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Farizah Ibrahim, N., & Wang, X. (2019). A Text Analytics Approach for Online Retailing Service Improvement: Evidence from Twitter. *Decision Support Systems*, *121*, 37-50. https://doi.org/10.1016/j.dss.2019.03.002

Peer reviewed version

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10.1016/j.dss.2019.03.002

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A Text Analytics Approach for Online Retailing Service Improvement: Evidence from Twitter

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Abstract

The purpose of this study is to identify the customers' primary topics of concern regarding online retail brands that are shared among Twitter users. This study collects tweets associated with five leading UK online retailers covering the period from Black Friday to Christmas and New Year's sales. We use a combination of text analytical approaches including topic modelling, sentiment analysis, and network analysis to analyse the tweets. Through the analysis, we identify that delivery, product and customer service are among the most-discussed topics on Twitter. We also highlight the areas that receive the most negative customer sentiments such as delivery and customer service. Interestingly, we also identify emerging topics such as online engagement and in-store experience that are not captured by the existing literature on online retailing. Through a network analysis, we underscore the relationships among those important topics. This study derives insights on how well the leading online retail brands are performing and how their products and services are perceived by their customers. These insights can help businesses understand customers better and enable them to convert the information into meaningful knowledge to improve their business performance. The study offers a novel approach of transforming social media data into useful knowledge about online retailing. The incorporation of three analytical approaches offers insights for researchers to understand the hidden content behind the large collections of unstructured bodies of text, and this information can be used to improve online retailing services and reach out to customers.

Keywords – Online retailing; Social media research; Text analytics; Topic modelling; and Sentiment analysis

1   Introduction

Consider the customer who found the perfect gift at a great price while shopping during Black Friday or, conversely, the customer whose delivery was late during Christmas. With whom do they share their experiences, and where do they make a complaint? Instead of telling family and friends or calling customer service, customers often resort to social media to share their good experiences and channel their complaints. The messages or tweets of praise or their complaints about products and services posted on social media platforms are then viewed and shared immediately by millions of people across the world. The amount of data generated by social media users not only presents challenges for online retailers in managing customer relationships (Bee and Tan 2014; Coyle, Smith, and Platt 2012; Habibi, Laroche, and Richard 2014), but also provides opportunities to measure customers' opinions and tailor their products and service provisions to meet their customers' needs (He et al. 2016).

Among the different social media platforms, Twitter has become one of the most popular for online retailers and customers to engage in dialogues, including sharing and delivering information and updates about products and services. According to survey data from Twitter in 2015, customers choose to discuss customer service queries with brand companies on Twitter rather than on Facebook. Meanwhile, the marketing literature (Chu and Sung 2015; Hewett et al. 2016; Smith, Fischer, and Yongjian 2012) has mentioned the need for robust research on online retailing using social media data that could contribute to services' improvement, which provides prospects for online retail brands to narrow their focus and obtain brand-related insights from customers on the Twitter microblogging platform. Twitter allows customers to freely share brand-related information and express opinions on products positively or negatively and facilitates interactions with brand companies. The insights from customers' opinions on and comments about brand-related tweets are significant and relevant to shaping brand perceptions (Smith et al. 2012). Such user-generated content regarding brands enables customers to express themselves and their views towards products and services and consequently empowers retail brands to convert this information into meaningful knowledge about customers' needs.

While Twitter is hypothetically known as a rich source with potentially useful information, unfortunately, its content has not been well studied (Zhao et al. 2016). Tweets are unstructured with a limit of 280 characters. Harvesting Twitter data into valuable business insights is also a daunting task for many

organisations (Sheng, Amankwah-Amoah, and Wang 2017). The large volume of textual data available on Twitter is greater than what traditional methods can manage. Critically, few studies (He et al. 2016; Matthias et al. 2017) have explored ways to transform Twitter data into competitive advantages for businesses, and even fewer studies are conducted in the context of online retailing, a fast-growing sector in many developed and developing economies (Ibrahim, Wang, and Bourne 2017; Liu, Burns, and Hou 2017). A natural question is how companies can learn from customer tweets to improve their online retail service provision. To answer this, a set of key questions is addressed in this research.

- What are the most common topics that are discussed and shared among Twitter users regarding online retail brands?

- What are the areas that customers complain about most on Twitter regarding online retailing?

- Are there any relationships between the areas of customers' complaints? If so, how do they relate to each other?

To answer these questions, we collected Twitter data from five leading UK online retailers, Amazon, Argos, Asda, John Lewis and Tesco. The data cover the timeframe of the two most important trading periods for online retailing: Black Friday sales and Christmas, Boxing Day and New Year's sales. The latent Dirichlet allocation (LDA) (Blei, Ng, and Jordan 2003) topic modelling approach was used to identify key insights hidden in these unstructured textual data. The unsupervised topic modelling approach is a widely used algorithm in the computer science and engineering fields (Guo et al. 2016). However, in using this dataset for topic modelling, challenges abound because tweets are (1) much shorter than online reviews or company reports; (2) composed of various unstructured styles of writing; (3) diverse in their topics due to a wide platform; (4) informal and use slang text; (5) ungrammatical and contain spelling errors; and (6) noisy. Nevertheless, in this study, we will address these challenges associated with the nature of Twitter data and extract the tweets topically to summarise and analyse the content.

This study makes some key contributions. First, our research contributes to the online retailing and social media literature by presenting a novel approach of transforming social media data into useful knowledge about online retailing. Although Twitter offers great potential for business research with large volumes of textual data available, harvesting this rich information sources also comes with unique challenges (Sheng et al. 2017; Zhao et al. 2016). This new approach allows us to generate and extract

relevant topics inferred from the corpora of tweets, from which we can gain insights on how well the leading online retail brands are performing and how the products and services of the leading online retailers are perceived by their customers. The incorporation of three analytical approaches (i.e., sentiment analysis, topic modelling, and network analysis) organises and offers insights for researchers to understand the hidden content behind the large collection of unstructured textual data.

Second, our research generates some novel findings. For instance, the topic modelling results highlight the popular topics regarding online retailing that are talked about and shared among the Twitter users. According to Thakur (2018), what customers talk and share on Twitter is becoming an important factor that influences online shopping, especially purchase decisions. This view is also supported by Cheung, Xiao, and Liu (2014) and Lee, Hansen, and Lee (2016), who highlighted that the information from online social community and Facebook Likes, respectively, has influenced and induced customers' purchase decisions. In addition, we identify two emerging areas, "online engagement" and "in-store experience", that have not been captured by the existing literature on online retailing. These results show that the rich information from the digital environment influences customers' experiences across online and offline retailing channels and demonstrate the importance of integrating multiple channels and designing the processes that facilitate a seamless "omnichannel retailing" experience (Verhoef, Kannan, and Inman 2015).

Finally, our research makes important practical contributions. For example, our results show that the identified topics are somehow significant, and this knowledge can be used to better understand customers' needs and reach out to customers. The identified emerging online retailing topics such as online engagement and in-store experience can help retailers heading in the direction of omnichannel operations, in which the coexistence of offline and online channels enables them to evolve and streamline their operations (Wiener, Hoßbach, and Saunders 2018). The insights derived from our analysis can act as a foundation for online retailers to improve their online service provision.

In the following sections, we review related works and then discuss the research methodology. The analysis and results follow. Next, we discuss the implications of this study and conclude with the main research findings, contributions, and future research extensions.

2   Related Work

To provide the research background and highlight our contributions, we mainly review three research streams: (i) social media research, (ii) topic modelling applications, and (iii) sentiment analysis.

2.1   Social media research

The popularity of social media has attracted researchers' attention in recent years (Chan et al. 2016; Ibrahim et al. 2017; Sheng et al. 2017). The nature of microblogging itself provides researchers with a large amount of texts and potentially contains useful information that is not comparable to conventional sources. Recent social media studies have examined Twitter from a variety of perspectives, including trending topics (Yildirim, Üsküdarlı, and Özgür 2016), stock market prediction (Daniel, Neves, and Horta 2017), breaking news, and political events (Guo et al. 2016; Kim et al. 2016).

Valuable information and knowledge pulled from this content are useful for business intelligence at various managerial levels in organisations and contribute to business success (Ramanathan, Subramanian, and Parrott 2017) and brand-building (Cawsey and Rowley 2016). For instance, Cawsey and Rowley (2016) argued that social media is a strategic approach for brand-building and highlighted that brand image and brand awareness enhancement were the most common incentives for adopting social media. Wang, Yu, and Wei (2012) revealed that customers use social media to socialise and talk about products and found peer communication has a positive connection with customers' attitudes about products.

In another line of studies, Smith et al. (2012) examined brand-related, user-generated content on Twitter, Facebook, and YouTube to identify the differences among the three platforms. Findings of the study highlighted that brand centrality was the important dimension for brand-related, user-generated content on Twitter. Furthermore, Liu, Liu, and Li (2012) suggested Twitter is an important channel for communication since the source of expertise, trustworthiness, and multimedia numbers in a message have significant impacts on the spread of information through retweeting in microblogging. Chan et al. (2016) conducted a mixed-methods approach to analyse social media data for new product development by extracting the data generated on the Facebook account of Samsung Mobile.

Despite emerging social media platforms and the large-scale data available on each platform, research collecting and analysing data from microblogging platforms, especially Twitter, in the retail industry remains limited. The mentioned studies mainly focused on Facebook, YouTube, and online reviews and

stressed the use of those social media platforms and their influences on their services. Furthermore, as Lansdall-Welfare, Dzogang, and Cristianini (2016) argued, evaluating large scale data from the public domain such as social media platforms using traditional methods (e.g., survey and interviews) can be prone to error. Therefore, this research serves to expand knowledge regarding analysis, content, and concepts applied in social media research to online retailing application with new microblogging platforms.

2.2   Topic modelling

The topic modelling approach is becoming a popular tool for extracting important topics from social networks and facilitates researchers' understanding of large collections of unstructured data. It is an unsupervised probabilistic model employed to reveal and annotate large documents with thematic information (Blei 2012). In topic modelling, techniques based on latent Dirichlet allocation (LDA) and probabilistic latent semantic analysis have been widely used (Nikolenko, Koltcov, and Koltsova 2016). The approach has been effectively applied in a variety of tasks, including sentiment analysis (Liu et al. 2017), customer behaviour (Tirunillai and Tellis 2014), and forecasting (Roy et al. 2013). Kim et al. (2016) used the LDA topic modelling technique and found that topic coverage on Twitter was more precise and entities such as people, organisations, and locations can be extracted from the tweets. Similarly, Yildirim et al. (2016) identified topics in Wikipedia using the LDA approach.

Although this approach can be traced back further in the application of more conventional text data, our review mainly focuses on applications in social media research. For instance, Roy et al. (2013) used the same approach in their study of social streams topics using 10.2 million tweets and YouTube videos. He, Zha, and Li (2013) analysed unstructured content of pizza chains on Facebook and Twitter to find emerging themes using the text mining approach and demonstrated the power of text mining to extract business value from the social media data. More recently, Tirunillai and Tellis (2014) applied the LDA approach to extract the dimensions of the quality of customer satisfaction on microblogs and then proposed a unified framework to improve customer satisfaction. In the same vein, Liu et al. (2017) analysed tweets for 20 brands to identify customers' most-discussed topics within and across five industries. Their findings revealed a few dominant topics marketers can use to identify customers' interests and preferences.

Harvesting and analysing a vast amount of data to gain valuable business knowledge could be a daunting task for companies, as Sheng et al. (2017) argued. Given this evidence, topic modelling is

employed to extract relevant information and identify customers' concerns regarding online retail brands. Therefore, this motivates us to identify the topics of concern in the context of online retailing, including those that receive the most negative customer sentiments.

2.3   Sentiment analysis using Twitter data

Twitter is a microblogging social application that allows people to post messages and reply to and forward (retweet) posts of up to 140 characters (Smith et al. 2012). Sentiment classification analysis on Twitter often focuses on the sentiment polarity of the short and informal tweets. Sentiment analysis is often performed to extract opinions, sentiments, and subjectivity in unstructured text to identify the expressions indicating positive (favourable) or negative (unfavourable) opinions towards the subject (Pang and Lee 2008). The lexicon-based technique is used to identify the sentiment using a term-based matching technique based on a list of words. This technique has been effectively used in previous studies that did not require training and testing to analyse small amounts of text data (Bollen, Goncalves, et al. 2011).

Various studies have adopted sentiment in their Twitter analysis, focusing on diverse areas, including retail, finance, and airlines. For instance, Jansen et al. (2009) examined how Twitter users describe their interests, express their attitudes and share information, news, and updates about their daily activities. Their findings revealed that 19% of the tweets contain brand-related information in the form of both positive and negative sentiments. Meanwhile, Bollen, Mao, and Zeng (2011) conducted an experiment to measure the sentiment of random sample data on Twitter and found that the Dow Jones Industrial Average prices have a significant correlation with Twitter sentiments. In the airline industry, Bee and Tan (2014) collected 10,895 tweets to study consumers' opinions towards the low-cost airlines industry in Malaysia. The findings revealed that customer sentiments were segmented into four main topics: customer service, ticket promotions, flight cancellation, and post-booking management.

In these studies, there appears to be strong interest in understanding sentiments of customers on social media. Stieglitz and Dang-Xuan (2013), who explored users' behaviour of sharing information on social media, found that sentimental and emotional tweets influenced the retweet behaviour of users. In addition, Chu and Sung (2015), who studied the factors that engage brand followers on Twitter, revealed that those with positive sentiments towards brands were most likely to talk about the brand.. More recently, Daniel et al. (2017) used sentiment analysis to detect event popularity for a financial market by using financial

community tweets on Twitter. They demonstrated that tweets from the financial community on Twitter were a good indicator of financial events. Although previous studies have focused on diverse contexts, there is a distinct lack of studies conducted in understanding customer sentiments and how customers perceive products and services in the context of online retailing.

2.4   Summary

This section provides an overview of some important literature featuring social media, topic modelling, and sentiment analysis in different focus areas. Overall, while social media research has demonstrated potential benefits for businesses, very few studies have attempted to examine Twitter data to develop a better understanding of consumers' behaviour towards online retailing. The topic modelling approach has shown great potential in extracting key topics from unstructured data (Guo et al. 2016). However, the nature of the Twitter message and its unique attributes partially acts to differentiate our research from previous research. Among the most relevant studies, Kim et al. (2016) extracted topics from Twitter using sentiment analysis and LDA topic modelling during the event of the Ebola virus. However, in this context, we focus on online retailing in a social media setting and use sentiment analysis, topic modelling, and network analysis to provide a more in-depth understanding about what normally pleases or displeases customers. Although previously studies on social media data have aided access to large-scale empirical data from online social networking platforms includes Facebook and Twitter in so many ways (Burgess and Bruns 2012; Manovich 2012), there are arguments in the recent literature that companies still require more accurate analysis to evaluate customers' opinions (Ghiassi, Zimbra, and Lee 2017) and handle dynamic data. Thus, researchers need new statistical methods such as topic modelling and sentiment analysis and simulation models to fully evaluate the change (Nusratullah et al. 2015). Therefore, this research addresses this challenge by integrating multiple Big Data analytics techniques to measure various aspects of the social media data and offer a better understanding of shared topics and concerns regarding online retailing among Twitter users.

3   Methods

3.1   Model framework

The workflow of this study consists of four steps: (1) collect tweets that mention the five brands; (2) pre-process the tweets by removing unnecessary noise; (3) extract tweets using topic modelling to find latent

concepts relevant to the brand discussion; and (4) explore the sentiment of tweets to understand the expression of customers' attitudes.

3.2 Tweets pre-processing

Five leading brands, Amazon UK, Argos, Asda, John Lewis, and Tesco, were selected from the UK's top 20 online retailing sites. Tweets that mentioned these five brands were collected using a customary keyword— [brand name] lang:en since:[start date] until:[end date]—and pre-processed for the analysis. The dataset represents the tweets associated with the brands from 20 November 2016 to 20 January 2017, the period covering Black Friday, Christmas, Boxing Day, and New Year's sales events in the UK. The dataset includes 386,379 qualified tweets as shown in Table 1.

Table 1: Dataset

Start Time (GMT)	End Time (GMT)	Amazon # of tweets	Argos # of tweets	Asda # of tweets	John Lewis # of tweets	Tesco # of tweets
Nov 20, 2016 00:00	Jan 20, 2017 23:59	186,885	31,509	60,139	25,991	81,855

As Figure 1 shows, we first filtered non-English tweets, cleaned the text by removing numbers and punctuation, and converted all text to lowercase. We then tokenised the words by breaking up the texts into discrete words. We also removed all the stop words and reduced the words to their stems. A Mallet LDA was then executed to find which topic each tweet has been assigned into.
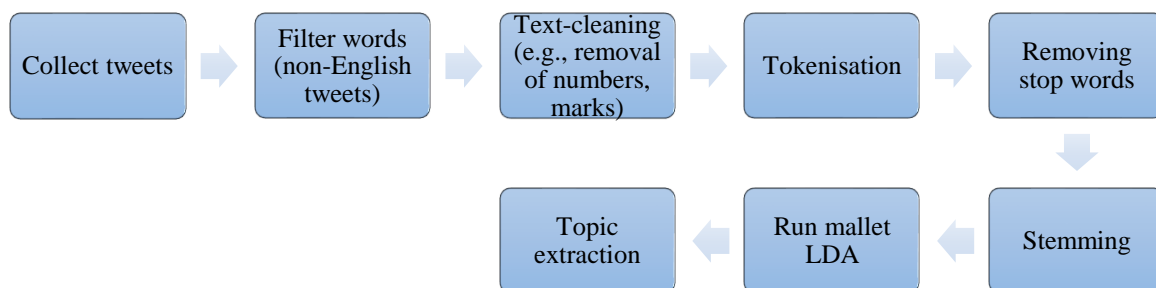
Figure 1: Overview of pre-processing and topic modelling approach

3.3 Processing topic model: LDA analysis

LDA is a statistical unsupervised machine learning technique to identify latent topic information from a large corpora (Blei et al. 2003). It is widely known for identifying patterns in texts that pinpoint emerging topics. This model is used to identify and extract topics tweeted by customers. In the LDA model, K is the number of topics; D, the number of documents; N_d, the length of the $d-th$ document; θ_d, the ability distribution of the $d-th$ document; φ_k, the word probability distribution of the topic k; W_{dn}, the $n-th$

word in the $d - th$ document; and Z_{dn}, the word's topic. In this study, the Mallet LDA library toolkit (McCallum 2002) was used for the modelling topic from the tweet corpora to glean insights about the context of online retail brands discussed on Twitter. We chose the MALLET library to perform the LDA computation because it enables the programme to browse words that are frequently found together or that share a common connection. Furthermore, the LDA helps identify additional and hidden terms within topics that may not be directly instinctual and manually observed but relevant.

3.4   Determining topic number

One challenge in using the LDA approach is to choose an optimal number of topics because different numbers of topics will also affect the outcome of the analysis (Kim et al. 2016). Therefore, determining the number of topics should be data-driven. Gibbs sampling (Geman and Geman 1984) was applied to determine the optimal latent number of topics by experimenting with different values of *k* to check for stability. Gibbs sampling is an iterative algorithm often used in statistical physics that involves sequentially sampling variables of interest through some number of iterations, stopping when it finds the conditional distributions for each hidden variable in the model (Blei 2012; Xuan et al. 2015). It allows researchers to learn the distributions of latent variables to discover their semantic document structure. We ran the sampling algorithm for 1000 iterations and tried different values of *k* by adopting the Griffiths and Steyvers (2004) approach, and the one with the largest likelihood was selected. This approach used the sampling algorithm to establish the number of topics in which samples are obtained from the posterior distribution at a different number of iterations to stabilise the loglikelihood until it reaches the optimum peak. One thousand iterations were chosen because the training likelihood improves after a large number of iterations (Namata et al. 2009). Experimenting with different iteration parameters is necessary to check for stability and, more importantly, to try a range of different values of *k* to find the optimal number of topics.

Using Gibbs algorithm, we tried different values of *k* that fit to the model and found the optimal value. We followed the example from (Griffiths and Steyvers 2004) for each value of *k* to extract the log-likelihood values from each model and then computed the harmonic mean of the log-likelihood values to get the final *k*. From the graph, we plotted the results, and the peak of the curve showed us which value of *k* maximises the harmonic mean of the log-likelihood. We took it as the maximum value and assigned it to variable *k* = topic number. Applying it to our dataset, we obtained 72 as the optimal topic number.

3.5   Literature Analysis of Online Retailing

Many studies have investigated the variables and factors associated with online retailing in various settings.

Many of these studies have adopted different aspects and combinations of factors and constructs of online

retailing from empirical and exploratory research studies reported in the literature. Accordingly, this study

integrates six common constructs from the literature as the main themes: delivery, customer service,

product performance, security and privacy, website design, and transaction (Collier and Bienstock 2006;

Francis 2009; Luo, Ba, and Zhang 2012). The main purpose of this review is to make sense of and verify

the topic modelling findings. These constructs were selected because they were often discussed in the

literature on online retailing and were significant and relevant to this study. Next, a comprehensive list of

themes and factors was created (see Table 2) for further analysis. The list of themes and factors will be

used as a guideline for mapping and verifying our topic model results in the results section.

Table 2. Key themes and factors of online retailing

Theme	Factor	Description	Reference
Delivery	Delivery timeliness	Timely delivery. Receive product according to the promised time	(Cheung, Lee, and Rabjohn 2008; Luo et al. 2012)
	Accuracy	Receive product at the desired location and be billed the correct amount	(Collier and Bienstock 2006; King, Racherla, and Bush 2014)
	Flexibility	Advantage to choose preferred delivery time	(Francis and White 2002; Jiang, Yang, and Jun 2013)
	Product condition	Receive products in good condition	(Collier and Bienstock 2006; Francis 2009)
	Reliability	Reliable delivery	(Ahn, Ryu, and Han 2004)
	Shipping cost	Charges and shipping process	(Jiang and Rosenbloom 2005)
	Tracking	Tracking option	(Jiang and Rosenbloom 2005)
Customer service	Customer support	Follow-up service post-purchase or complaints handling by service personnel	(Francis 2007, 2009)
	Competence	Professional customer service staff perceived as competent	(Ahn et al. 2004; Francis 2009; Francis and White 2002)
	Comprehensiveness	Clear and complete policies and procedures	(Cheung and Thadani 2012; Yoo, Sanders, and Moon 2013)
	Helpfulness	Provide helpful answers to customers' questions and resolve problem	(Francis 2009; Francis and White 2002)
	Responsiveness	Responds promptly to user requests and complaints	(Francis and White 2002)
	Return and refund	Ease of returning product and getting refund	(Ahn et al. 2004; King et al. 2014)
	Empathy	Understand and address customers' specific needs	(Ahn et al. 2004)
Product	Loyalty	The attitudinal and behavioural response towards one or more brands over time	(Hsin Chang and Wang 2011; Yoo et al. 2013)

	Brand experience	Customer exposed to specific brand-related stimuli (i.e., colours, shapes and design elements)	(Brakus, Schmitt, and Zarantonello 2009)
	Product experience	Consumers directly or indirectly express opinions and evaluate products	(Brakus et al. 2009)
	Prior experience	Previous experience of the user using the same products or the same site	(Seckler et al. 2015; Weisberg, Te'eni, and Arman 2011)
	Product availability	Presence of diverse products in online store to satisfy the broad shopping interests of potential customers	(Ahn et al. 2004; Chang, Torkzadeh, and Dhillon 2004)
	Product knowledge	Knowledge about the product	(Lim and Chung 2011)
	Product price	The selling price of the product	(Fang et al. 2014; Luo et al. 2012)
	Repurchase intention	The willingness to purchase a product again in the future from the same company based on previous experience	(Hsin Chang and Wang 2011; Kim et al. 2012)
	Willingness to recommend	Willingness to recommend products to others in the future	(Cheung and Thadani 2012)
Security and privacy	Trust	Positive belief about the perceived reliability of, dependability of, and confidence in a person, object, or process	(Harris and Goode 2004; Weisberg et al. 2011)
	Confidentiality	Concern about the confidentiality of personal details retained by the website operator	(Francis 2007, 2009)
	Card safety	The safety of used credit card/debit card for payment	(Francis 2007, 2009; Francis and White 2002)
	Secure information	The safety of information provided, such as personal details not being shared with other companies or Internet sites	(Collier and Bienstock 2006; Francis 2009)
Website	Ease of use	Easy to use and locate information and easy to find products on e-retailer's website	(Ahn, Ryu, and Han 2007)
	Ease of navigation	Easy and quick to navigate	(Cheung et al. 2008; Collier 2006)
	Credibility	Accurate and updated information on the web site (e.g., sold-out products, correct price)	(Rose et al. 2012; Seckler et al. 2015)
	Functionality	The technical functioning of the website (e.g., always up and available and valid links)	(Collier and Bienstock 2006)
	Site design	The design of the website (e.g., text, format, style and colours)	(Luo et al. 2012; Seckler et al. 2015)
	Navigation speed	Speed of web pages to download and display	(Cheung et al. 2008; Collier 2006; Rose et al. 2012)
Transaction	Shopping convenience	The extent to which a customer feels that the purchase process is simple, and user-friendly	(Jiang et al. 2013)
	Online payment	Purchase interaction involves typing in payment using credit or gift card information	(Chang et al. 2004; Jiang et al. 2013)
	Transaction systems	Involves transactions during purchase and selecting products (e.g., app)	(Francis 2009; Francis and White 2002)
	Ordering system	Involves ordering system during purchase (e.g., shopping cart)	(Francis 2009; Francis and White 2002)

4   Analysis and Results

In this section, we present the results of the LDA topic model analysis of our tweet corpora. We validated

our results by mapping and comparing the factors discovered in our LDA analysis with the existing

literature on online retailing. Subsequently, we performed a network analysis on the main themes and

associated topics to identify the relationship between the important factors for online retailing. In the last section, we particularly examine the tweets with negative sentiment and performed the same analysis to understand what causes customer dissatisfaction.

4.1 Factors of brand-related tweet content

In this study, 72 topics were extracted using the LDA method. Table 3 illustrates a snapshot of the top 10 out of the 72 topics according to their weight. The accumulated weight indicates the distribution of words that put the highest weight in that topic and shows importance of the extracted topics in online retailing. As seen, many of these topics captured important aspects of online retailing operations. Each topic was visualised as word clouds in which keywords with high probabilities were enlarged based on their proportion of probability in the topic. From the LDA output, we observed several interesting concepts or terms that were clearly relevant to online retail brand operations, such as "delivery", "order", "service", and "shopping".

The topics were manually labelled into themes or categories based on the combination of human judgement (Guo et al. 2016) with reference to the literature on online retailing. We assigned the extracted topics into eight categories, of which six (delivery, customer service, product, security, website, and transaction) were from the comprehensive review illustrated in Table 2. If the extracted topic could not be associated with the factors included in Table 2, we labelled the terms that can best explain the combination of these keywords. The labelling process was first conducted by two researchers independently. Then the researchers compared their results and confirmed the topic name by consensus. This labelling and mapping process were based on the researchers' interpretation of the literal meaning of the most frequent keywords and their logical connections with online retailing related themes/factors identified in Table 2. For instance, in Table 3, the topic was named "delivery timeliness" based on the word "order" and "delivery", and both keywords appeared at the top of the list. Furthermore, time-related keywords (e.g., time, day, today) were included in the topic keywords list. Subsequently, after the identification, a candidate topic name was further tested via a logical connection to other top 10 words within the same topic based on human judgement. If a connection was found, the name was confirmed; otherwise, the naming process was restarted. For example, topic 27 it was named "reliability" based on the words "online", "poor", and "waiting", whereby people expressed that they had to wait for their delivery due to the poorly managed and

unreliable delivery service. The tweets with the keywords "morning" and "collect" also demonstrated the failure of the delivery service to follow and deliver customers' items at the paid, promised time. To verify the interpretation of topic labels, we also referred to the original tweets that contained these keywords to check whether the topic labels reflected the original meaning of tweets.

Table 3. Topic modelling results

Topic No.	Weight	Topic Keywords	Word cloud	Factor		
				Researcher A	Researcher B	Final
39	0.938	Order, delivery, day, today, time, delivered, service, customer, email, and days		Delivery timeliness	Delivery timeliness	Delivery timeliness
32	0.925	Home, week, online, give, price, put, win, delivery, pay, and offer		Delivery timeliness	Flexibility	Flexibility
63	0.811	Disappointed, customers, thought, arrived, box, lot, response, part, shop, and longer		Responsiveness	Responsiveness	Responsiveness
16	0.758	Shopping, year, night, kids, voucher, care, pls, company, friend, and products		Prior experience	Prior experience	Prior experience
58	0.599	Day, big, open, bag, slot, tomorrow, amazing, bags, eat, and due		Sentiment	Flexibility	Flexibility
37	0.532	Store, Christmas, food, today, great, good, time, bought, staff, and shop		Product experience	Brand experience	Store-related issues
11	0.480	Ruined, guarantee, changing, terrible, entire, stated, difficult, load, moon, and complained		Responsiveness	Responsiveness	Responsiveness
27	0.472	Online, poor, waiting, collect, car, milk, people, manager, morning, and turkey		Reliability	Delivery timeliness	Reliability
12	0.303	Prime, account, Christmas, package, book, shipping, app, seller, waiting and tracking		Delivery timeliness	Transaction system	Transaction system
29	0.297	Kindly, suggestion, addressed, handbag, dey, apologize, apt, Michael, regency and diary		Willingness to recommend	Willingness to recommend	Willingness to recommend

Figure 2 lists important factors extracted from the dataset with the weights measured by the word distribution for each factor. Among them, delivery flexibility carried the highest weight of 1.524. In other words, statistically, delivery is the topic mentioned most and was a primary concern for Twitter users regarding online retailing. Responsiveness is the second-ranked factor in the topic list. Unlike the first one, responsiveness is related to customer service in that customers tweeted about how well customer service personnel answered their requests and complaints. Delivery timeliness is the third most important factor in the topic list. As observed, many customers talked about deliveries arriving late, changes in delivery time, late order status, missing packages, and stolen packages. These findings align with recent studies indicating that customers often shared their feelings on social media platforms if they experienced unsatisfactory delivery service such as delays and wrong orders (He et al. 2016; Xu et al. 2017).

The remaining topics are associated with prior experiences, store-related issues, product experiences, reliability, product availability, and brand experiences. As observed, customers talked about their purchase experience with the same retailers, experience with in-store staff, and the reliability of the delivery company. Additionally, some other factors were related to shopping convenience, accuracy, loyalty, trust, and the like. As seen in the examples of tweets, customers mentioned ordering system errors, apps errors, apps and website outages, cart disappearances, and support for system problems.
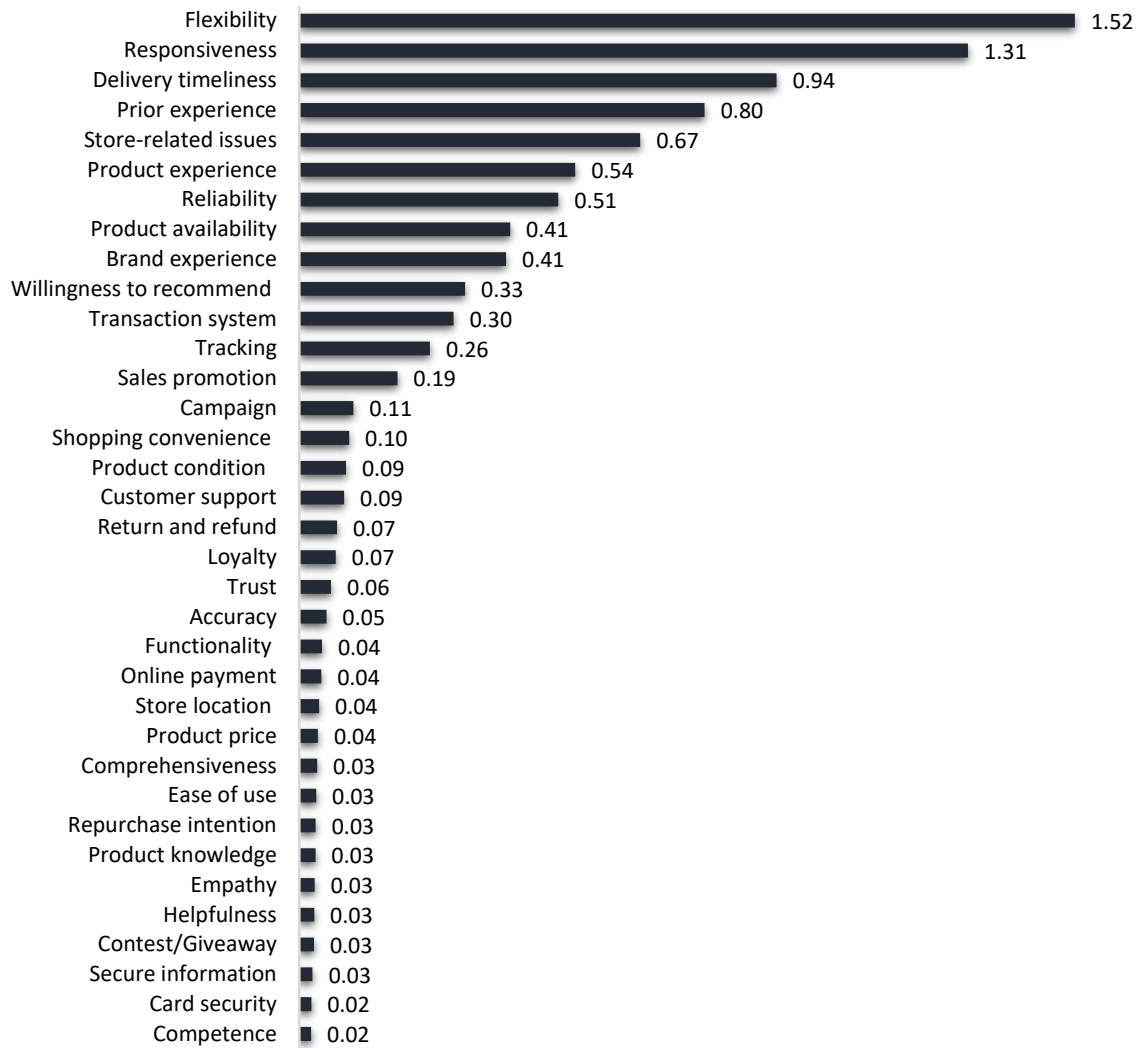
Figure 2. Extracted factors

4.2 Factor comparison

In this section, we compare the emerging factors from our LDA analysis with the factors from the literature

(see Table 2). Delivery is the top area of concern for most customers shopping online with the total weight

of 3.373 in the aggregated topic categories (see Table 4). Delivery includes timeliness, accuracy, flexibility,

and reliability. For instance, customers appeared to tweet about problems with late and unreliable

deliveries, inaccurate delivery locations, tracking options, and lazy delivery guys. It also implies that

delivery is customers' most important concern during the Black Friday, Christmas, and Boxing Day

holiday period. While delivery-related topics are mentioned most on Twitter, product-related topics, such

as prior experience, product experience, product availability, and brand experience, are among the priorities

for customers. For instance, customers tweet about their current and past experiences with the product, the

design of the product, their reviews of product performance, product characteristics, global brands, the

originality of the product, and their experiences with the services given or products they purchased. It is not

surprising to see that topics associated with products have the second highest weighted aggregated category

in Table 4 with the total weight of 2.658. This agrees with the findings of Chu and Sung (2015) and Wang

et al. (2012), who showed Twitter is a platform that enables customers to solicit information and provide

comments about their product consumption experiences, and the communication that occurs on social

media could influence consumers' attitudes towards products.

Table 4. Comparison factors between LDA analysis and prior studies

Category	Total weight	Weight	Factors	LDA analysis	Literature
Delivery	3.373	1.524	Flexibility	/	/
		0.938	Delivery timeliness	/	/
		0.509	Reliability	/	/
		0.257	Tracking	/	/
		0.092	Product condition	/	/
		0.053	Accuracy	/	/
Product	2.658	0.797	Prior experience	/	/
		0.542	Product experience	/	/
		0.414	Product availability	/	/
		0.406	Brand experience	/	/
		0.326	Willingness to recommend	/	/
		0.072	Loyalty	/	/
		0.037	Product price	/	/
		0.032	Product knowledge	/	/
		0.032	Repurchase intention	/	/
Customer service	1.594	1.315	Responsiveness	/	/
		0.088	Customer support	/	/
		0.074	Return and refund	/	/
		0.035	Comprehensiveness	/	/
		0.03	Empathy	/	/
		0.029	Helpfulness	/	/
		0.023	Competence	/	/
New – In-store experience	0.709	0.67	Store-related issues	/	X
		0.039	Store location	/	X
Transaction	0.444	0.303	Transaction system	/	/
		0.098	Shopping convenience	/	/
		0.043	Online payment	/	/
New – Online engagement	0.328	0.193	Sales promotion	/	X
		0.106	Campaign	/	X
		0.029	Contest/Giveaway	/	X
Security and privacy	0.112	0.062	Trust	/	/
		0.026	Secure information	/	/
		0.024	Card security	/	/
Website	0.077	0.044	Functionality	/	/
		0.033	Ease of use	/	/

Note: Number of factors—LDA:35, Literature:30

The next important category is customer service with the aggregated weight of 1.594. Factors such as responsiveness, customer support, returns and refunds, and competence of customer service personnel were significantly extracted from our tweet corpora. For instance, customers voiced complaints about issues related to customer service, including a hard-to-reach customer service hotline, dissatisfaction, cancellation orders, and slow-to-respond sellers on the website. Such complaints suggest the importance of customer service in brand-customer interaction, an area online retail companies should take into account when managing their relationships in this fast-rising social media era (Hennig-Thurau et al. 2010).

As mentioned, two new categories emerged from our LDA analysis, online engagement and in-store experience. In the context of this research, online engagement occurs when a customer participates in online activities leading to customer gratification. Such participations explain how activities can enhance the customer-retailer relationship to become effective through engagement and benefit retailers, which is the purpose of this research. Accordingly, the advent of social media has generate a more sophisticated view of customer-retailer engagement (Hudson and Thal 2013) and developed an interest in customer engagement by listening and learning from them (Gorry and Westbrook 2011). As Table 4 shows, we identified three topics that represent online engagement: sales promotion, contest/giveaway, and campaign. Promotion refers to the activities of selling, advertising, and direct marketing, and contest refers to competitions hosted by the online retailer to engage with its followers and simultaneously attract potential new customers. In fact, some companies use Twitter to create buzz about their products and encourage the public's participation in their events or giveaways. This result supports the argument that brands attempt to create a long-term relationship with customers by engaging with them (Kim and Ko 2012). Contests and giveaways held on Twitter (e.g., RT to win a #freekindlelimitededition by Amazon) brought numerous new followers to the social media platform and attracted many others to join the competition because these tweets often got retweeted. These results align with the work of Hoffman and Fodor (2010), who claimed that an online engagement strategy is a relevant gauge of the effectiveness of a company's social media marketing activities because it allows brands to proactively engage with customers. It is also one of the quickest ways to build a Twitter community and prompt people to spread awareness of the brand. This community platform has empowered brands to exchange brand-related information and engage with customers and thus has emerged as a promotional tool for marketing (Araujo and Neijens 2012).

In-store experience, the other new category that emerged from the analysis, includes store-related issues and store location. It can be explained as customer experiences or general issues in the bricks-and-mortar stores. With the growing use of mobile, Internet technologies, and social media, the retail landscape continues to change as consumers use the online and offline retailing channels interchangeably and seamlessly during their search and purchase process. Retailers are offering many new services such as reserve online and pick up from store, store delivery, and return to store, requiring the integration of online and offline retailing and redesign of their processes to build a seamless shopping experience (Hübner, Wollenburg, and Holzapfel 2016; Verhoef et al. 2015). Therefore, in-store experience plays a crucial role in offering such a seamless cross-channel shopping experience. In-store experience emerged as an important topic among the Twitter users, demonstrating the significance of perceived service from offline retail stores in the overall shopping experience. For instance, customers mentioned "store" in their tweets, pertaining to problems or experiences they had in the physical stores. Our topic model analysis detected that customers normally mentioned several problems such as staff and services in store locations, citing the name of the specific store in their tweets such as "haslington" and "highwood". Thus, they specifically targeted those stores and reviewed their respective stores. Of the five online retail brands in this study, four have physical stores all over the UK, except Amazon. Therefore, it was not surprising that customers spoke out about the physical stores on Twitter to express their opinions or channel their complaints. The insights derived from analysis can help retailers accommodate customers' problems and allow them to take immediate action to respond to customers' concerns. This factor is essential because the information tweeted by customers on Twitter could influence other customers' opinions and views and negate the effect of the brand-customer relationship, especially on trust (Habibi et al. 2014). It is evident that online information influences customers' experiences across shopping channels as well as in-store. As the natural borders between the online and offline channels start to disappear, it is important for retailers to integrate multiple channels and design the processes that facilitate a seamless "omni-channel retailing" experience (Verhoef et al. 2015).

Based on the comparison results, we also observed that some factors and categories for online retail identified in the prior studies were not discussed or were mentioned less frequently by Twitter users. More specifically, factors such as shipping cost, confidentiality, credibility, ease of navigation, site design, and

ordering system, which were highlighted in the online retailing literature, did not emerge in our LDA analysis. For instance, we found that navigation and website design were rarely mentioned by customers on Twitter, perhaps because online retailers have already developed websites with up-to-date web technology and have provided an efficient and responsive website for customers. Due to the nature of online retail businesses, a user-friendly, well-designed website is a must for companies to compete (Baloglu and Pekcan 2006).

Findings from this analysis yield insight for social media strategy and future promotional strategies. Newly emerged categories such as online engagement and in-store-experience could help create a unique way to position the brand to help companies engage with customers, creating a win-win situation. Online engagement, for instance, is critical both for engaging existing customers and attracting new ones. Contests or giveaways encourage customers to actively visit a brand's page and retweet questions. Such activity can create buzz and spread the word among social media users. In addition, campaigns and promotional tweets increase brand awareness and inform customers about new products or services. They can contribute to the development of a Twitter community that shares interests and enhances social connection and content discovery. Companies should adopt a proper strategy that facilitates regular content updates and initiates and maintains daily communication with customers to maximise the impact (Hoffman and Fodor 2010).

4.3   Network analysis

A network analysis was conducted to examine the relationship among the topics and categories derived from the LDA analysis. Network analysis in social media research is performed to detect and interpret patterns of social ties, model the connections, and observe the growth and dynamics of the activities in social network platforms based on mathematical models and graph theory (Feicheng and Yating 2014; Toral, Martínez-Torres, and Barrero 2010). It can also be used as a marketing tool, estimating network size and predicting a network's progress over time (Abascal-Mena, Lema, and Sèdes 2015). In this study, network analysis is performed to identify the relationship between the main topics derived from our topic modelling analysis. To visualise the connection between factors and categories, the list of keywords was compiled according to its associated category and factor in Node XL. After that, the tool was computed to visually map the network, revealing the structure of the relationship, its close bond, and insightful connection about the keywords.

Figure 3 illustrates the result, wherein the clusters represent the identified topics, and each contains 20 nodes of the associated keywords. The topic clusters were grouped together under the associated categories. The network graph shows that the nodes at the centre (e.g., "time", "today", "shop", "Christmas", "day", "customer", etc.) occur more often across several topics instead of only one topic. Because these keywords are embedded in the factors such as delivery timeliness, product availability, brand experience, campaign and store-related issues in purple-coloured nodes, they are the five main clusters, with 8.37% of modularity with the most overlapping keywords, meaning these factors represent the core factors in online retailing businesses. While the result reflects the nature of online retailing service operation, the time elements embedded in these key factors also highlight the importance of time-based competition in this fast-moving and competitive industry sector. Furthermore, these factors represent more than half of the categories (e.g., product, customer service, and delivery) discovered in the literature as well as the new categories extracted from the Twitter data. Using a social network analysis, Bonchi et al. (2011) recommended that the product has a strong impact on improving customer experience, followed by delivery and customer service.

Interestingly, customer service, security and privacy, and website do not have a strong connection with other themes, as the keywords under them are exclusive to the respective factors as opposed to delivery timeliness and product availability with their significant overlap. While the results demonstrate the important role that these factors play in the online retailing service provisions, a strong interconnection between delivery timeliness and product availability highlights the joint effect of these two factors on the core retailing service operations. Intuitively, low product availability has a knock-on impact on the delivery timeliness, and achieving delivery timeliness will require improvement in product availability. In contrast, factors (e.g., customer service, security and privacy, and website) play their independent roles in supporting the online retailing service operations. According to Abascal-Mena et al. (2015), it is possible to see clusters or groups that are disconnected from other factors because they are grouped according to their exclusive interactions and have some degree of independence. The observation offers an overall picture of the topic modelling results that provides a more in-depth examination of relationships between online retailing topics as well as their corresponding categories.

Figure 3. Topic network

The main purpose of the network analysis is to focus on the connections between the data and the visual structure of the data. The result allows us to highlight the important nodes (in this case, a keyword) and leads to some new discoveries. This analysis brings together statistics and visualisations to help simplify the statistical results and allow us to focus on the statistically significant keywords. It is important because the result focuses on the relationships of how the elements are connected instead of individual elements. This approach covers the statistical measure of content and data visualisation that helps retailers understand the structure of the relationship between different factors. This visual representation of the network analysis is useful in understanding the relationship between the core factors in online retailing and emphasises the interconnected factors that are most significant in improving customers' online retailing experience.

4.4 Sentiment analysis and topic modelling for tweets with negative sentiment

Tweets with negative sentiment are often associated with customers' complaints and concerns regarding products and services (He et al. 2016; Ibrahim et al. 2017; Xu et al. 2017). Sentiment analysis is also a popular measure for marketers to evaluate the success of social media initiatives in their marketing strategies (Hoffman and Fodor 2010). To improve service provision, it is essential for online retailers to understand which online retailing service consumers are dissatisfied with or the aspect that has garnered criticism. To achieve this, we performed a sentiment analysis to examine the sentiment of tweets for all five brands. The same topic modelling approach was applied to identify topics that emerged from those negative tweets.

First, a sentiment analysis was performed on the overall tweets using the same sentiment analysis tool, SentiStrength, which has been widely used in previous works that explore customers' views and opinions on social media (Hewett et al. 2016; Tse et al. 2016). Derived from the overall sentiment results, the negative sentiment tweets were specifically chosen for the next analysis to obtain an in-depth understanding about what normally displeases or plagues customers. Of the 386,379 tweets, the majority were neutral. We observed a small percentage of negative (8%; 35,785) and positive (9%; 31,987) tweets. Surprisingly, negative sentiments were slightly higher than positive sentiments for the whole dataset. This result contradicts Roshanaei and Mishra's (2015) study that found negative users are not interested in sharing their negativity on social media compared to other users. Nevertheless, it is also understandable since it is more common for customers to resort to social media platforms to write their complaints following online retailers' ineffective management of customer complaints.

Next, we calculated the optimal number of topics generated from our negative sentiment dataset. We followed the same steps and algorithm as in Section 3.4 to determine the value of *k*. The total number of negative tweets is relatively smaller compared to the original dataset, which leads to nine as the optimal topic number. Then, we extracted eight topics using the same LDA method after merging the duplicated ones. Figure 4 describes the results. As seen, delivery timeliness not only tops the topic list according to the weights, but it is also the area of concern for most consumers, or the area that produces the most dissatisfaction, followed by customer support, competence, and product price. We also observed that the difference in weights among these topics is minimal.

In terms of categorised themes for online retailing, customer service has the highest weight in the negative sentiment dataset, including four factors (e.g., customer support, competence, helpfulness, and responsiveness). More often, unpleasant and disgruntled customers turn to Twitter to voice their complaints about the poor service they received. Customer service, then, plays a critical role in online retailing service provision. This further supports the idea that companies that acknowledge customer service concerns and quickly react to customers' dissatisfaction could influence people's perceptions of brand trust and attitudes (Bee and Tan 2014; Coyle et al. 2012). Furthermore, delivery timeliness and reliability were the main concerns of customers, which aligned with our findings in Section 4.1. These findings also align with Cao, Gruca, and Klemz (2003), who associated customer satisfaction with customer experience on delivery, and Collier and Bienstock (2006), who argued delivery is the most important aspect of service quality in the online shopping experience.
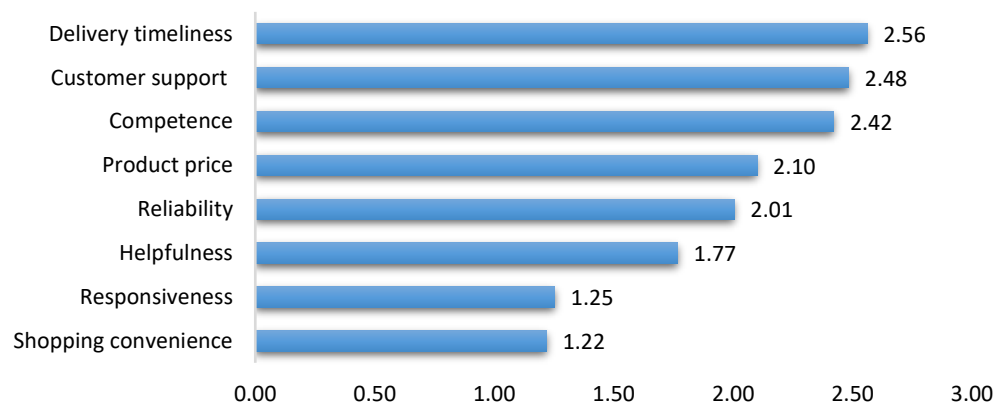

Figure 4. Extracted factors from negative sentiments

Interestingly, we discovered a strong negative sentiment when consumers talk about "product price" on social media. Unlike the whole dataset, in which product price carries a relatively low weight, product price emerged as a significant factor among the tweets with negative sentiment. This finding supports the view of Chen, Fay, and Wang (2011), who found that customers will feel unhappy and their satisfaction level will be low when product price is high, which in turn leads customers to tweet or post reviews to vent their negative feelings. This discovery also supports the argument that product price influences customers' motivation to inspect more closely the content of trust arguments in e-commerce (Benbasat and Kim 2009).

We also applied a network analysis of the detected topics. Figure 5 illustrates the results. Reliability and product price appeared to be related with overlapping keywords such as "disappointed" and "called".

The keyword "disappointed" indicates that the two clusters shared opinions mostly about their disappointment in the brand's reliability and product. It corroborates the ideas of Ahn et al. (2007), who found the reliability of the service had a significant impact on the quality of online retailing operations. However, our results also suggest that most of the remaining keywords are not connected among the identified topics. One explanation is that different sets of complaints filed by customers covered various types of products or different aspects of the online retailing service.
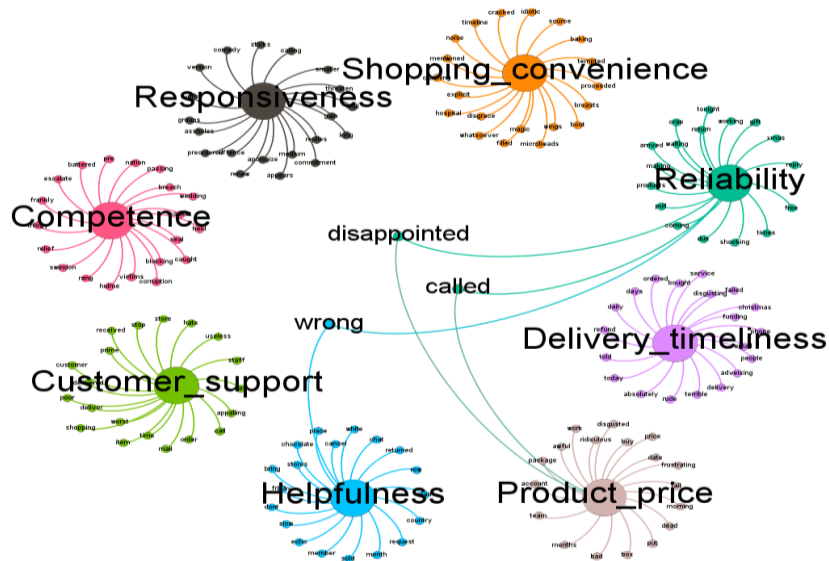

Figure 5. Topic network for negative sentiments

By providing insights on the areas for online retailing service improvement, this study also offers important management implications to online retailers. The topic modelling results regarding negative sentiment tweets highlight the areas of customers' concern. With a solid understanding of customers' behaviour on social media, brands can develop a competent strategy focusing on the specific area that customers care about most. As a result, online retailers can refine their focus and concentrate on their weaknesses in their online retailing service operation that require urgent actions.

5   Discussion

In this study, our focus was to gain a better understanding of the discussions shared on the Twitter platform and to identify customers' main concerns to improve online retailing services. We explored tweet content using a topic modelling approach to find natural and hidden topics within the tweet text. Such information acts as a source on how to handle and meet customers' expectations. In fact, most companies have already used social media platforms such as Twitter to increase customer satisfaction and inspire loyalty

(Ramanathan et al. 2017). Companies tend to use social media platforms as their marketing playground to promote brands and products and solicit feedback from the social media masses. Companies are also experimenting with social media by gathering feedback, customer impressions, and sentiments to develop business tactics and strategies.

5.1   Theoretical contribution

Online retailing has grown substantially in the past two decades and is expected to continue to grow in the foreseeable future. Many online retailers have turned to social media to seek competitive advantages in this competitive sector (Ibrahim et al. 2017; Ramanathan et al. 2017; Yoo et al. 2013). Whereas a few previous studies have demonstrated the generic information of what people talk about on social media (Madani, Boussaid, and Zegour 2015; Pépin et al. 2017; Yildirim et al. 2016), most of these efforts have not established what customers' specific utmost concerns are based on what they feel and the hidden relationship that exists in the conversation. The literature has demonstrated the difficulties of analysing Twitter data due to its volume and unstructured format and called for more accurate analysis (Gandomi and Haider 2015; McAfee, Brynjolfsson, and Davenport 2012). However, this study overcomes this challenge by integrating multiple techniques of Big Data analytics, including topic modelling, sentiment analysis, and network analysis, to measure different aspects of the social media data and offer a better understanding of the relationships between online retailers and customers.

More specially, the topic modelling approach identifies the popular topics discussed and shared among Twitter users regarding online retail brands. This is critically important for online retailers because what customers discussed and shared on social media platforms has significant influenced other users' future purchase decisions (Cheung et al. 2014; Lee et al. 2016; Thakur 2018). Through a comparison with the existing online retailing literature, two emerging areas, "online engagement" and "in-store experience", were identified, which indicates the influence of the digital environment on customer experience across online and offline retailing channels and highlights the need of facilitating a seamless "omni-channel retailing" experience (Verhoef et al. 2015). In addition, applying the network analysis to the topic modelling results allows us to study the interaction between important factors of online retailing. The simple visualisation representation sheds light on not only their weightage, but also on how the key factors relate to each other, thus implying relationships and bonds between them. Using this method, we are able to

distinguish the areas having close bonds from the stranger. This analysis is supported by the previous literature that used the similar method to identify the most relevant user in the field, the influence users, and keyword analysis (Park et al. 2016; Riquelme and González-Cantergiani 2016). Furthermore, the incorporation of sentiment analysis helps derive insights into how well the online retailing services of the leading retail brands are performing and how their customers perceive their products and services. These insights can bring the retailers' attention to the factors that lead to customers' dissatisfaction and act as a foundation for improving their online service provision.

Overall, the incorporation of three analytical approaches and the application of tweet data in the context of online retailing embrace significant potential for online retail and social media scholars who seek to understand the role of social media in improving online retailing.

5.2   Practical contribution

In general, this study has important managerial implications. Our research adds value to online retailers by enabling them to understand their customers better and to focus on the areas that need improvement. At the same time, our analysis could lead to the development of new strategies for better services and improved customers' experiences. Building a relationship with customers should be a priority for companies, and social media platforms should be fully utilised to achieve the desired outcome. Effective social media management gives companies access to a place in which customers meet and converse and enables them to understand and listen to their customers' concerns. In contrast to traditional methods, in which companies tend to talk rather than listen, the social media age offers the opportunity for companies to talk less and listen more, which yields greater benefits.

Furthermore, the results from this study can be used by managers and practitioners to offer a scope of service within customers' expectations and show that they care about their customers. For instance, the tweets associated with delivery can explain why delivery has garnered so much attention from customers: it is at the core of online retail business. Improvement in delivery timeliness might be challenging and require more investment, but showing concern while handling customers' queries and complaints might also lessen resentment and placate the customers. By understanding customers, brands can convert these online conversations into valuable knowledge that can benefit their businesses. We noticed from the analysis that customers share diverse content on social media. Since companies are aware that building great customer

service and experience is a complex task, they should invest in social media management activities to improve those experiences. Establishing a systematic monitoring tool of social media to manage customers' queries and experiences is a top priority to effectively handle customers (Ibrahim et al. 2017).

We also observed that a detailed focus on the analysis of consumer-generated content could help online retailing brands manage customer relationships effectively and efficiently. Ideas and experiences shared by customers on social media platforms allow companies to connect with them and stay abreast with what is occurring on Twitter. To connect with customers, online retailers should monitor the conversations about their products and services and engage with customers. Timely engagement in this low-cost and high-efficiency platform allows companies to improve their customers' experiences (Kaplan and Haenlein 2010). Moreover, this platform is an opportunity to satisfy customers and, at the same time, to plot strategies for a competent business, which helps create a major shift in business practice and also affects business culture. It will be beneficial for brands to turn to social media because it plays an important role in effectively improving customer experience and acts as a marketing tool to increase the effectiveness of marketing communication.

6   Conclusions

In this study, our objective was to analyse Twitter content to discover emerging topics associated with online retailing to better understand customers' needs. Using the topic modelling approach, we generated some insights from an analysis of the tweets of five leading online retail brands in the UK during the most crucial trading period. The findings of this study identified delivery, product, and customer service as the most-discussed topics on Twitter in general, respectively. Slightly different, an analysis of the negative tweets indicated that delivery and customer service were the main areas customers highlighted that needed improvement. Two new categories (i.e., online engagement and in-store experience) that emerged from our LDA analysis were also proposed in this study.

Overall, the increasing significance of user-generated content e.g., social media data, has provided businesses great opportunities and challenges of exploiting the large volumes of data to create business values (Sheng et al. 2017; Wang, White, and Chen 2015). Our research presents a novel approach that effectively integrates a number of business analytics methods and enables firms to transform social media data into useful knowledge about customers' perceptions about their service provisions. The proposed

analytical techniques uncover the hidden patterns and ensure the robustness of results. They help identify customers' primary topics of concern regarding online retail brands as well as critical improvement areas in a timely manner. In doing so, these techniques provide insights into how business analytics can be marshalled to deepen our understanding of the complex process inherent in identifying customers' concerns and capture value from user-generated data for service improvement. The study answers some key questions of social media research and provides solutions for researchers and practitioners to harvest social media data and transform them into useful business insights. Our study also contributes to the growing body of literature on online retailing by identifying a comprehensive list of important factors for online retailing through a systematic review and validating the list through our topic modelling analysis of Twitter data. Through the analysis, we identified new emerging topics that are shared and discussed among social media users and captured the relationships between the important factors of online retailing.

This research can be extended in several ways. For instance, although LDA topic modelling is an effective data-driven approach, the labelling of identified topics still requires human interpretation, and the process is challenging due to the nature of unstructured and massive data like Twitter (Gandomi and Haider 2015; McAfee et al. 2012). Future research could address this limitation and make this human interpretation of topic labelling more objective. In addition, a longitudinal analysis can be performed to analyse the trends of tweets on Twitter and variations of topics and sentiments over time since the dataset contains hundreds of thousands of tweets over a two-month period. Furthermore, because this paper mainly focuses on listening to and understanding customers' concerns expressed on social media platforms, one natural extension is to incorporate the obtained knowledge to develop new strategies and services and evaluate how these business interventions are perceived by social media users. Finally, as Bradlow et al. (2017) argued that it is a mix of new data sources rather than a rise in data volumes that drives improved outcomes in retailing, it will be valuable to incorporate an analysis of social media data and transactional data from online retailers using analytics tools and domain knowledge.

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Appendix

```
> harmonicMean <- function(logLikelihoods, precision=2000L) {
+     llMed <- median(logLikelihoods)
+     as.double(llMed - log(mean(exp(-mpfr(logLikelihoods,
+     prec = precision) + llMed))))
+ }
```

Appendix 1: Finding the optimal number algorithm