. However, many companies are lagging behind of using social media as a tool to improve their branding and need to be shown some lights of how social media could help to engage with the new generation of consumers. Given the relevance of engagement shown by other studies, we seek to fill the gap by exploring the relationship of sentiment of tweets articulated on microblogging site and its dissemination of information.

Thus, our study is designed to explore the relationship and trends of engagement between companies and customers that will be helpful and useful for practitioners. There are numerous concerns on how this brand community will impact company retail businesses. Hence we investigate,

1) What are the overall sentiment trends of online retail brands on the social media?
2) What are the patterns of engagement between companies and customers on the microblogging platform?
3) How does the engagement affect the users' sentiment on the social media?

To address these research questions, five popular online retail brands were selected and tweets that mentioned these brands over a month period were downloaded and analysed. The expressions or sentiments of these tweets were evaluated and categorised to determine the collective characteristics of tweets expression towards the brands. This analysis provided insights into the overall sentiments and trends in brand microblogging on social media. Further, Amazon UK was selected to examine how the company communicates and engages with customers through its Twitter account. 22,519 posted tweets were analysed and the analysis provided insight into patterns of the engagement between company and customers. It is then followed with the examination of how different types of responses from Amazon affect the sentiment of Twitter users throughout the conversations and the overall pattern of emotional dynamic transitions.

The remaining of the paper is organised as follows. Section 2 reviews the important literature relevant to this study. Section 3 outlines the research methods adopted in this study. Section 4 gives an overview of the analysis results. Finally, we provide a discussion of our results, implications of the research, limitations, future research and conclude the paper.

2 Literature Review

Social media such as microblogging services is changing the way people interact and search for information and opinions on online digital platforms. The term social media generally refers to web sites and online tools that facilitate interactions between users by providing them with opportunities to share information, opinions and interests (Hansen, Shneiderman, & Smith, 2010). Interactions facilitated by social media have become an integral part of people's daily lives in contemporary society and a powerful instrument for promoting interactions between customers and online retailers in business sector. Several studies demonstrated that social media has changed the way organizations or companies interact with their customers and also in some ways changed the way business is conducted (Leeflang, Verhoef, Dahlström, & Freundt, 2014; Patino, Pitta, & Quinones, 2012; Schultz & Peltier, 2013). Businesses start to apply Internet technologies including social media to run its operations since more people in recent years prefer to shop online for convenience and better prices (To & Ngai, 2006).

2.1 Engagement and social media

Engagement in social media is widely termed as communication or interaction among users on social media platforms. Brodie, Ilic, Juric, and Hollebeek (2013) argued that it can also be referred to a psychological state and process that could lead to customer loyalty. In our own interpretation, engagement can be conceptualised as the state of being engaged, connected, involved and interested in something. In this paper, we focused on microblogging, that is referred as a simple online tool to blog a simple and small statement for communication in a real-time fashion (Bae & Lee, 2012; Castillo, Mendoza, & Poblete, 2013). Several studies on social media and engagement show a diverse area of implementations (Chae, 2015; Ebner, Lienhardt, Rohs, & Meyer, 2010; Golbeck, Grimes, & Rogers, 2010; Hennig-Thurau, Wiertz, & Feldhaus, 2014; Meske & Stieglitz, 2013). In government sector for example, public organizations have started to explore the potential of social media as a mediating technology for facilitating their relationships with clients (Effing, Hillegersberg, & Huibers, 2011). Majority of the previous works focused on studying social media applications in specific context such as politics (Stieglitz & Dang-Xuan, 2013), education (Ebner et al., 2010; Williams, Terras, & Warwick, 2013) and health sector (Beykikhoshk, Arandjelović, Phung, Venkatesh, & Caelli, 2015; Ji, Chun, Wei, & Geller, 2015).

Among the various others, engagement between customers and enterprises like retailers has attracted a lot of attention recently. In a case study of IKEA, Okazaki et al. (2015) examined customer engagement on Twitter and demonstrated that engagement happened in three different forms including objective, subjective and knowledge sharing. Their unique contributions offer an insight to understand engagement on social media network. Armstrong and Hagel (2000) highlighted that engagement through online communities enable businesses or online retailers to expand their markets. In fact, it has become a new business communication channel that allows companies to interact and get engaged with Internet users or customers (Lin & Lee, 2006).

The existing body of literature offers various insights about the role of engagement on social media (Gorry & Westbrook, 2011; Hudson & Thal, 2013; Zheng, Cheung, Lee, & Liang, 2015). Among them, Zheng et al. (2015) showed that user engagement on Facebook influenced the loyalty of customers to the business or brand. Prior research also revealed social media as important tools that enhance engagement and ease online activities (Komito, 2011; Ransbotham & Kane, 2011; Yang, Tang, Dai, Yang, & Jiang, 2013). Also, the advent of social media has led to an explosion of interest in customer engagement and the opportunities of developing close relationship with customers (Gorry & Westbrook, 2011; Hudson & Thal, 2013). Nagarajan, Purohit, and Sheth (2010) and Boyd, Golder, and Lotan (2010) studied about engagement through retweeting behaviour on Twitter pertaining to real world events and public timeline. Macskassy and Michelson (2011) on the other hand, investigated the retweeting behaviour on Twitter by comparing retweet behaviour models and found the factors that motivate people for propagate or diffuse information on social media.

2.2 Social media and brands management

Social media also appears as a platform that affects company's branding given that customers speak of brand satisfaction, image and awareness on social media. As said by Scott Silverman, the director of Internet retailing at the National Retail Federations, "Branding is a tremendous advantage and cross-promoting it over the Internet and physical stores will open up new selling opportunities" (Bernstein, Song, & Zheng, 2008). According to Brown, Barry, Dacin, and Gunst (2005), microblogging (e.g. Twitter) has influenced in branding area and brand managers were required to actively engage in social media as users communication has been associated with brand satisfaction. In other studies, Gensler, Völckner, Liu-Thompkins, and Wiertz (2013) and Sashi (2012) highlighted that communities formed on social media through conversations and dispersed of information help build brand credibility and reputation. Several studies mentioned about how customers utilised social media to interact with companies and their brands such as the usage of Facebook pages to demonstrate customer engagement (Gironda & Korgaonkar, 2014; Muk & Chung, 2014), customer retweet behaviour (Kim, Sung, & Kang, 2014) and consumer-generated brand content across Facebook, YouTube and Twitter platforms (Smith, Fischer, & Yongjian, 2012).

Some studies have examined the relationship between social media and brands. He, Wu, Yan, Akula, and Shen (2015) examined the relationship between social media sentiments and business performance. They then proposed a framework on enhancing marketing intelligence. Chang, Hsieh, and Tseng (2013) performed an analysis related to brands in order to reveal role of communication in influencing brand community members' decisions. They discovered that electronic word-of-mouth (eWOM) affecting brands sentiments thus affecting the decisions. Laroche, Habibi, Richard, and Sankaranarayanan (2012) investigated the effects of brand communities on the main community elements, brand trust and brand loyalty. They found that brand communities based on social media have positive effects on community markers as well as on value creation practices such as social networking and brand use. Habibi, Laroche, and Richard (2014) developed a model to examine how customer relationship with brand community's elements (e.g. brand, product, company) on social media has significantly influenced on brand trust. Meske and Stieglitz (2013) examined the adoption of social media in small and medium-sized enterprises and found a way to overcome obstacles that limit its wider adoption. Chamlertwat, Bhattarakosol, Rungkasiri, and Haruechaiyasak (2012) proposed a system based sentiment analysis to analyse customer opinions.

The reason for brand getting affected by the engagement on social media may be drawn from emotions put by customers when they mentioned brand names in their tweets. Emotions involved on social media become a concern when they involve two parties such as customers and companies and often reflect the state of individuals (Barnaghi et al., 2016). Jansen et al. (2009) studied Twitter as a tool to examine the effectiveness of eWOM advertising by investigating the structure of postings and the change in sentiments or emotions. Huberman, Romero, and Wu (2008) examined social interactions on Twitter and Kim, Bak, and Oh (2012) investigated the emotional transitions that influence the conversation partners and pattern in overall emotional exchange. In another study, Roshanaei and Mishra (2015) studied the behavioural attributes of social engagement and proposed a list of emotional states that can be used to improve future interactions.

Another strand of literature has revealed why companies using social media to promote products and services. Among them, Zhou and Duan (2015) analysed data from Download.com and Amazon.com to investigate the impact of WOM to sales outcome. They found that external WOM (third party websites) moderated the sale outcome role of internal WOM (the retail websites). He, Zha, and Li (2013) demonstrated that social media competitive analytics facilitates organisations to identify the strengths and weaknesses of their products and expands organisations to enhance business effectiveness.

2.3 Sentiment analysis in social media research

Sentiment analysis is a growing area of natural language processing (NLP) (Esuli & Sebastiani, 2010; Hatzivassiloglou & McKeown, 1997) and it forms a semantic interpretation in linguistic sciences. It has been widely used in linguistic and machine learning studies with various classifier and language models (Pang & Lee, 2008). In this study, sentiment analysis was chosen because the character limitations of Twitter data and the informal language used on the platform make it diverse from other analyses on news page or online reviews. The combination of text, emoticons and hashtag in a text with length limit of characters works well with sentiment analysis since other neuro-linguistic programming solutions are unlikely to work well in this kind of condition and limitation (Katz, Ofek, & Shapira, 2015). The data is also publicly available for researchers. Large number of publicly available tweets and its real-time nature is believed ideal for sentiment classification (Ji et al., 2015).

Sentiments are closely related to how people behave and different context of relationships have been emerged from it. Mining sentiment on Twitter provides a prodigious potential that enables researchers to understand various human beliefs and behaviour better with its rich sources and great accessibility (Katz et al., 2015). Stieglitz and Dang-Xuan (2013) performed sentiment analysis technique to mine more than 165,000 tweets in examining the relationship of social media content with user's behaviour of sharing information. They found a significant relationship between emotional Twitter messages and retweet behaviour of the users. Ji et al. (2015) analysed tweets sentiments on public health concern: epidemic, clinical science and mental health and proposed a tool for disease monitoring that can be used by public health specialist. Lee et al. (2013) conducted sentiment analysis to analyse tweets about MyStarbucksIdea. They have come out with a recommendation system from the sentiment extracted and give firms ideas for improvement and innovation. Asur and Huberman (2010) conducted sentiment analysis using LingPipe linguistic package to predict revenues for box-office movies based on viewers' tweets.

2.4 Summary

Collectively, these studies showed that community on social media is increasingly becoming relevant and vital as it becomes more rampant nowadays in public and businesses sector simultaneously. However, we found that most of studies in the existing literature mainly focused on engagement in government, politics and education but little in online retailing especially those that use microblogging platform like Twitter. This argument is supported by Oliveira, Huertas, and Lin (2016) that highlighted there were less prior works on the engagement between social media users and companies. Therefore, our research will utilise data from microblogging platform that have different structures and patterns from the normal well-formed platforms. This complements to the existing literature that often use online reviews and Facebook as the sources of data. Besides, our attempt is different from previous studies because we conducted different analysis by focusing more on emotional transitions involved in between customers and companies through various types of indicators such as length of tweet, the number of replies, the attitude of sentiment and media types and this will be very different from other studies.

3 Research Methodology

Research design for this study is displayed in Fig. 2. Dataset was obtained by crawling from Twitter. Five leading brands were selected based on brands ranked in the Top 10 on the UK's retailer websites. Tweets were extracted using Twitter Search application programming interface (API) and were cleaned to remove the unnecessary noise and duplications. Sentiment analysis was executed to obtain research insights.

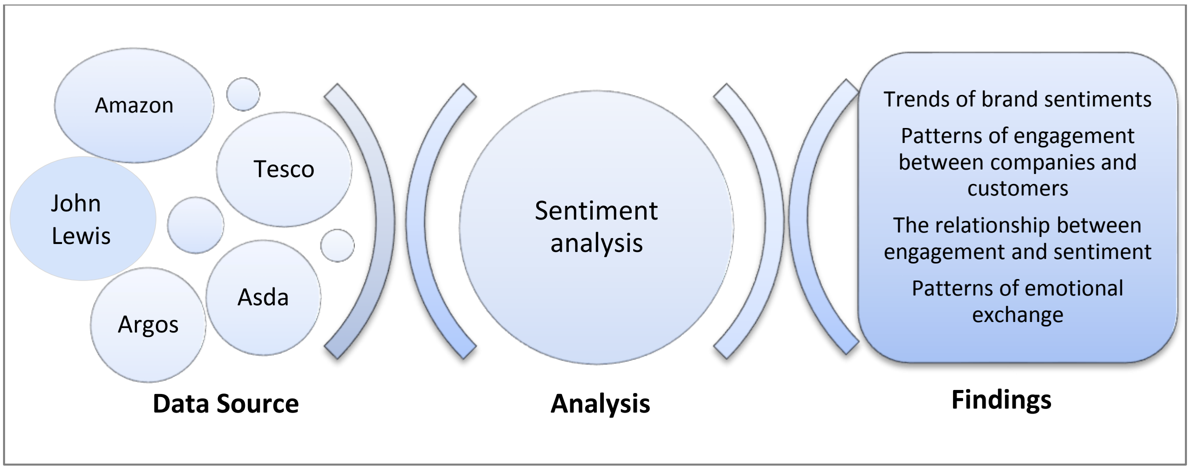


Figure 2. Research design

3.1 Data collection

Tweets were collected using NodeXL Pro (Version 1.0.1.362) through Twitter search API for one-month period from 10 April to 10 May 2016. NodeXL is a program that enables researchers to perform keyword searches to download social media comments. The program offers Twitter API but because of the API limitation of no access to historical data, only real-time recent tweets were retrieved and used in this study. Using this program, tweets were extracted from five leading retailers in the UK (Amazon UK, Tesco, Argos, John Lewis and Asda) over a period of one month and that gave us 76,166 tweets. Customary keywords were submitted using keyword: [brand name] lang:en since:[start date] until:[end date]. Using Amazon as an example, the search term used was @amazonuk lang:en since:2016-04-10 until:2016-04-11. The same process was repeated for all brands as shown in Figure 3. Twitter data were chosen in this study because of rich and varied source of information provided including tweet content, number of followers and amount of retweets.

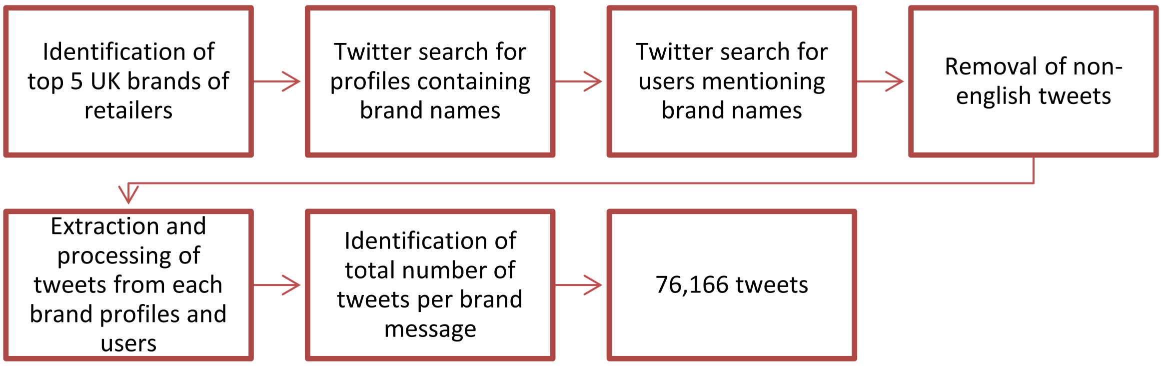


Figure 3: Data collection summary

3.2 Data analysis

In this study, tweets that mentioned a brand name such as expression of opinion and brand were collected and cleaned to analyse the sentiment of each tweet. The analysis was conducted to classify the sentiment based on their polarity. To classify the polarity, the adopted program computes the occurrence frequency of the word in a large annotated corpus of text (Medhat, Hassan, & Korashy, 2014). For instance, if the positive word occurs more frequently in a text, the polarity will be positive and if more negative words are frequent, it will be polarity negative text. Otherwise, the polarity will be neutral if the text has equal frequencies of positive and negative words.

In this study, sentiment analysis was conducted using SentiStrength, a program that compares social media text against a lexicon-based classifier of sentiments. This program has received much attention in recent years because of its consistent performance for sentiment detection on social media data (Saif, He, Fernandez, & Alani, 2016). It measures the strength of sentiments by giving scores ranging from +5 to -5 with positive numbers indicate favourable attitudes while negative numbers indicate negative attitudes (see Table 1). Also, the program provides a separate score for negativity and positivity of the sentiments and gives the average sentiment strength of the tweet. The rationale for this dual score is the emotion psychologists believe that humans can feel positive and negative emotions at the same time (Norman et al., 2011). They believed that there might be separable systems in human brain that are associated with current processing of positive and negative affordances hence the prevalence of mixed emotions. The examples of words included in this program dictionary consist of: positive sentiments - good, happy, great, fantastic, wonderful, lovely, excited, lovely, nice, and kind; negative sentiments - terrible, lazy, crazy, hurt, bad, and disappointed. Taboada, Brooke, Tofiloski, Voll, and Stede (2011) used this program in their study to identify the strength of sentiment using 10 scores of sentiment besides polarity detection. In this study, we summarised the codes into three categories which are positive, neutral and negative as shown in Table 1.

Table 1. Coding scheme in SentiStrength

Score	**Code**	**Description**
-5, -4, -3, -2	Negative	Extreme, strong, moderate and mild negative sentiment
5, 4, 3, 2	Positive	Extreme, strong, moderate and mild positive sentiment
-1, 0, 1	Neutral	No sentiment, no negativity and positivity

To explore the patterns of engagement between companies and customers on microblogging platform, a case study on a specific brand was conducted and tweets between the company's Twitter account and customers that mentioned about that specific brand were analysed. Amazon UK was selected for this case study as it is one of the most popular brands mentioned on social media. In this study, we focus on the Twitter account of Amazon UK, the UK-based online retailers. Amazon UK is active on Twitter through username: @amazonuk and as to date, has 1.69 million followers. The company first opened its Twitter account on October 2010 with the profile said "Follows Amazon.co.uk and we'll deliver news, giveaways and deals straight to your timeline. For customer support, @AmazonHelp are here 24/7 every day." AmazonHelp is another account of Amazon that is responsible to answer customers' queries and complaints. Data were collected from both Amazon UK and AmazonHelp Twitter accounts for a month period and that gave us 22,519 tweets. The twittered frequency, word frequency and time were measured and patterns of communication were interpreted.

To explore the relationship between engagement and sentiment on social media and the patterns of overall emotional exchange, data were collected using NodeXL and sentiment analysis was conducted over tweets from @amazonhelp. The influence of level, length, media types and sentiment of tweets from @amazonhelp on the change of emotion in customers' sentiments was evaluated. More details will be explained in the result section.

4 Results

4.1 Overall trends of brand sentiment

4.1.1 Statistical approach on brand sentiment

From an analysis of 76,166 tweets collected for five brands of UK online retailers, sentiment analysis was conducted for each brand, as shown in Figure 4. A detailed analysis was performed for the specific tweets that make up this sentiment. Of the 15,350 tweets expressing sentiment, 12% of tweets show positive sentiments and a significant amount of tweets (8%) has negative sentiments. As shown in Figure 4, 80% of the overall tweets that mentioned those brands were neutral in sentiment. This indicates that people use Twitter for general information, asking questions, other information-seeking and –sharing activities about brands or products, in addition to expressing opinions about brands or products

In this study, the studied brand tweets were statistically compared to identify the differences among brands. All brands received more positive tweets about their products compared to negative tweets. Lowest percentage of negative sentiments was detected from Amazon and highest percentage of positive tweets was from Argos. Interestingly, the highest percentage of negative sentiments was also from Argos. It shows that the sentiments for Argos are more diverse and it is more likely because it sells a wide range of products from gadgets, electricals, clothing, sports equipment, furniture, toys to jewelleries. Besides, there were similar patterns and consistent range of percentages of negative sentiments discovered from across the five brands. This shows that the portion of negative sentiments is believed to be reliable and significant. This differentiation among brands within an industry section shows that microblogging is a promising measure for companies to use for competitive intelligence such as for developing better products based on the knowledge discovered on social media. It is important for companies to know people's opinions about their brands and products for brand management. Companies can use microblogging as a part of their marketing campaigns in an attempt to differentiate themselves from their competitors. It is critical to recognise company's position in the market especially in its own industry sector and to compare with its competitors.

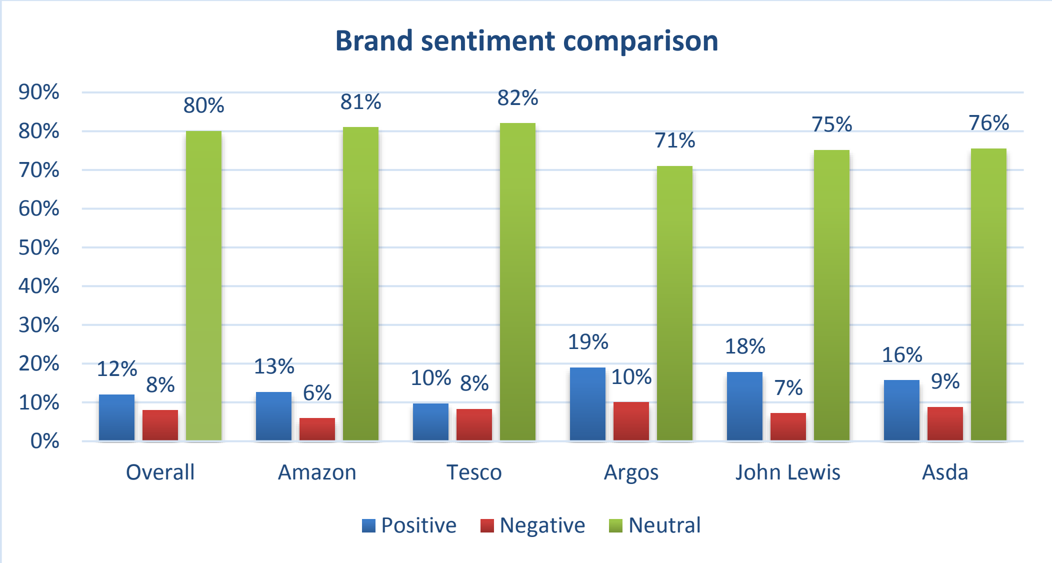


Figure 4. Brand sentiment comparison

To understand public tweets about the brands, Table 2 reports the means and standard deviations of positive, negative and neutral tweets related to the selected brands. All standard deviations were considerably smaller than their means for positive tweets and were in the same range as all of them are above the standard deviation of 0.3. The means of positive tweets for all brands varied from 2.107 to 2.21; and the standard deviation varied from 0.326 to 0.440. Means and standard deviations indicate some differences in the tweets. The lower the standard deviation, more significant the data is and greater precision. As shown in Table 2, standard deviation of Asda was the lowest and followed by Tesco and John Lewis for positive sentiments. For negative sentiments, standard deviation of Amazon was the lowest showing that their scores are the most significant compared to others.

Table 2. Means and standard deviations of tweets for all brands

By sentiment score	Amazon		Tesco		Argos		John Lewis		Asda	
	Mean (μ)	Std. Dev (σ)	Mean (μ)	Std. Dev (σ)	Mean (μ)	Std. Dev (σ)	Mean (μ)	Std. Dev (σ)	Mean (μ)	Std. Dev (σ)
Positive	2.21	0.440	2.116	0.328	2.197	0.4138	2.140	0.367	2.107	0.326
Negative	-2.306	0.505	-2.378	0.553	-2.364	0.549	-2.366	0.563	-2.460	0.635
Neutral	0.096	0.601	0.153	0.661	0.113	0.685	0.155	0.644	0.133	0.651

Note: Max (positive, negative, neutral) score = (4, -2, 1). Min (positive, negative, neutral) score = (2, -4, -1)

4.1.2 Word frequency

Word frequency was counted by examining the most frequently mentioned words for each brand. These words derived from the cumulative words of the tweet contents. The results are illustrated in Figure 5 where it shows the top 100 most frequent words and the frequency was encoded according to the font size. The brand name itself was removed from the frequency calculation as they are often most frequently quoted by the users. The similar mentioned words were calculated across five brands and the analysis showed that 29 similar pattern of words (e.g. buy, good, great, like, love, more, please, really, thanks, today, want) were consistently mentioned in each brand dataset. Sensing from this, words such as ‘thanks’, ‘good’, ‘like, and ‘love’ that emerged in all series of dataset lead our research to perform sentiment analysis over these tweets. ‘Thanks’ demonstrates the sentiment embraced by the brand companies and is related to branding image and customers’ perception towards them. In another way, it shows that customers were pleased and satisfied with the service they received. This sentiment in some way reinforces on why we want to analyse sentiment of tweets mentioned by customers about the brands.

Another interesting finding is that other rival groceries brands e.g. Sainsbury’s and Morrisons are frequently mentioned along with Tesco and Asda. It shows that, in this competitive industry sector, customers are most likely doing price and service comparison between different brands in their tweets. People tends to compare things they want to or have purchased, so it is reasonable to expect that they were talking about that respective brand products and at the same time try to make comparison with other brands. The figure also reveals the presence of large numbers of words related to online retailers’ operations, promotions, sentiment or even other rival brands such as ‘FastTrackFriday’, ‘delivery’, and ‘service’. It is not surprising as delivery and service are among the most important factors influencing customers purchasing decision when they shop online.

(a) Amazon

(b) Tesco

(c) Argos

(d) John Lewis

(e) Asda

Figure 5. Word Cloud of 100 most frequent words for each brand

4.2 Patterns of engagement

For engagement patterns between brands, customers and potential customers, we explored two aspects of the engagement patterns: frequency and time. This measures how often Amazon and its customers tweet each other and when they tweet.

4.2.1 Frequency

In terms of frequency, Figure 6 informs us that Amazon merely posted 75 tweets in the period of study. The highest number of tweets recorded was five on the 20th April 2016. Whilst the account cannot be considered as a really active account, they tweeted everyday within the period of study in various frequencies except on the 2nd May 2016. It was an exception since it was a public Bank Holiday in the UK for that date. Since @amazonuk is the main account, the content of the tweets is mostly about product information, promotion and advertising and this probably triggered why there were not many retweets over those types of tweets. However, it turned into a different situation when they hold and posted a promo or contest on their account. Highest amount of retweets was recorded on 22/4/2016 (3732 retweets) and 15/4/2016 (3526 retweets). It was when Amazon posted tweets about Russel Hobbs and Philips contest. From the distribution of Twitter networking between Amazon and its followers in Figure 6, we can see that users regularly engage with Amazon for at least one retweet per tweet. It shows that Twitter has become a medium to spread and disseminate information as argued by Roshanaei and Mishra (2015) that customers are more likely retweeting any information on this platform. However, there was no active two-way conversation between Amazon and customers in this account because as mentioned before, Amazon has its second account that is @amazonhelp that handles and looks after customer relationship management.

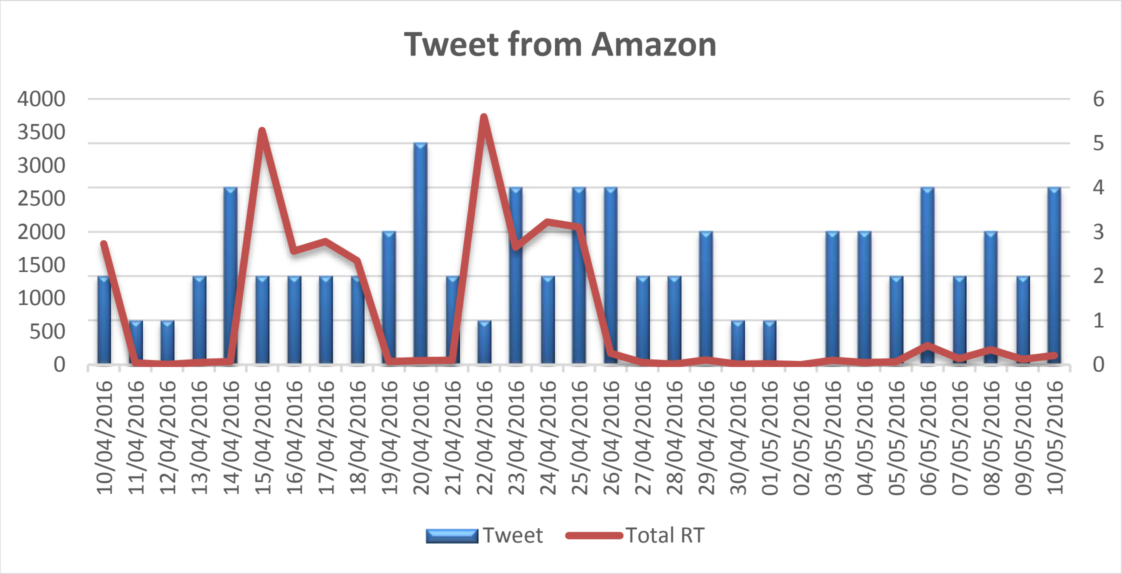
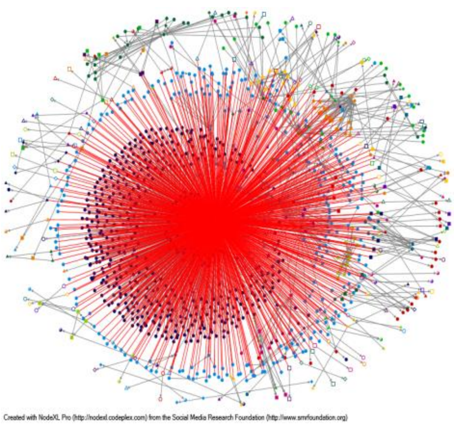


Figure 6. Amazon UK tweets and total retweets

4.2.2 Time

Concerning time aspect, three types of engagement patterns were evaluated comprising weekly pattern, one-day timeframe pattern and weekday and weekend timeframe pattern (for all brands). Firstly, Figure 7 shows a strong weekly pattern of communication. Amazon and its customers twittered frequently during the weekend (see graph 17/4/2016) and Friday (see graph 15/4/2016) and less during the middle of the week (see graph 13/4/2016 and 14/4/2016). There are two prominent spikes in the graph, in part due to Amazon running a contest of @Philips steam generator iron on 15/4/2016 that requires its followers to retweet in order to enter the contest. The contest was held for two days (15/4/2016 and 17/4/2016) and both strong spikes were seen from the graph of the respective dates. This indicates that events such as contest can attract customers to engage with Amazon through retweeting and there were clear differences between the day that contest was held and the other days. Retweeting here implies the increment in terms of communication reach and spreading the buzz of information to new and interested potential customers.



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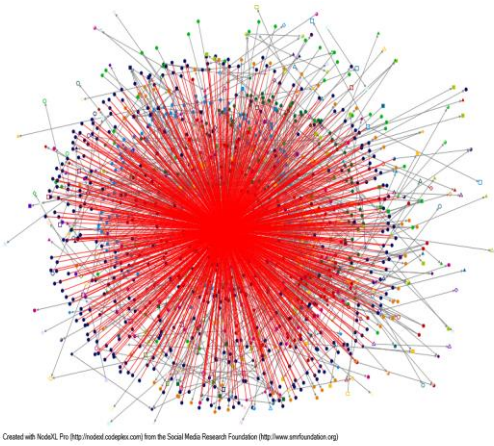

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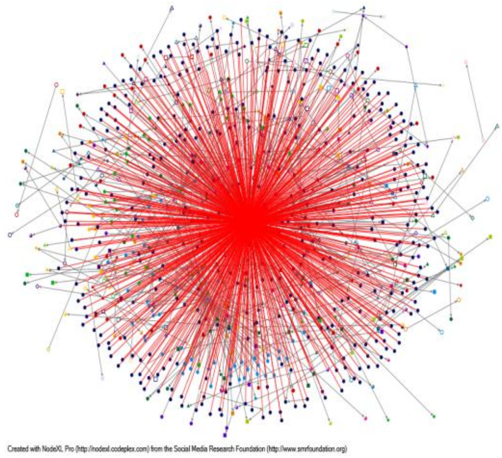

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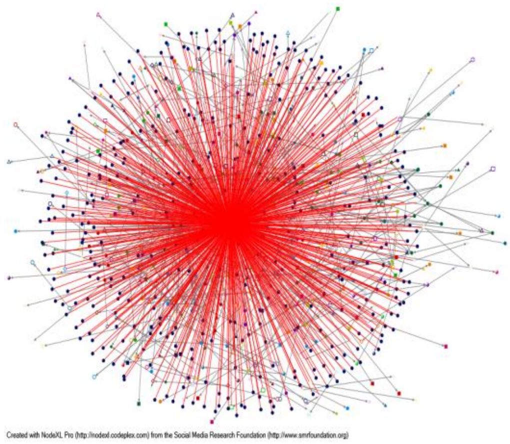

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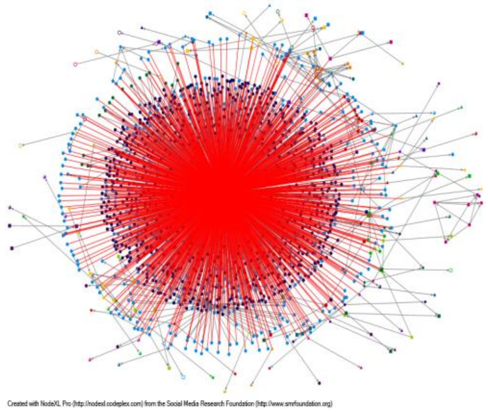
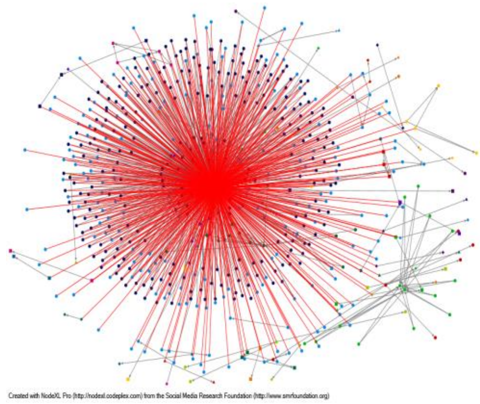
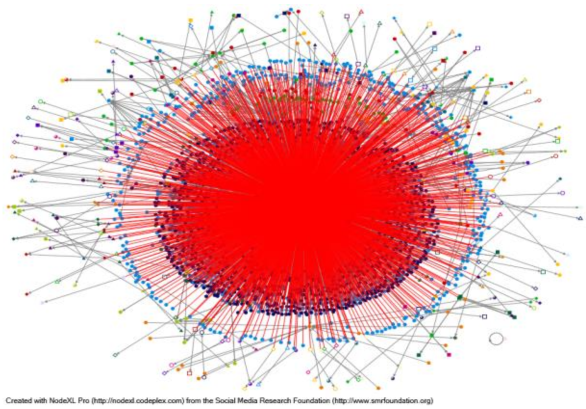




Friday - 15/4/2016 Saturday - 16/4/2016

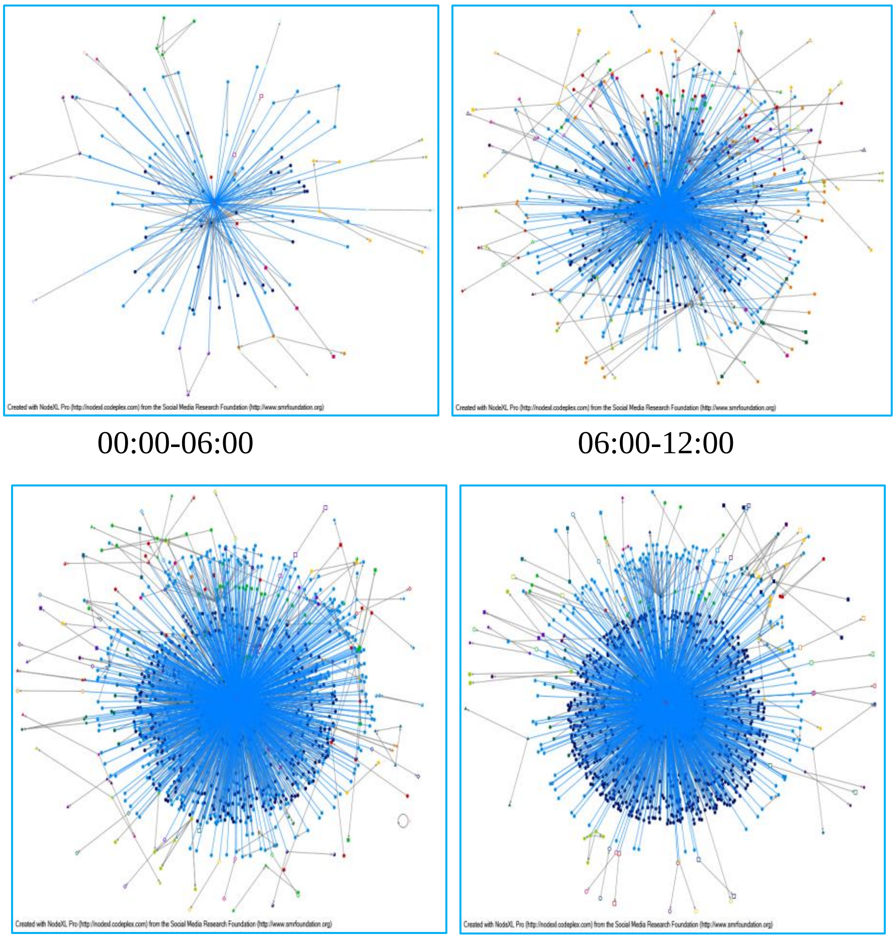


Sunday - 17/4/2016

Figure 7. Twittering network between Amazon and its customer

Further analysis was conducted to look into one-day timeframe engagement pattern. Figure 8 shows a trivial engagement during daytime hours starting from 06:00 in the morning until 18:00 in the evening. Small amount of engagement happens during traditional work hours 9-5pm and a few tweets were sent between 00:00am and 06:00am. However, there was high level of engagement at night time starting from 18:00 in the evening until late night where tweets were retweeted and mentioned extensively by customers. This shows that users are more active on Twitter after 6pm and this could be a critical timing for social media marketing teams to deploy their marketing campaign and promotion strategies since the tweet reach is most likely higher at that time. It is also a good tactic for a company to increase and maximize the engagement.

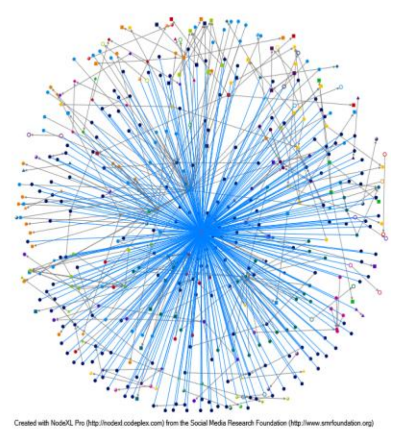
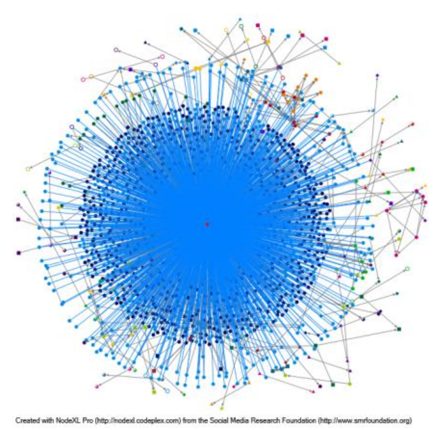
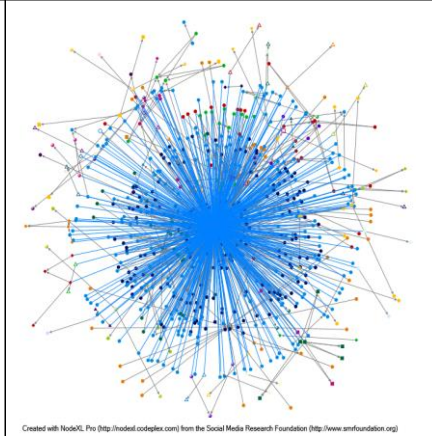
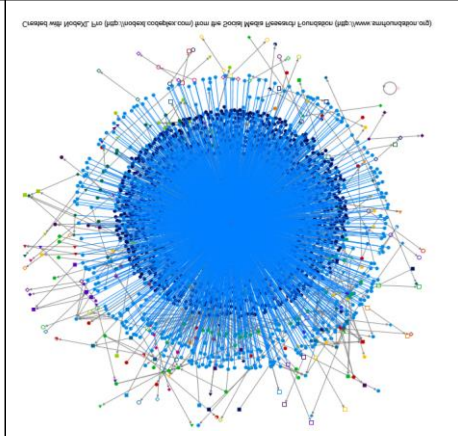
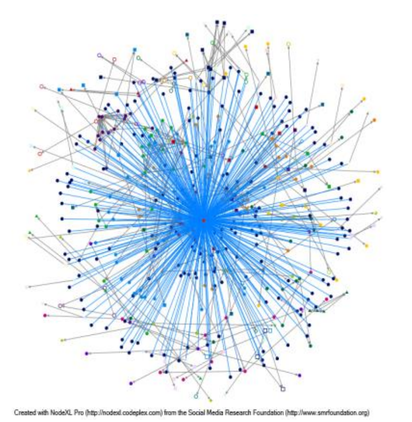
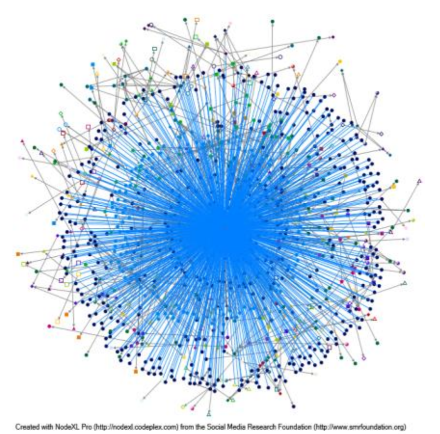
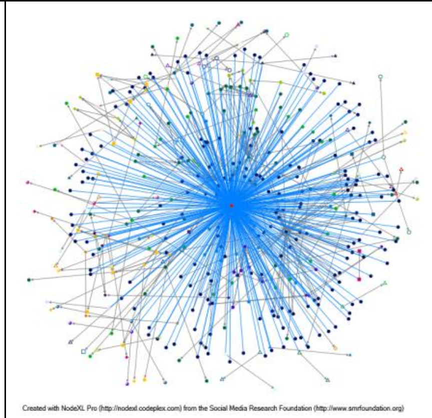
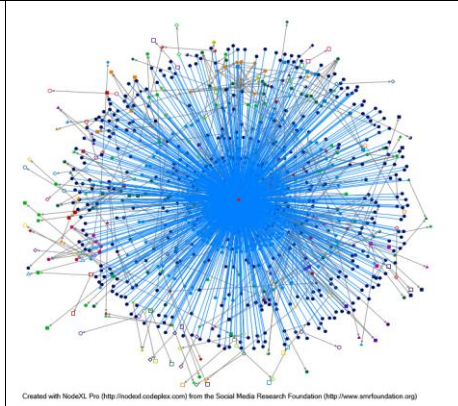
The differences of engagement pattern between weekdays and weekend timeframe were also observed. Figure 9 indicates weak engagement on the weekday’s morning (between 00:00 to 12:00) mostly for all brands but high engagement at weekday’s night time as expected. However, Figure 9 shows a slightly higher level of engagement on weekend’s morning compared to weekdays. High level of engagement was recorded on the weekend starting from 12:00 to 24:00 for all brands. This implies that the evening and weekend are when most people are on Twitter and it is the prime time where brands can make use of their social media for marketing purposes.



00:00-06:00 06:00-12:00

12:00-18:00 18:00-24:00

Figure 8. Twittering network between Amazon and its customers based on timeframe

Brand	Weekday – 15/4/2016		Weekend – 17/4/2016	
	0000-1200	1200-2400	0000-1200	1200-2400
Amazon				
Tesco				

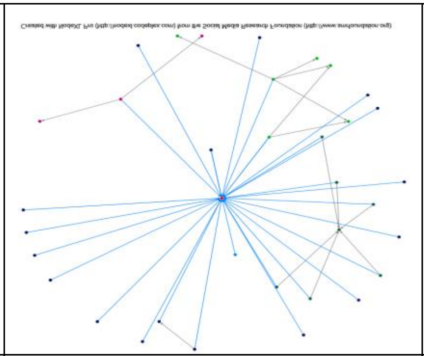
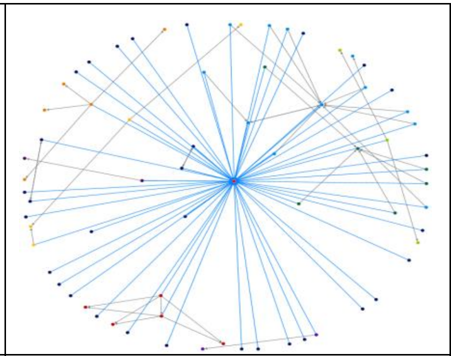
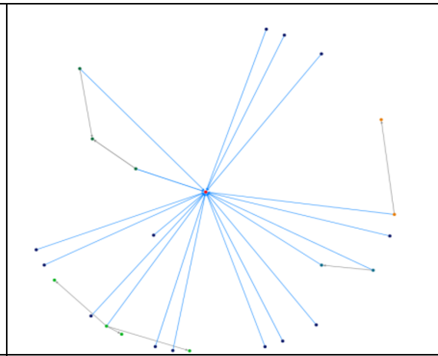
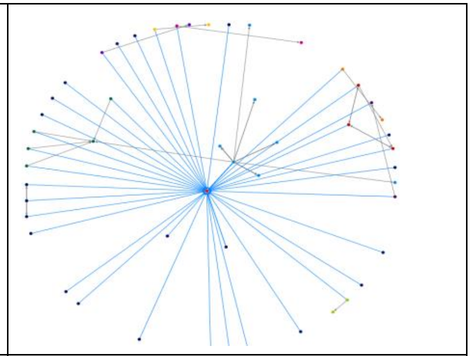
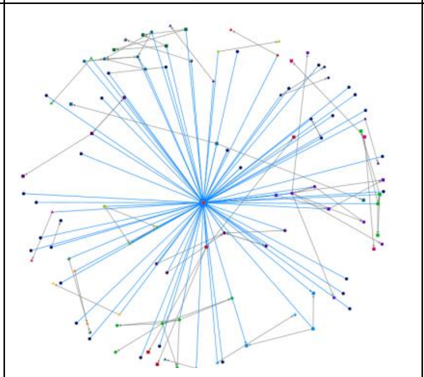
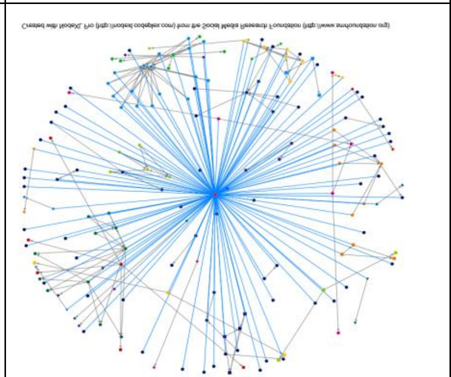
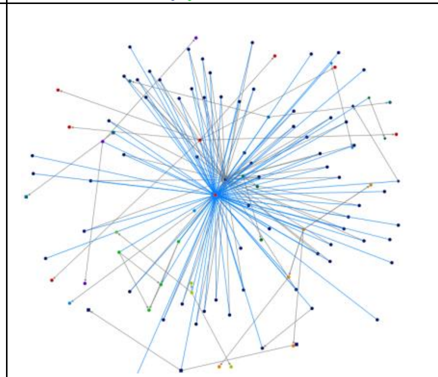
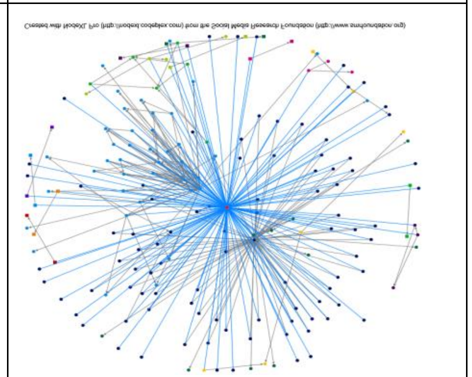
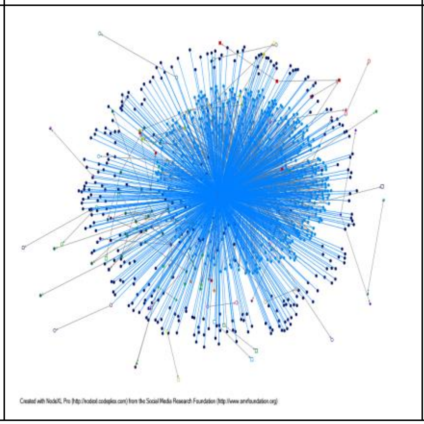
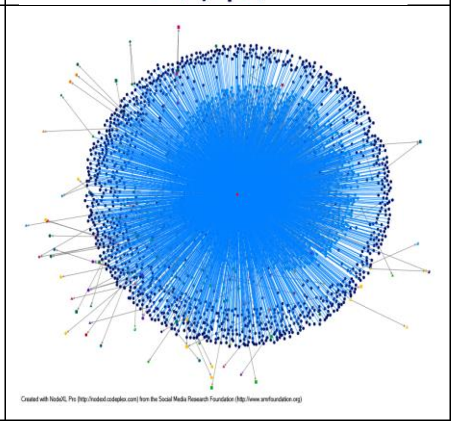
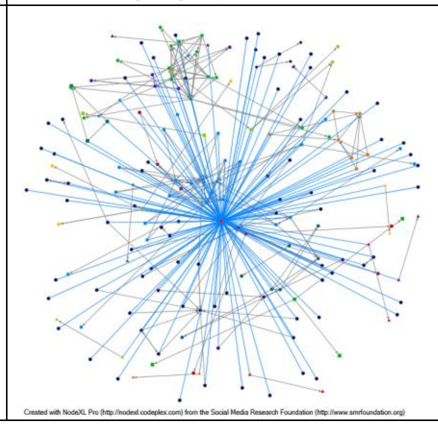
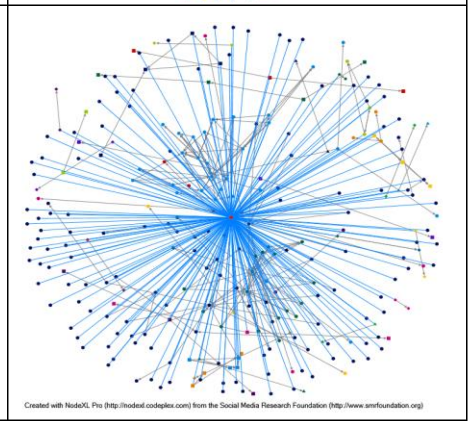
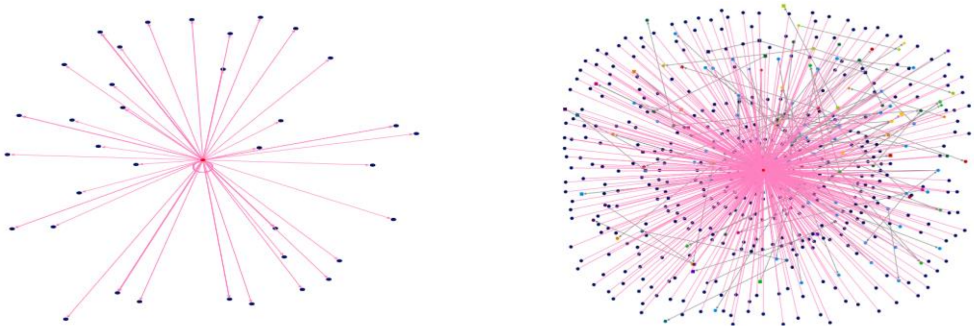
Argos				
John Lewis				
Asda				

Figure 9: Timeframe engagement pattern – comparisons weekend and weekdays for 5 brands

4.3 Impact of engagement on customer sentiments

For this research, we used the same sentiments data. Analysis was conducted to examine overall pattern of dynamic emotional transitions occurred during conversations and how number of replies, sentiment of tweets, length and media types impact and have influence on the engagement. In this section onwards, we selected data tweets from @amazonhelp account because it has high engagement compared to @amazonuk as can be seen through network sparks in Figure 10.



@amazonuk @amazonhelp

Figure 10. Comparison of engagement between @amazonuk and @amazonhelp on 15/4/2016

4.3.1 Overall sentiment

Of the 3360 tweets sent by AmazonHelp (see Figure 11), majority of them were neutral (91.7%) and observed a small percentage of negative sentiments (2.1%). Expectedly, positive sentiments (6.2%) were slighty higher than negative sentiments of tweets sending by AmazonHelp. In contrast, negative sentiments (7.2%) were higher than positive sentiments (4.2%) of the tweets received by AmazonHelp from customers. The neutral sentiments remained higher as usual. It indicates that the sentiments of AmazonHelp’s tweets sent to customers were more positive than those from customers to them. As a well-known brand of e-retailer company, it is important for them to assist customers positively regardless of unpleasant complaints sent to them. It also shows that higher negative sentiments were tweeted from customers as this account itself is a channel for customer complaints and queries. This result is somehow contradict with the finding from Roshanaei and Mishra (2015) that negative users are not interested in sharing their negativity in social media compared to other users. This can be explained by the fact that AmazonHelp Twitter account itself is responsible for catering enquiries and complaints from customers. When there is a dedicated channel that is specifically provided to customers for expressing their opinions, customers are more likely to send negative tweets through this channel. From the retailers’ perspectives, they can monitor the online user community’s sentiment more effectively and take necessary action when it is needed.

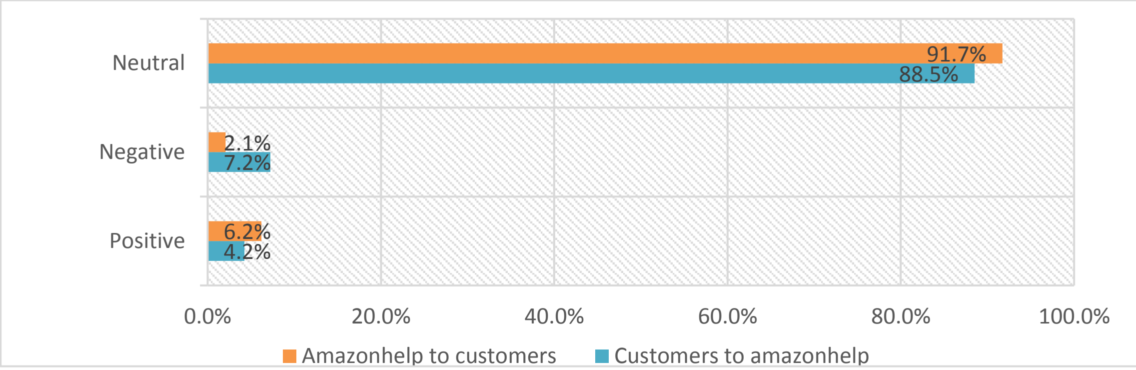


Figure 11. Twittering network of sentiments sent and received by AmazonHelp

Now, we explore the impact of engagement on customers' sentiments in general. Figure 12 illustrates the changes of sentiments which are divided into three stages: the beginning, the middle, and the end of conversation. There was a 4.8% decrease of negative sentiments and a 0.3% increase of positive sentiments for customers' tweets and retweets between the beginning and the final stage of conversations. This finding is supported by Stieglitz and Dang-Xuan (2013) that negative tweets should be handled consequently by companies until it turns into positive since it will induce more replies and feedback from customers which would help sustain positive image of company.There was only a minor transformation on the average score of sentiments that goes from -0.2 at the initial stage to a positive score of 0.05 at the end of the conversation. This is due to the fact that the sentiment of the majority tweets is neutral. Nevertheless, it shows that company engagement with customers has a positive impact on the customers' sentiments towards the brand.

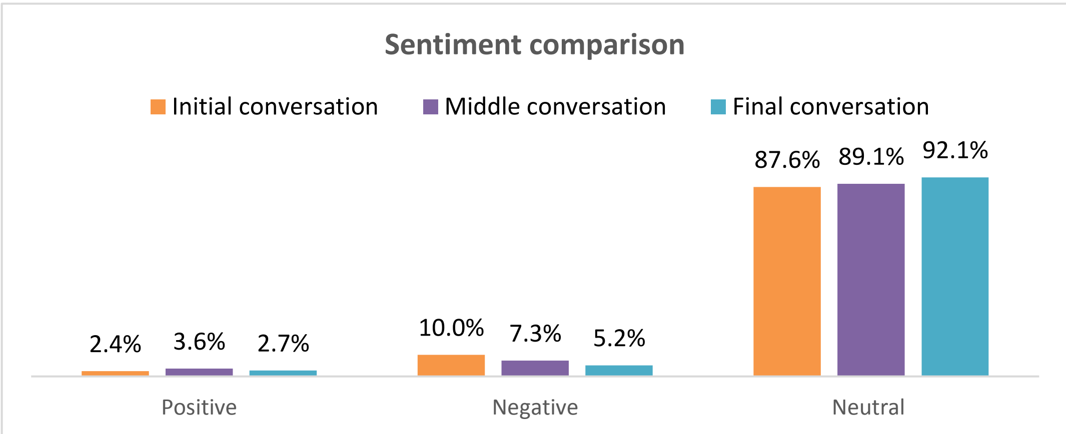


Figure 12. Change of sentiment over conversation

4.3.2 Effect of the level of engagement

Figure 13 provides the statistic for the change of customer sentiments after receiving replies from AmazonHelp. Level of engagement was categorised according to replies from AmazonHelp as follow: 1 reply indicates low level of engagement, 2-3 replies represents medium level of engagement, and the conversations that invovled more than 3 replies are defined as high level of engagement. The results are displayed in Figure 13, in which, there was a decrease of negative sentiments and an increase of neutral sentiments for three different levels of engagement defined in this study and in contrast, the percentages of positive sentiments remained similar across three different levels of engagement. Most of negative customer sentiments were converted into neutral sentiments after the interactions with AmazonHelp. Furthermore, there was a more significant reduction of negative sentiments through medium and high levels of engagement comparing to low level of engagement. The tweets with negative sentiments are often related to customer complaints or disatisfaction about the product or service. Users tend to talk negatively when they are angry and feel unhappy about something and Twitter is an easy accessible platform for them to speak out their frustration comparing to other channels. It often requires long conversation to solve users' problems or complaints, and it is more challenging to convert the negative sentiment to the positive one than the neutral sentiment. It is critical for the online retailers as suggested by Grégoire, Salle, and Tripp (2015) that customers tend to share their positive experiences online and would continue to buy products from the company if the recovery of the service is appropriately done and their problems are addressed satisfactorily. Higher level of engagement (e.g. more interactions with these customers) will help to improve their perception of customers service and brand image. It is also the reason why many companies have their own designated team and resources to indicatively monitor tweet posts from customers.

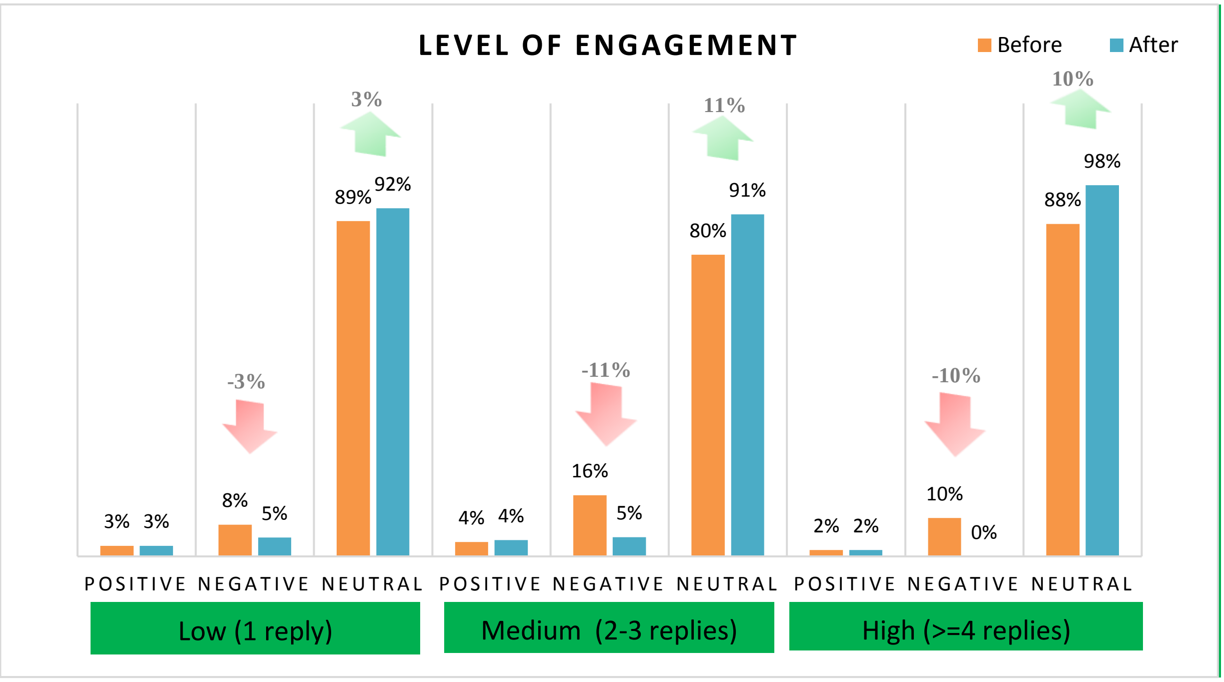


Figure 13. The effect of engagement level on customer sentiment

4.3.3 Effect of the attitude of engagement.

Further analysis was conducted to examine how the attitude of AmazonHelp could affect the sentiment of customers throughout the conversation. The analysis results are illustrated in Table 3. Positive replies from AmazonHelp led to a significant deduction of negative tweets by the end of the conversation. It means that customers who started their conversation negatively or being neutral ended up either being positive or neutral when AmazonHelp replied to them in a positive manner. It shows that Amazon are aware that negative tweets need to be handled carefully since negative sentiment can be easily spread on Twitter and damage the brand image and company reputation. It is also not surprising to see that negative sentiments of replies from AmazonHelp led to a sharp drop in positive sentiments of customers. The tweet replies from Amazon with neutral sentiment seem to have a less impact on consumers' sentiment compared to positive or negative replies, although the neutral sentiment replies also improve customers' sentiment. Overall, it shows that the attitude of retailers' engagement with Twitter users plays an important role in influencing customer's sentiments and making impact towards their brand perceptions. This observation indicates that Amazon Help must have a proper manner in communicating and initiating engagement with online users as Twitter is a social media platform that is always under the eyes of public. The result is consistent with the finding obtained by Bae and Lee (2012) that showed how the audience's sentiment change was influenced by the sentiment of the popular users that they communicated with.

Table 3. Effect of engagement attitude on sentiments

<table>
<tr><th colspan="2">Sentiment of engagement (from Amazon)</th><th>%</th><th colspan="2">Initial sentiment (customer)
n1</th><th colspan="2">Final sentiment (customer)
n2</th><th>Change of sentiment
n2 − n1</th></tr>
<tr><td colspan="2" rowspan="3">Positive</td><td rowspan="3">2.3%</td><td>Positive</td><td>0</td><td>Positive</td><td>27%</td><td>+27%</td></tr>
<tr><td>Negative</td><td>64%</td><td>Negative</td><td>0</td><td>-64%</td></tr>
<tr><td>Neutral</td><td>36%</td><td>Neutral</td><td>73%</td><td>+37%</td></tr>
<tr><td colspan="2" rowspan="3">Negative</td><td rowspan="3">2.1%</td><td>Positive</td><td>10%</td><td>Positive</td><td>0</td><td>-10%</td></tr>
<tr><td>Negative</td><td>20%</td><td>Negative</td><td>0</td><td>-20%</td></tr>
<tr><td>Neutral</td><td>70%</td><td>Neutral</td><td>100%</td><td>+30%</td></tr>
<tr><td rowspan="9">Neutral</td><td rowspan="3">+1</td><td rowspan="3">20.6%</td><td>Positive</td><td>5%</td><td>Positive</td><td>2%</td><td>-3%</td></tr>
<tr><td>Negative</td><td>10%</td><td>Negative</td><td>2%</td><td>-8%</td></tr>
<tr><td>Neutral</td><td>85%</td><td>Neutral</td><td>96%</td><td>+11%</td></tr>
<tr><td rowspan="3">0</td><td rowspan="3">43%</td><td>Positive</td><td>1%</td><td>Positive</td><td>2%</td><td>+1%</td></tr>
<tr><td>Negative</td><td>12%</td><td>Negative</td><td>4%</td><td>-8%</td></tr>
<tr><td>Neutral</td><td>87%</td><td>Neutral</td><td>93%</td><td>+6%</td></tr>
<tr><td rowspan="3">-1</td><td rowspan="3">32%</td><td>Positive</td><td>2%</td><td>Positive</td><td>4%</td><td>+2%</td></tr>
<tr><td>Negative</td><td>15%</td><td>Negative</td><td>7%</td><td>-8%</td></tr>
<tr><td>Neutral</td><td>83%</td><td>Neutral</td><td>89%</td><td>+6%</td></tr>
</table>

4.3.4 Effect of the tweet length

This section explores how the tweet length from AmazonHelp influences the sentiment of customers' tweets. The analysis results are described in Figure 14, which illustrates the change of sentiments between the beginning and the end of conversations. AmazonHelp's replies were classified into three categories: short length that contains tweet up to 15 words, medium length that contains tweet up to 20 words, and long length that contains more than 20 words. There was a clear trend of decrease in negative sentiments and increase in neutral sentiments across the three categories. However, overally, there was more significant decrease of negative sentiments (-10%) for lengthy tweets than those with short tweets (-3%). The negative customer sentiments were often transformed into neutral sentiments after the conversations as seen from all three categories. There was more significant increase in neutral sentiments after the intervention of medium and long replies from Amazon. In contrast, the tweet length appears to not have much impact on the positive sentiments as shown in Figure 14. This may be explained by the fact that it often requires lengthy reply to solve customers' problem, and meanwhile, customers do appreciate more on firms' effort in replying in detail.

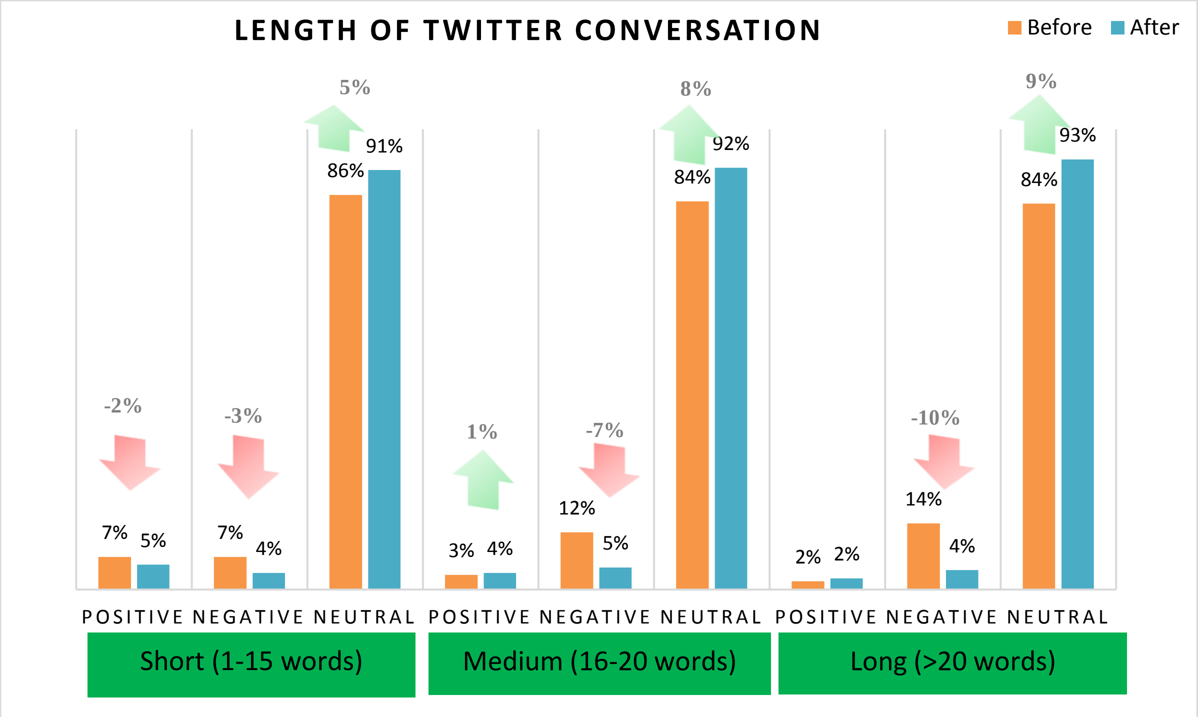


Figure 14. Engagement over words' length

4.3.5 Effect of the media types of engagement

The majority of the tweets posted were in a form of text (66.5%). It is followed by tweets containing links (33.3%). Further analysis was performed to assess the impact of the media types on customer sentiments. The result is displayed in Figure 15. There were 2% and 4% decrease of negative sentiments for customers' tweets in the containg link and text only categories respectively. While the text tweets from AmazonHelp seems to have no influence on the number of tweets with positive sentiments, the tweets containing link certainly led to more tweets with positive sentiments. It shows that the presence of link in a tweet is more likely to solve customer problems and queries hence had made customers change their attitudes from negative to positive by the end of conversations. Normally, link tweets posted consist of links to complaint form, refund and review form. This result implies that types of media such as text and link play a significant role in influencing customer sentiments. Tweet contained embedded links are more favourable by users in Twittersphere. It will be valuable for the social media teams of online retail businesses to construct and systematise their tweets with the aim of getting better perception. This finding is in line with Kwon and Sung (2011) and their study indicated that tweets embedded with link influence customer to engage and generate exposure to brands.

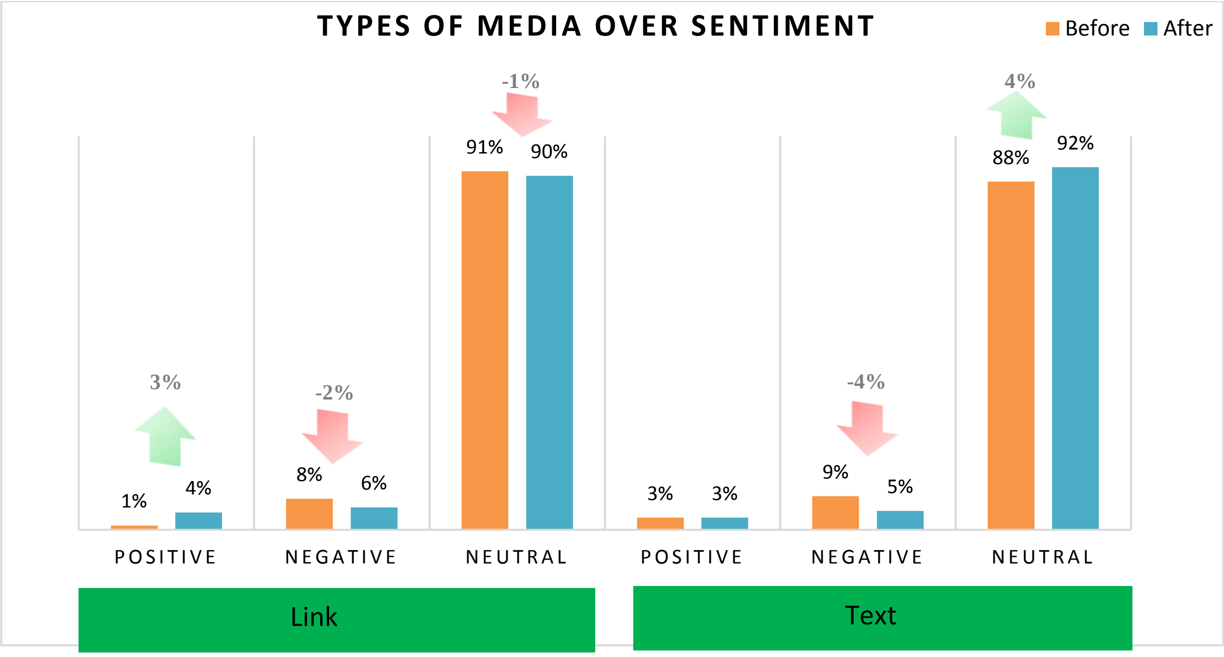


Figure 15. Types of media over sentiment

5 Discussion and Implications

Several insights emerged from this study as an attempt to explore online retailers' customer engagement on microblogging platform. Specifically, we examined the effect of engagement on customer sentiments through the statistical analysis of sentiment data of five leading online retailing brands in the UK. We then explored word frequency, timing and different types of engagements to understand the engagement patterns. Different analyses were performed to examine the impact of different levels of engagements (number of replies), attitude (sentiment of replies), length of words, and media types on the change of customer sentiments. Our results indicate that the way online retailers engage with microblogging users has a substantial influence on the customer sentiments, which is closely associated to customer perceptions of retailing service and brand image. For instance, we found that the number of replies has a positive effect on the change of customer sentiments especially the negative sentiments. In other words, the high number of replies, which implies more interactions with customers, could make customers change their mind as they feel the brand companies' willingness to help customers. It shows a similar effect when applying to positive and lengthy replies from the focal company. A possible explanation might be that, customers tend to reply back positively when they receive positive reply from customer service personnel and longer sentence might also help because it requires time and resources to do so, which demonstrates companies' enthusiasm to take care of customers (Choi, Hwang, Kim, Ko, & Kim, 2014). Thus, Twitter accounts for companies are probably a smart idea to both monitor brand community discussions and convey information to customers. Gathering information on how people engage and converse about some particular products opens the door for advertising opportunity as it could be helpful when designing a marketing campaign. This could encourage companies to market their products or services by embracing Twitter for the marketing promotions.

Companies receive positive brand exposure via followers and others who microblog about the companies and their products. Neutral or no sentiment tweets suggested that people are seeking for information and asking questions about brands through tweeting. We found that majority of the tweets were neutral as customers use microblogging platform for sharing opinion and disseminating information. Nevertheless, sentiment analysis of tweets enables companies to identify customers with different needs. For instance, negative sentiment tweets certainly indicate something is not going right for a product or service. As such, companies monitoring sentiment of tweets concerning brands is really vital and they should be proactively evaluating these sentiments in order to get valuable information and further enhance their branding efforts. Our sentiment analysis also illustrates that the presence of link in the tweets stimulates an improvement of customer sentiments since it is considered as an important and helpful information given by brand retailers to solve customers' problems. Moreover, numerous studies found links as redirecting-information cues (Kwon & Sung, 2011) and could encourage people to engage more through retweeting (Suh, Hong, Pirolli, & Chi., 2010).

We observed some patterns on how online retailers are leveraging microblogging for branding. For instance, they could provide a place where customers can give opinion, provide feedback, complaints and get answers for their queries. This could be done by creating Twitter account as a place to engage with customers as a new way to enhance branding image. For instance, one way of doing this is by having multiple accounts for various purposes like Amazon. @amazon and @amazonuk are used for the purpose of information dissemination, campaigns, marketing, survey and events meanwhile @amazonhelp is for suggestions, queries and handling complaints. These few accounts are believed to accommodate the unpredictable demands and swings in customer traffic.

As the literature on relationship marketing shows, customers who are satisfied with how company manages the complaints will commit to a high degree of engagement where an effective company-customer interaction is essential for a strong company-customer bond (Cambra-Fierro, Melero-Polo, & Javier Sese, 2015). A decrease in negative word-of-mouth would increase profitability, competitiveness and stabilise relationships with the companies (Kaltcheva, Winsor, & Parasuraman, 2013). This study contributes to the literature on customer relationship management by exploring the factors that influence customers to engage on social media. Specially, we show how different types of engagements with Twitter users influence customers' sentiments. This research is of interest to researchers and practitioners because company-customer engagement has been considered as an emerging topic in the relationship marketing and customer management literature (van Doorn et al., 2010; Verhoef & Lemon, 2013).

A rapid growth of microblogging has encouraged companies to come up with a systematic way to engage customers on microblogging sites. Companies could take advantage of microblogging to provide information and use it to sustain the connection with customers hence improve brand image. However, a systematic monitoring tool is needed to trace and attract potential customers. Sometimes, if customers receive negative or late response from companies about their complaints, it could go viral on the Internet and cause major problems for companies (Grégoire et al., 2015). With microblog monitoring tools, companies can track the sentiment of the microblog postings and immediately intervene with unsatisfied customers on social media. Amazon for instance, does not only track customers who mentioned Amazon's Twitter account (@amazon) but also random tweets that contain 'Amazon' word in it. This is an effective approach to maintain a good relationship with customers. This is also supported by Balaji, Jha, and Royne (2015) that companies should invest in various monitoring tools to carefully monitor, track, provide support and respond to customer complaints on social media. If this can be managed effectively, it can pave the way for customers to become engaged and bring long term competitive advantages to the company. A correct way of handling customer complaints on social media should be a top priority for companies. Customers' dissatisfaction, unhappy experiences and venting frustrations discussed on the social media can spread much faster and wider than other media platforms, which may seriously damage the brand image. By employing a timely and effective way of engaging with customers, companies can find themselves in a win-win situation where they can get feedback that provides a better understanding of customer needs and expectations and leads to improved services. In fact, new customers can be won over from other competitors.

Altogether, our findings emphasize the way how companies engage with the Twitter users could have a profound effect of customer sentiments. The emotional tone in the message can stimulate engagement behaviour by creating emotional connection between customer and brand retailers. De Bruyn and Lilien (2008) stated that marketers cannot control how brand information is disseminated. However, scholarly work on marketing and advertising suggests that the manner in which messages are designed can influence consumers' disposition. As such, providing positive reply, rich information content, and lengthy replies might help to get positive sentiment of tweets from customer as well as develop a strong online community.

6 Conclusion

This paper studies the sentiment trends, the patterns of engagement and the relationship between types of engagements and customer sentiments on social media microblogging platform, Twitter. Applying data mining and text analytics techniques, sentiment presents in customers' and brands' tweets were identified. Then, sentiment analysis was performed to give meaningful insights into opinions and trends around engagement activities happened on this digital platform.

This study provides interesting findings. Firstly, the results indicate that Twitter is normally used for information seeking, sharing and handling complaints. The findings also show that customers mentioned other brand competitors in the same tweet. This helps companies to differentiate themselves and strengthen their positions in the market. Second, different patterns of engagement between customers and company are illustrated through statistic and graphs. For instance, high level of engagement was detected in the network during weekend and contest day. Contrarily, low level of engagement was recorded on the normal working days because many customers were not really active on Twitter during that period. Third, the analysis results show that level, attitude, length and media types of tweets have a significant impact on customer sentiments, and as a result, their perceptions about the product, service and brand image changed. We learned that those factors lead to emotional transitions of tweets, influence and change the sentiment of customers' replies from the beginning to the end of conversations. Patterns of emotional change were shown in the graphs.

It is clear that the increasing popularity of social media motivates companies to engage with customers for brand image and product marketing, but the challenge is how to do it right or how to address the comments and queries appropriately. Overall, our findings demonstrate that social media platform like Twitter is a good avenue to explore the trends of marketplace. Businesses could leverage the microblogging to improve their brand images by analysing the proper way to engage with customers. One limitation of this study is it only focused on five retail brands that are based in the United Kingdom. Whilst it provides some interesting insights, it would be valuable to validate our findings by conducting similar studies in other geographical areas in future research. Another limitation of this study is that only descriptive statistical approach was used to examine the effect of user engagement on customers' sentiments and parameters studied were not correlated between them. One future research extension is to consider applying advanced statistical programmes where mere conclusions could be drawn. Another future work direction is to extend analysis incorporating social network analysis, content analysis and PageRank in understanding the central phenomenon of engagement in social media research.

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