A Social Media Analytic Framework for Improving Operations and Service Management: A study of the retail pharmacy industry

Abstract

The revolution in the digital economy is forcing the retail pharmacy industry to develop new business models to achieve operational excellence. A large amount of user-generated content on social media can be captured and analysed to help organisations gain insights into market requirements and enhance business intelligence. Accordingly, this study proposes an analytic framework for retail pharmacy organisations to: a) use social media and highlight the most-discussed topics by consumers, b) to identify the key areas for improvement based on the most negative comments received, and c) to determine the connections among the important concepts and enhance customer loyalty by adding values to consumers. We conduct an in-depth analysis on the Twitter platforms of the three largest retail pharmacy organisations in the UK: Boots, Lloyds and Superdrug. The findings show that issues with marketing, customer service and product are the key improvement areas for the retail pharmacies. Particularly, Boots received an overall better sentiment performance than Lloyds and Superdrug. We also determine the relationships among the important concepts discussed by consumers. The analysis generates insights into the use of social media for supporting pharmacy organisations in developing their social media strategies as well as improving their operations and service quality.

Keywords: Social media analytics; retail pharmacy industry; Twitter data; text mining; sentiment analysis

1.0 INTRODUCTION

Social media is revolutionising the way people consume, communicate, collaborate and create (Aral and Walker, 2012; Chae, 2015; Laurell and Sandström, 2017; Cui et al., 2018; Wang et al., 2020). It represents one of the most transformative impacts of information communication technologies on business, both within and outside organisations (Aral et al., 2013; Itani et al., 2017). In particular, social media has changed the ways firms associate with their competitors and marketplace (He et al., 2016), making a new world of opportunities and challenges for all aspects of the firm (Itani et al., 2017; Meel et al., 2019), from marketing and operations to innovation management and company finance (Kalampokis et al., 2013; Schumaker et al., 2016; Bollen et al., 2011; Bashir et al., 2017; Zhan et al., 2020). In addition, it has changed production activities among many retailers and manufactures (Singh et al., 2017). Online reviews generated from different social media platforms can be captured for retail networks to develop a model with unique marketing strategies and service operations. This will change manufacturers' and retailers' operation and production planning by offering them more purchasing options to select from (Ramanathan et al., 2017). Besides, since consumer behaviour has always been unpredictable (Aral and Walker, 2012; Itani et al., 2017), social media can help overcome this by allowing greater interaction between marketing and operations activities within the retail operations network (Chen et al., 2015; Wang et al., 2020).

In order to extract value from social media, organisations need to be able to quickly understand the user-generated data and transform those data into relevant information (Davenport, 2013; Chae, 2015). By gaining a better understanding of their customers and competitors, organisations can innovate more rapidly and effectively (Wang et al., 2016; Chan et al., 2017a). For example, operations managers can integrate the information generated from social media analytics to make fact-based decisions or to gain a better understanding of their services and products (Macnamara and Zerfass, 2012). Also, organisations are increasingly expected to harvest social media data from different platforms to gain a comprehensive understanding of both their customers and their competitors, and thus to achieve competitive advantages (Aral, 2013).

However, retail operations and service management have been relatively slow to address the potential value and application of social media for research and practice (Aral et al., 2013; Chae, 2015; Schoenherr and Speier-Pero, 2015). While the use of big data and analytical models has been increasingly studied in the context of the operations (Trkman et al., 2012; Zhang et al., 2011; Zikopoulos and Eaton, 2011; Tan et al., 2015), the focus has generally remained on traditional data sources (e.g., survey and point-of-sale transactional data) and analytical models (e.g., optimisation algorithms), and their application to operations planning and management practices (Zikopoulos and Eaton, 2011; Trkman et al., 2012; Tan et al., 2015). Some studies have pointed out that harvesting social media data can be very time-consuming and challenging (Macnamara and Zerfass, 2012; Bello-Orgaz et al., 2016). Furthermore, the global increase in the quantity of social media data requires organisations to adopt automatic analytic techniques to analyse not just their own social media platforms but also the information generated from their competitors (Chen et al., 2015; He et al., 2016). Therefore, organisations need to develop the right skills and infrastructures to harvest values from social media and support their business operations in the production of goods or services (Davenport, 2013).

The present study concerns the retail pharmacy industry, one of the largest and most important markets, with a direct impact on people's health (Jambulingam et al., 2005; Mousazadeh et al., 2015). In this rapidly growing market, retail pharmacies are transforming their operations in order to become more customer-centric through market research, surveys and the development of customer advisors to gain direct feedback for further improvements (Kukreja et al., 2011; Bharadwaj et al., 2012; Chen et al., 2015). In particular, with the advent of information communication technologies, there is a huge amount of customer-generated data available on different social media platforms, which can be captured and analysed to identify customer opinions (Dahan and Hauser, 2002; Davenport, 2013). Compared to the survey-based data, the social media data reflect the "real signal" from the customer, and this is not measured by intension. It reflects the "perception" of a service or a product provided by the firms. Therefore, effective management of social media data can offer insights into customer purchasing behaviour and attitudes concerning one or more specific issues (Bharadwaj et al., 2012).

The main aim of this study is to transform the social media data, which is unstructured text data into supportive information for improving operations and service management. This is challenging for managers since most of the social media data is provided by laypeople (Tse et al., 2018). The managers and the academics need to mine the useful information from the massive unstructured data and transform them into some quantified measurements which can help to improve the operations in the retail pharmacy industry (Xu et al., 2016). To the best of our knowledge, much of the recent literature has been too general for application by a retailer, as studies have focused on trends in the use of big data (LaValle et al., 2011; Chen et al., 2015; Brynjolfsson and McElheran, 2016) and analytical models (Tan et al., 2015; Trkman et al., 2012; Chan et al., 2015), whereas this study is more specific and therefore more directly applicable. While it is imperative to understand the value of social media analytics in the context of the retail pharmacy industry, as echoed by industry reports and academics (Aral et al., 2013; Schoenherr and Speier-Pero, 2015; Cerhoef et al., 2015), it is clear that the application of social media in the retail pharmacy industry is at a primitive stage. This leads to the following research question:

> How can retail pharmacy managers harvest social media data to improve their operations and service management?

To address the question, we propose a framework for analysing social media information, explore the current use of different analytics, and develop insights into the potential role of social media in: a) highlighting the most-discussed topics by consumers, b) identifying the key areas for improvement based on the most negative customer comments received, and c) determining the connections among the important concepts and enhance customer loyalty by adding values to consumers. The three largest retail pharmacy organisations in the UK are selected in the analysis. This study is important in several ways. First of all, this study contributes to social media literature with the development of an analytic framework for retail organisations to use social media data in their operations and service improvements. Moreover, this study summarises the relevant studies and determines eight constructs from the existing literature as the key subjects for the retail pharmacy industry. Furthermore, the findings offer managers insights into the use of social media for supporting pharmacy organisations in developing their social media strategies as well as improving their operations and service quality.

The rest of this paper is organised as follow. Section 2 reviews the literature on social media and analytics methods; it provides an understanding of the current trends, techniques and technologies that can be used to analyse social media data. Section 3 proposes an overall conceptual framework for applying different analytical approaches to analyse social media data from competing organisations. Section 4 explains the methodology of the present case study of the three largest retail pharmacy organisations in the UK, consisting of data collection, data coding and data analysis, and Section 5 presents the findings. Finally, Section 6 discusses the managerial and resaerch implications, points out the limitations of the current study and makes recommendations for future research.

2.0 LITERATURE REVIEW

According to Kaplan and Haenlein (2010, p.61), the term social media refers to "*a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0, and that allow the creation and exchange of User Generated Content*". Compared with traditional methods of acquiring information on and from customers (e.g., filling in questionnaires and conducting interviews), social media provides a broader range of conduits through which operations managers can glean valuable information and market research data, making it possible to understand customers in ways that were not previously possible (Capgemini, 2012; Ahmad et al., 2013; Xu et al., 2016).

He et al. (2016) recently studied how some firms can use social media to identify their consumers’ requirements and then innovate quickly to meet these requirements. Such organisations are considered to be much more competitive than others (BCG, 2015; Chan et al., 2015; Kache ad Seuring, 2017). These champions of innovation can integrate their key abilities and company targets with their social media analytics. Since social media is a relatively inexpensive way to reach a vast audience, it is an excellent means for organisations to communicate with customers, to facilitate social communities, to foster stronger relationships with customers and to identify new market opportunities (Kaplan, and Haenlein, 2010; Macnamara and Zerfass, 2012; Bello-Orgaz et al., 2016). Ramanathan et al. (2015) further pointed out the role of social media for a retailer by indicating that social media can capture emotional experiences to guide other shoppers. Particularly, an analysis of reviews of a company’s products or services on social media can help to identify potential future problems or identify solutions to attract or retain customers (Heller Baird and Parasnis, 2011; Kumar et al., 2016). By such analysis, a retailer can work on its operations to improve operations management and customers’ shopping satisfaction (Chae, 2015; Chen et al., 2015; 2017a). For example, with a rising number of negative posts on social media related to Airbnb’s hosts refusing guests based on race, Airbnb quickly changed its users’ agreement to allow for instant and guaranteed alternative bookings for guests who believe they have been refused a booking due to discrimination (Wang, 2017).

The main types of social media are social networking, such as LinkedIn, blogs and microblogs like Reddit; collaborative projects, such as Wikipedia; content communities, like YouTube; and virtual social worlds (He et al., 2016; Kaplan and Haenlein, 2010). Among various social media networks, this study pays attention to one particular social media platform, Twitter, which has become one of the most widely used platforms for academic studies in the practical application of social media data (Bennett, 2013; Chae, 2015; Singh et al., 2017). Notably, there are numerous examples of research applications of Twitter data in different fields, including finance (Bollen et al., 2011), marketing (Roshanaei and Mishra, 2015), politics (Grover et al., 2016), supply chain management (Chae, 2015), sports management (Schumaker et al., 2016), and environmental management (Lansley and Longley, 2016). It is anticipated that Twitter’s consequences will be far-reaching in academia and to inspire other research fields (Chae, 2015).

2.1 Social media analytics

To gain competitive advantages in this rapidly changing business environment, social media analytics becomes a useful tool to harvest information about their competitors, customers and the market more generally (Dahan and Hauser, 2002; Davenport, 2013; Iran et al., 2017; Cui et al., 2017). Zeng et al. (2010) defined social media analytics as applying advanced informatics techniques and analytics tools to capture, monitor and analyse social media data to extract useful information and patterns. Particularly, there has been a significant increase in attempts to apply social media analytics to support managers in operations and service management. Table 1 provides a summary.

Table 1: Studies based on social media analytics in operations and service management

Literature	Method	Content
Bhattacharjya et al., 2016	Machine-based interpretation	Exploring the state of logistics-related customer service
Fan et al., 2016	Data coding and $\chi 2$ analysis	Testing methods of service recovery in the operations management context
Chae, 2015	Descriptive and content analysis	Proposing a framework to assimilate social media data into supply chain management
Tan et al., 2015	Competence set analysis	Harvesting big data to enhance supply chain innovation
O'Leary, 2011	Case analysis	Investigating the insights derived from social media and the amalgamation of conventional knowledge management
Singh et al., 2017	Text mining and hierarchical clustering	Proposing a social media analytic approach to support supply chain management in the food industry
He et al., 2016	Text mining and sentiment analysis	Developing a framework to analyse social media content from business competitors
He et al., 2015	Volume and sentiment analysis	Proposing a framework for social media competitive intelligence to improve business performance
Chan et al., 2017a	Statistical cluster analysis	Proposing an approach to investigate the interrelationships amongst important factors.
Ramanathan et al., 2017	Survey questionnaire	Developing a conceptual model for understanding how retailers can leverage social media data to satisfy customers
Tse et al. 2018	Machine learning and descriptive analysis	Investigating the insights of customer attitude towards the company remedy action after product recall management incidents
Cui et al., 2018	Machine learning and nonlinear boosting methods	Exploring the possibilities social media offers in improving firms' operations and supply chain performance
Singh et al., 2018	Text analysis and hierarchical clustering	Proposing an approach that considers social media data for the identification of supply chain management issues.
Burdisso et al., 2019	Text classification technique	Introducing a supervised text classification technique to manage early risk detection issues.

In short, the studies shown that the appropriate use of social media analytics could not only capture salient but normally hidden customer behaviour, but also be applied to generate insightful knowledge to assist managers in operations and service management. However, little is known about how social media analytics should be integrated into operations and service management in the retail pharmacy industry. Additionally, the use of social media in retail operations and service management is typically related to several phases of data management, each of which needs different data-driven methods and activities. Therefore, these methods and activities need to be detailed within an integrated framework that can support managers improve their operations and service management that address customers' unmet needs.

2.2 Text mining, sentiment analysis and social network analysis

Currently, there is a variety of analytic techniques – including text mining, statistical analysis, sentiment analysis and social network analysis – that organisations can use to unlock the power of social media data from different online platforms to gain insights about customers' experiences and sentiments. According to Gandomi and Haider (2015), social media analytics can be categorised as content-based analysis, which focuses on the analysis of the customer's comments on specific services or products, or structure-based analysis, which looks at social networks and relationships. As emerging technologies, text mining, sentiment analysis and social network analysis have become the most widely used methods for extracting intelligence from social media data (He et al., 2016; Chae, 2015; Singh et al., 2017; Grover et al., 2019).

Text mining is the extraction of insights from textual documents and tries to convert unstructured user-generated data into meaningful summaries. It has been used to analyse large amounts of social media data (Corley et al., 2010; He et al., 2013; Singh et al., 2018). For example, Risius and Beck (2015) analysed five million tweets from the official Twitter accounts of 28 multinational companies and identified different social media management practices in terms of communication approaches, social media marketing strategies and setting up featured topics. To identify the most discussed topics, Latent Dirichlet Allocation (LDA) is a robust and widely used topic-modelling algorithm for text mining (Blei 2012; Ibrahim and Wang, 2019). It adopts a three-layer Bayesian framework of topics, keywords, and documents. Particularly, the documents were regarded as a probability distribution of implicit topics while topics as a probability distribution of keywords. The probabilistic structure can be evaluated by LDA applying Gibbs sampling with a conjugate prior distribution (Blei et al., 2003; Blei 2012).

Sentiment analysis is often applied to monitor brand reputation and to help organisations understand the perceptions consumers have about their services and products (Liu, 2010;

Grover et al., 2019). It analyses users' opinions of services, products, organisations and many other things (Gandomi and Haider, 2015). In particular, sentiment analysis is helpful to analyse the spectrum of sentiment – negative, neutral or positive – in textual documents and even measure the weakness and strength of sentiment expressed by customers (Liu, 2010; Waller and Fawcett, 2013). Naïve Bayes and Support Vector Machine are the two main methods used to categorise textual data into positive, neutral or negative groups (Liu, 2010; Singh et al., 2017). From business perspectives, sentiment analysis enables organisations to capture consumer sentiments on specific products, services or events through their posts on social media platforms. It has been proven to be a valuable technique in many fields, and especially in marketing and customer relationship management (Gandomi and Haider, 2015; Lansdall-Welfare et al., 2012).

Social network analysis is the approach of capturing and analysing data from social platforms such as Twitter, Facebook and LinkedIn. It has been commonly used in different fields such as tourism, information system, innovation and marketing to enable managers in tracking online conversations about salient information and knowledge (Aral et al., 2013; Kache and Seuring, 2017). In social network analysis, a graph is generated to explore a specific social network structure constituted by links and notes (He et al., 2016). While nodes indicate individual factors within a social media network, links refer to social exchanges, connections and relationships among the factors (Roshanaei and Mishra, 2015). Based on the number of nodes and links, social network analysis can be used to deal with social media data in real-time, especially with tweets include textual information, internet URLs and images (Bennett, 2013; Chatfield et al., 2015). The social network graphs generated enable managers to visualise a vast amount of dataset together with complicated multi-directional information flows for a comprehensive overview to enhance their interpretations (Aral and Walker, 2012).

3.0 A FRAMEWORK FOR SOCIAL MEDIA ANALYTICS

The rapid increase in the amount of social media data has become a significant issue for most organisations, as they do not have the systematic approaches and analytical skills to process such vast quantities of user-generated data (Aral et al., 2013; Singh et al., 2017). Therefore, what managers need is a framework that takes social media data as inputs to improve operations management and make more informed strategic decisions. Accordingly, this study proposes such a framework. It integrates analytical approaches from a variety of disciplines (e.g., statistics, social science, computer science) to conduct a data-intensive analysis of social media data. This section illustrates the overall process of the proposed framework, as shown in Figure 1. The proposed framework has three main phases. The first phase is data collection and management. The second phase involves data classification and coding of the content. The final phase is data analysis and information interpretation to support decision making.

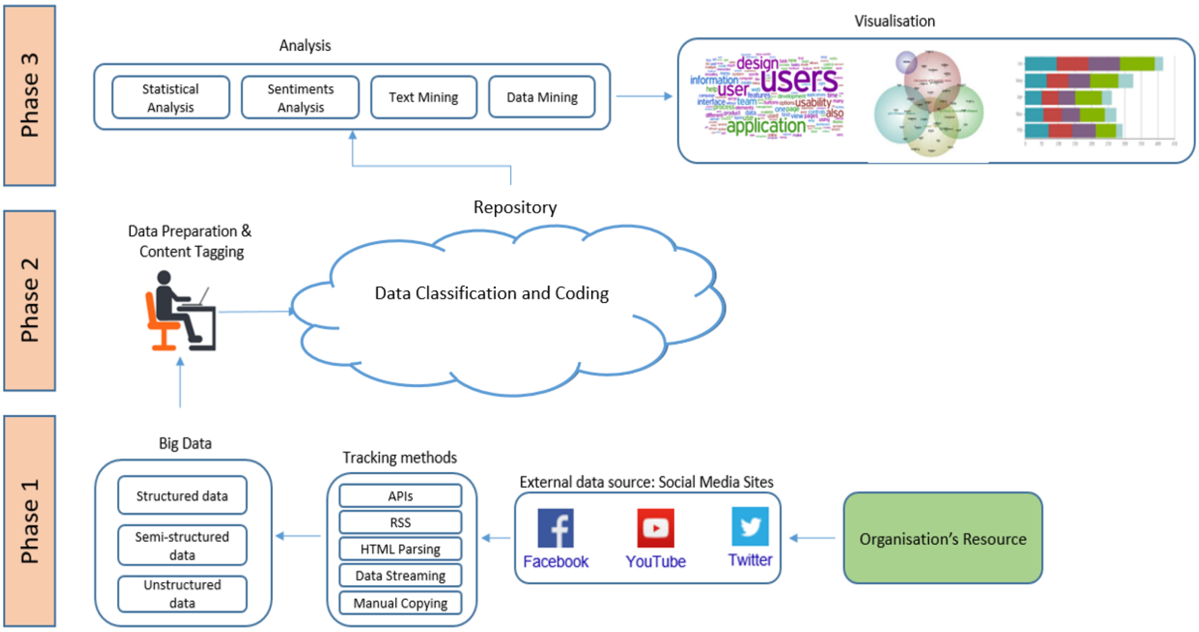


Figure 1: A social media analytic framework

The first phase starts with accessing an organisation's resources (e.g., physical capital, human capital and organisational capital) in order to adopt social media analytics within business operations. For example, organisations need to consider a capital investment by having qualified trained workers and a changed organisational structure to facilitate the transformation of social media data into insights (Bello-Orgaz et al., 2016). Then, both internal and external data sources need to be considered during the data collection (Chen et al., 2015). Data from internal sources can be obtained from various systems, such as the enterprise resource planning system, product or service feedback system or other systems that collect operational data, such as point-of-sale transactional data (Trkman et al., 2012). External data sources are mainly social media platforms such as Facebook, Youtube, Twitter, Instagram and many more. These data can be captured manually, by RSS feeds or using more advanced methods such as APIs, HTML parsing and data streaming (Kalampokis et al., 2013). Some data management tools, such as IBM Social Media Capture 4 and NVivo's NCapture, can be used to facilitate data collection from different social media sites. The data collected is categorised as structured, semi-structured or unstructured for analytic purposes.

In the second phase, a back-end repository plays a vital role in storing longitudinal social media data for subsequent analysis, as web-based social media data can be easily changed or removed by companies and its users (He et al., 2016). It also involves experts tagging the data to indicate their content. After review and content tagging, data must be prepared in accordance with the proposed extract, transform and load structure in preparation for them to be loaded into the relevant data platforms (Bello-Orgaz et al., 2016). For example, as one of the most powerful platforms for big data analytics, Hadoop – a collection of open-source software utilities that facilitate applying a network of many computers to solve problems involving massive amounts of data and computation - consists of different applications such as HBase, Mahout, Hive or Spark.

The final phase consists of analysing the data using different methods, such as statistical analysis, text mining, sentiment analysis and statistical modelling. This can be assisted by business analytical techniques to present the findings in a form that can be easily understood by the organisation. For example, informational and analytical reports for different customer segments can offer fact-based decision support about critical business operations such as customer services, marketing and operations management (Zhang et al., 2011; Itani et al., 2017). Based on the framework, organisations can incorporate social media data into their innovation process.

4.0 METHODOLOGY

In this study, we demonstrate our data analytical process by collecting social media in the retail pharmacy industry. The retail pharmacy industry in the UK is highly competitive (Jambulingam et al., 2005; Chen and Fu, 2015). Apart from providing over-the-counter and prescription medications, many retail pharmacies offer other goods and services, including opticians, household items, cosmetics and stationery. Successful retail pharmacy chains adopt social media via different online platforms both to attract new customers and to retain connections with their current customer base (Kukreja et al., 2011). This study examines the three largest retail pharmacy organisations in the UK, namely Boots, Lloyds Pharmacy and Superdrug, and analyses the content generated on their official Twitter platforms in terms of topics, categories, comments and sentiments.

4.1 Phase one: tweets pre-processing

We restricted the present study to data from Twitter for two main reasons. First, according to Bennett (2013), Twitter has become the fastest-growing social platform, ahead of the other social media platforms such as Google+ and Facebook. Second, unlike the data from other social media platforms, data generated from Twitter can be considered 'open' (Twitter, 2017). In particular, researchers and organisations can collect Twitter data by applying the Twitter API, and so Twitter data can be collected on an unprecedented scale. The data have previously been used to monitor and analyse challenging issues in diverse fields (Chae, 2015). In this study, tweets that involved the three pharmacy companies were collected, adopting a customary keyword and pre-processed for further analysis. The data refers to the customer's opinion information in which the nature of data is different from the traditional secondary data. Most importantly, the sample size in this study is equal to all (N=all). That means we have captured all the data which is existed in the company official Twitter account in the pre-set period of time.

Our data collection was conducted from 12 June to 12 September 2017 by using a programmable code written in R. We classify the collected data as three case company datasets since we have collected and captured the data by a specific syntax that enables us to capture separate sets of data from the selected pharmacy companies. The merged data were reviewed and cleansed, and duplicate tweets were deleted. As shown in Table 2, the total number of tweets extracted and qualified for this research was 96,443; only tweets posted in the English language were captured. During the data pre-processing, this study conducted data cleaning through removing punctuations, numbers, and transformed all text to lowercase. Then, tokenisation was applied to break up the texts into separate words. After that, stop words removal and data stemming were performed to reduce the data variety and improve performance accuracy.

Table 2: Dataset

Retail Pharmacy	No. of tweets	Negative No. of tweets after coding	Percentage
#Boots	50,039	8,484	16.95%
#Lloyds	12,692	1,572	12.39%
#Superdrug	33,712	1,714	5.08%
Total	96,443	11,770	12.20%

Start Time (GMT): 12 June 2017; End Time (GMT): 12 September 2017

4.2 Phase two: data coding

Although prior studies have examined the factors and elements related to the retail pharmacy industry in different contexts, the approaches tend to be general, and the outcomes are mixed (Goel et al., 1996; McGee et al., 2000; Lopez-Trigo et al., 2015). In particular, the majority of studies have applied various factors and integrations of constructs and elements of the retail pharmacy industry from exploratory and empirical research documented in the literature (Jambulingam et al., 2005; Ghoshal and Walji, 2006; Chen and Fu, 2015). Accordingly, this research summarises the relevant studies and determines eight constructs from the literature as the key subjects: product, marketing, technology, pharmacist, customer service, medication, waiting time, others. As a result, it extends the existing retail pharmacy literature to assess different aspects of the retail pharmacy industry and provide a better understanding of the interactions between retailer pharmacies and online consumers.

The primary objective of this review is to support and verify the text mining results in different topics. The subjects were identified due to the reasons that they were mostly discussed in different literature regarding the retail pharmacy industry. Also, they were relevant and significant to this study. A comprehensive list of elements with detailed descriptions was illustrated in Table 3 for continued analysis. The subjects and elements determined were applied as a roadmap for guiding and examining our results generated from the analysis. The data coding process formed an iterative procedure which went through several rounds, and after each round, the results were compared and discussed among the authors. In order to confirm the interpretation of subject elements, the authors also refer to the original data (i.e., tweets) which involved relevant keywords in verifying whether the subject elements suggested the same meaning as the tweets.

Table 3: Key subjects and elements of the retail pharmacy industry

Subject	Element	Description	Reference
Product	Product quality	The quality of the product can achieve customers' needs and provides them with satisfaction.	McGee and Love, 2000; Okunlola et al., 2007
	Product affordability	The selling price of the product is within most customers' budget.	
	Product availability	Measures the quantity of a product that is currently available in the store.	
Marketing	Marketing Campaign	A strategic plan to promote or improve awareness for a particular product or service.	Chisholm-Burns et al., 2012; Lopez-Trigo et al., 2015
	Discounts/reward card	Identifies the cardholder as a participant in a loyalty program to encourage them to use the service provided by the company.	
Technology	Online system quality	The technical functioning of the online system (e.g., order information, registration of user and website links).	Crawford, 2003; Ghoshal and Walji, 2006
	Prescription technology	Accurate and updated information prescription technology (e.g., clear information and correct e-prescription).	
Pharmacist	Pharmacist accessibility	The quality of being easy for pharmacists to meet patient demand.	Goel et al., 1996; Zaller et al., 2010
	Pharmacist knowledge	Pharmacists' skill or familiarity gained by experience or education.	
	Respect from pharmacist	The way of thinking and treating about the patient.	
Customer service	Payment process	The company handles customer payment transactions effectively and correctly.	Jahanshahi et al., 2011; Chen and Fu, 2015
	Staffing problem	Issues such as inflexible staff, no time for screening and not being able to fill a position quickly.	
	Unclear store contact details	Not obvious to know who should be contacted for customers' requests.	
	Store environment	The layout of the store is easy for customers to find products and services.	
	Delivery	Receive products in good condition and within the promised time.	
	Shopping experience	The overall satisfaction of the experience regarding products and services provided by the company.	
Medication	Medication affordability	The cost or price of the medication is affordable.	Okunlola et al., 2007; Ghoshal and Walji, 2006
	Medication management	A patient-centred care that optimises safe, effective, appropriate drug therapy.	
	Medication quality	The quality and performance of the medication can achieve customers' expectation.	
	Medication availability	Measure the quantity of a medication that is currently available in the store	
Waiting time	General waiting time	An approximate time interval for customers to wait after planning a request for service.	Okunlola et al., 2007; Arafeh et al., 2015
	Call response time	The total time it takes to reply to a customer request for service via phone calls.	
	Online response time	The total time it takes to reply to a customer request for service via emails and online applications.	
Others	Store policy	Guidelines that provide general practices to be followed by all employees and customers.	Zaller et al., 2010; Melton and Lai, 2017
	Shopping convenience	The extent to which as customers feel that the service process is effective and friendly.	
	Additional services	Other services such as nail service, brows service, photo printing, wellness counselling, optometry service and clinical homecare.	

4.3 Phase three: topic modelling and sentiment analysis

To conduct text mining, Latent Dirichlet Allocation (LDA) was performed for topic modelling. LDA is a sophisticated technique for determining key factors and highlighting emerging topics. It is a statistical unsupervised machine learning technique to determine primary topic information from a large amount of textual data (Blei et al., 2003). It has been used in many studies to analyse the user-generated content of collections of textual data (Blei 2012; Ibrahim and Wang, 2019; Lansley and Longley, 2016). In this study, LDA was applied to extract the key topics tweeted by online consumers. Compared to other algorithms for topic modelling, LDA can be applied as a dimensionality reduction technique which generates a generative probabilistic model that enables the technique to generalise its process to topic assignment to other, newly arrived datasets (Blei et al., 2003; Ibrahim and Wang, 2019). Sentiment analysis is an important technique for determining the success of efforts in their operations and service management. To conduct sentiment analysis, SentiStrength was applied, which is a highly popular technique to study the spectrum of sentiments (positive, neutral or negative) in each online post from different customers (Chae, 2015). Notably, SentiStrength applies a lexical process that utilises a list of sentiment-related words and has rules to manage social web methods and standard linguistic to determine sentiments, such as emoticons, deliberate misspellings and exaggerated punctuations (Thelwall, 2017). For the network analysis, Leximancer was adopted for determining the relationships among the topics discussed by consumers (He et al., 2016). It provides a simple user interface that allows users to generate the concept map for identifying the major issues and areas of concern. Compared to other qualitative data analysis techniques such as NVivo which requires the manual handling of data at different stages, the use of Leximancer offers a form of automated analysis based on the properties of texts (Soiriadou et al., 2014; He et al., 2016). Especially, the use of Leximancer has been recognised as an effective way to manage large quantities of qualitative data (Soiriadou et al., 2014).

5.0 FINDINGS

We collected quantitative data from each retail pharmacy organisation’s individual Twitter platform. The proposed analytic framework was applied to understand the key issues related to the three retail pharmacy organisations, based on their customer reviews on Twitter. It aims to help organisations to identify a wide array of strategic information such as the reasons behind customer comments, key areas for improvement in products or services, key topics/themes in the tweets, and trends in customers’ discussion about specific services and products. Based on the data analysis results, recommendations are provided for the development of a more customer-centric retail pharmacy operation.

5.1 Factors of company-related tweet content

Through the analysis, 56 topics were identified applying the LDA technique. The topics were subsequently categorised into subjects and elements according to the integration of the literature study of the retail pharmacy industry and human judgement. Particularly, the extracted topics were allocated into various subjects, which were determined from the comprehensive literature study demonstrated in Table 3. For some topics that could not be related to the elements identified in the literature, they were labelled with the terms that can best interpret the integration of various keywords.

Table 4 shows an example of the top 10 most discussed topics among the 56 topics based on their weight. In particular, the weight refers to the distribution of the keywords that contribute to the greatest weight in that topic and illustrates the significance of the determined topics in the retail pharmacy industry. The topics identified extracted some fundamental aspects of retail pharmacy operations. Also, the keywords with high probabilities were strengthened according to their weight of probability within the topic. From the results, several interesting factors that were explicitly associated to retail pharmacy operations and services management can be identified such as “product quality”, “delivery”, “waiting time”, “product availability” and “marketing campaign”.

Table 4: Key topics from LDA modelling

Topic	Weight	Factor	Main Keyword
1	0.814	Marketing campaign, product quality	Skin, normal, colour, package, product, sensitive, default, new, abnormal
2	0.808	Product availability, delivery	Stock, find, order, store, today, delivery, online discount
3	0.743	Shopping experience, additional services	Staff, service, boots, customer, like, shop, branch, rude, optician, customer
4	0.672	Store policy, shopping experience	Store, prescription, service, staff, talk, reason, disgust, customer, shop
5	0.643	Delivery, product quality	Bed, today, disable, leaving, work, day, delivery, suppose, guarantee, left
6	0.505	Call response time, prescription technology	Prescription, minute, wait, call, busy, time, information
7	0.411	Medication availability, general waiting time	Time, prescription, medication, wait, frequent, quality, return
8	0.408	Pharmacist accessibility, online system quality	Prescription, doctor, service, electronic, Sainsburys, process, submit, error, problem
9	0.345	Product availability, shopping convenience	Order, find, store, today, receive, local, stock, Boots, time, online
10	0.331	Discounts/reward card, payment process	Website, order, online, help, address, email, buy, place, try

Figure 2 illustrates the main subjects identified from the twitter data with the weights estimated by the text distribution for each factor. In particular, subjects relevant to delivery received the greatest weight of 1.33, which indicates that delivery is the subject mostly discussed by online consumers and was an important issue regarding the retail pharmacy industry. According to the tweets collected, many consumers discussed various online order status, changes in the delivery date, late deliveries, stolen and missing items. This is in line with the studies illustrating that consumers tend to share their opinions and feelings on social media especially when they received unsatisfactory delivery services such as incorrect order information and delays (Hanna et al. 2011; Kukreja et al., 2011; Itani et al., 2017). Project quality-related subjects are the second-ranked factor and shopping experience related subjects are the third most discussed factor in the list. Unlike delivery and product quality subjects, shopping experience associated with the consumers' perceived satisfaction regarding service and products offered by the companies. Captured tweets show discussed issues such as how well customer service personnel recommend products, offer excellent communication to answer their questions and customer complaints.

The remaining subjects are associated with the marketing campaign, waiting time, the online purchasing experience, medication availability, pharmacist accessibility and additional services such as nail service, brows service, photo printing, wellness counselling, optometry service and clinical homecare. As seen from the collected tweets, customers mentioned about their shopping experience with the same companies, interesting promotions and marking campaigns, received treatment from pharmacists and perceived performance of different medications. Additionally, some other elements were related to shopping convenience, online system quality, general response time, unclear store contact details and shopping environment. As observed, customers discussed the subjects such as technical functioning of the online system, total time takes to receive a replay for the company, not obvious to know who should be contacted for requests and the perceived quality of the products and services provided by the companies.

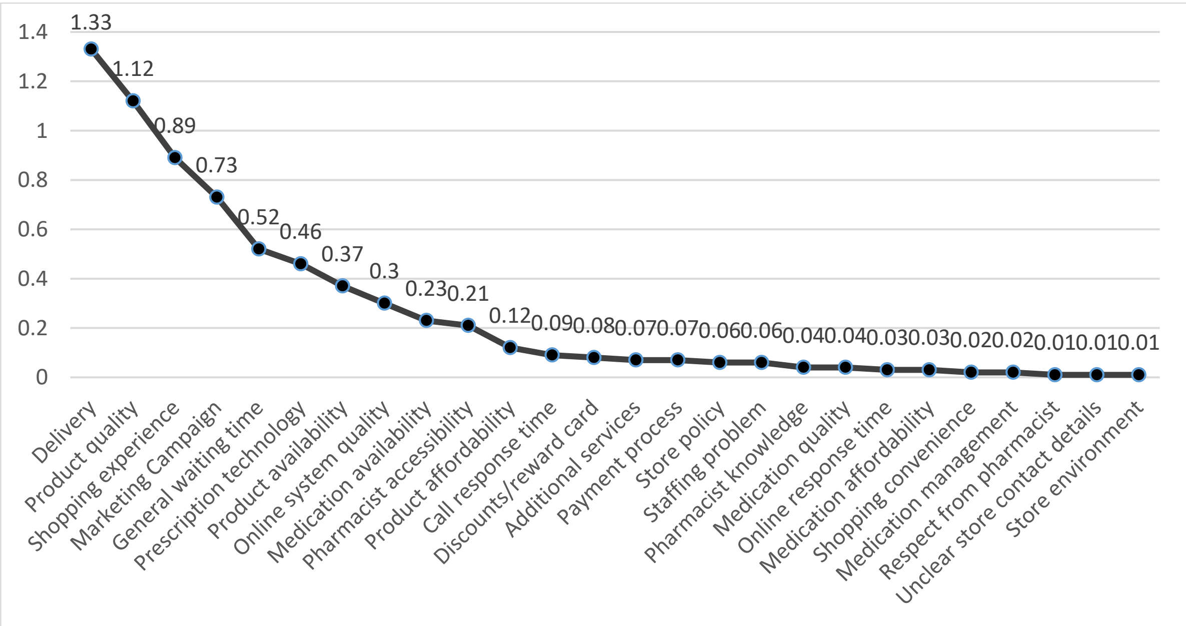


Figure 2: Factors Extracted from Topic Modelling

5.2 Topic modelling for service improvement

According to Ibrhim and Wang (2019), online reviews with negative sentiment are often related to consumers' concerns and issues regarding received services and products. To improve operations and service management, the managers must identify which aspects of operations or services provided are dissatisfied by a major group of customers or has generated criticism. To address this, this study identified the most important areas for operations and service improvement based on tweets with negative sentiment. Particularly, Figures 3–5 identify the key improvement areas for Boots, Lloyds and Superdrug, respectively.

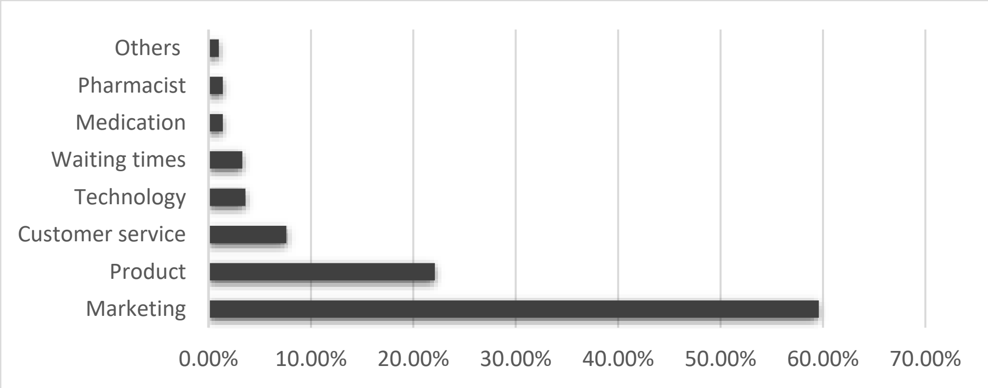


Figure 3: Improvement Areas for Boots

In terms of the key improvement areas identified for Boots (Figure 3), issues with marketing accounted for more than half (59.6%) of the negative tweets, while product-related issues accounted for another 22.1% of negative comments. Customer service issues accounted for 7.6% of negative comments, while all other categories, such as technology-related issues, waiting times medication, pharmacists and others each accounted for less than 5%. Based on the results, Boots needs to focus on its marketing strategy to improve its performance. It corroborates the ideas of Balasubramanian et al. (2003), who identified the marketing strategy had an important effect on customers' satisfaction level, which in turn leads consumers to post reviews and tweet to express their negative feeling. According to the tweets captured, Boots had an unsuccessful marketing campaign due to an inappropriate choice of words in its visual aids and marketing songs. For example, a visual aid indicating skin colour' normal' and the use of a Christmas song in a marketing campaign in June had sparked off unhappy tweets from the public. In terms of product-related issues, product unavailability was an important area to address. Our analysis suggests that products that customers liked had been discontinued in their local stores, without any replacements. According to Martinho et al. (2015), high product quality and high functionality are important factors in customer purchase. Therefore, products that are well-liked by customers should be improved or continued in order to satisfy the customer. Thirdly, customer service issues often related to a poor shopping experience. For example, some customers were not satisfied with the optical or photo printing services. Thus, continuous service improvement programmes should be reinforced in Boots to improve the customer shopping experience.

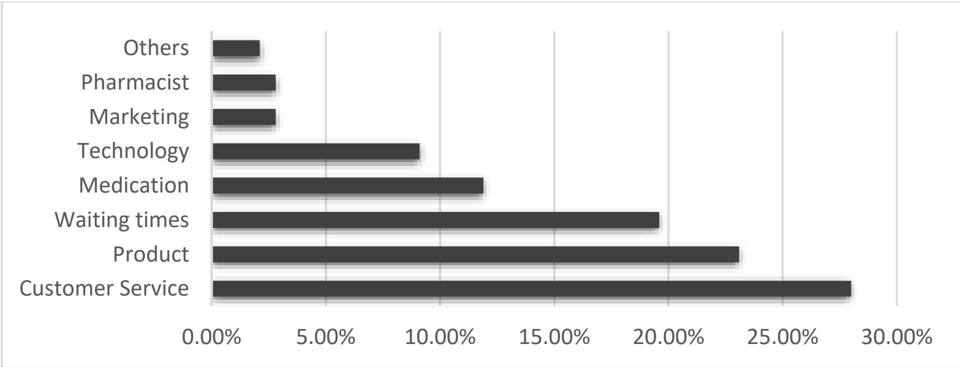


Figure 4: Improvement Areas for Lloyds

Figure 4 illustrates the key improvement areas for Lloyds, which were mainly customer service concerns (28.0%), product-related issues (23.1%), waiting time (19.6%), medication-related issues (11.9%), technology-related issues (9.1%), while other categories such as marketing issues, pharmacist and others accounted for less than 5%. In particular, according to the tweets collected, poor shopping experiences associated with staff service and prescription handling were the main customer service issues. This further in lines with the notion that firms recognise customer service issues and rapid response to customers' dissatisfaction could impact customers' perceptions of brand attitudes and trust (Bee and Tan, 2014). Also, the findings indicated forms of inconvenience and unpleasantness within the store. For example, one of the main product complaints concerned a bed for a disabled elderly person that it was not delivered within the company's promised time. This is in line with Cao et al. 's (2003) study, which connected customer experience with customer satisfaction on delivery. Also, Collier and Bienstock (2006) pointed out that delivery is the most significant element of service performance in the online retail industry. Therefore, it was necessary for Lloyds to improve its logistics processes to provide on-time delivery. Tweets about waiting times mostly related to the long waiting time for prescription medications, which could range from 30 minutes to several weeks. This had a significant impact on service satisfaction and customer loyalty. Hence, for Lloyds, it will be beneficial to invest in information communication technologies and find ways to create a more efficient work environment, to avoid such delays. Similarly, the availability of medications for the elderly, such as heart medications, was a matter of concern. As these medications tend to be repeat prescriptions, Lloyds may need to improve its forecasting abilities to ensure it always holds adequate stocks. The technology-related issues included problems with e-prescriptions, caused by both a lack of functionality in the prescription technology or unstable technology that resulted in prescription errors. Thus, measures to address this issue would require a review of the technology used by Lloyds.

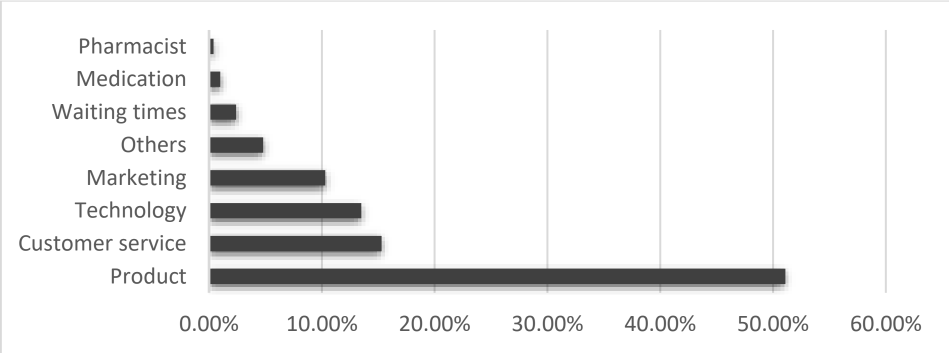


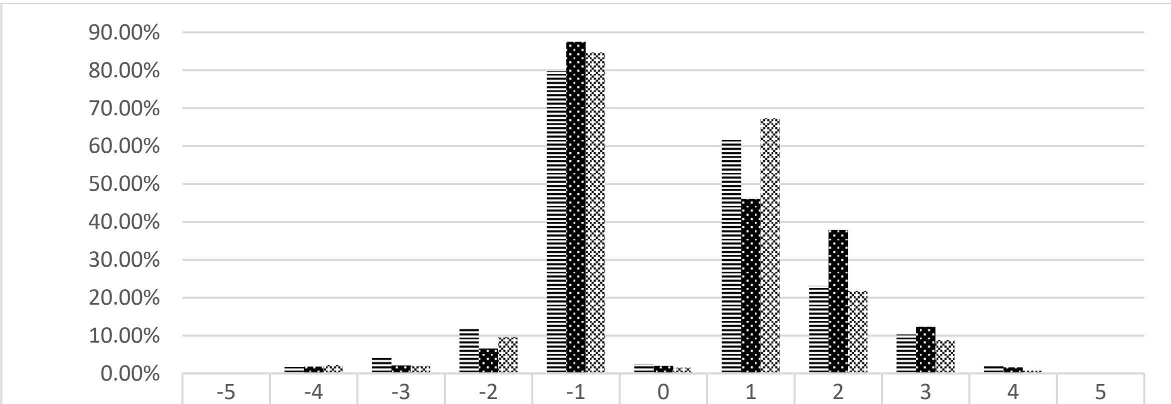
Figure 5: Improvement Areas for Superdrug

The key improvement areas identified for Superdrug (as displayed in Figure 5) were product-related issues (51.1%), customer services (15.3%), technology-related issues (13.5%), marketing issues (10.3%), while other categories such as others, waiting times, medication and pharmacist accounted for less than 5%. In terms of the product-related issues, our findings suggest that customers were not able to get their correct order (e.g., ordered online and picked up in-store) or were unable to find certain products at the stores. This finding supports the view of Jahanshahi et al. (2011), who identified that product quality could significantly influence customers' satisfaction level, which in turn lead s consumers to post reviews and tweet to express their negative feeling. Poor services rendered by staff and discriminatory treatment at the stores were the two main customer service issues. According to Western States Centre (2001), being an anti-racist organisation involves training and the encouragement of shared activities to facilitate communication and discussion. Structural change in the company may be required to ensure a balance of power between people of different racial or cultural backgrounds. Hence, to address such issues, Superdrug needs to incorporate racial understanding into its training curriculum. The structural reorganisation is also recommended; however, this may take a longer time to implement. Moreover, some tweets reported that customers had encountered problems with the use of the website during or after their purchase. Hence, Superdrug needs to schedule regular maintenance and updating of its technology to improve the experience of its customers. Regarding the marketing issues, some loyalty cardholders complained that they could not use their points properly. The effect of all loyalty programmes on customer retention has been well documented (Magatef and Tomalich, 2015). Therefore, it would be vitally important for

Superdrug to ensure that its customer loyalty scheme works properly and in the way customers expect.

5.3 Results of sentiment analysis

To understand the subjective information, the tweets collected were further analysed based on the weakness and strength of sentiment expressed by consumers. Among the 96,443 tweets, the majority were neutral while a relatively small portion of positive sentiment (10.2%, 9,837) and negative sentiment (12.2%, 11,770) tweets. Interestingly, negative sentiment tweets were greater than positive sentiment tweets of the dataset. This is distinct from Roshanaei and Mishra’s (2015) research that unpleased consumers are not keen to share their negativity on social media compared to other customers. However, this may occur due to the reason that it is more common for consumers to use social media networks and provide their complaints following retail pharmacy companies’ ineffective management of operations and customer services. Figure 6 shows the results of sentiment analysis for Boots, Lloyds and Superdrug. With ‘-5’ as the most negative sentiments and ‘5’ as the most positive sentiments, neutral sentiments were indicated as ‘0’.



	-5	-4	-3	-2	-1	0	1	2	3	4	5
Boots	0.20%	1.70%	4.10%	11.80%	79.80%	2.50%	61.90%	23.10%	10.30%	2.20%	0.10%
Superdrug	0.10%	1.80%	2.10%	6.60%	87.50%	2.00%	46.10%	37.90%	12.30%	1.60%	0.10%
Lloyds	0.20%	2.20%	2.00%	9.60%	84.70%	1.50%	67.30%	21.70%	8.80%	0.70%	0.10%

Figure 6: Results from the sentiment analysis of Boots, Lloyds and Superdrug

Based on the results, the sentiments are further grouped into ‘Low’, ‘Medium’, ‘Medium – High’ and ‘High’ to derive Table 5 to indicate the composites of positive or negative sentiments across the three retail pharmacies. Low sentiments are those that scored ‘1’ and

‘2’ or ‘-1’ and ‘-2’, medium sentiments were those that scored ‘3’ or ‘-3’ and high sentiments were those that scored ‘4’ and ‘5’ or ‘-4’ and ‘-5’. Medium to high sentiments was derived from medium and high sentiments. High sentiments represent strong sentiments, while low sentiments represent weaker sentiments. In general, by comparing customer sentiments, we identified that Boots received a higher percentage of high positive comments and a lower percentage of high negative comments from its customers than Lloyds and Superdrug. This may suggest that Boots has customers who are more highly in favour of Boots than other retail pharmacies. Superdrug had a combined higher score of medium to high positive sentiments (14.0%) than Boots (12.6%), however, which may occur due to its marketing strategy of using bloggers for its new products. While Lloyds had the best overall positive sentiment score, only 0.7% of its customers had a high positive sentiment. Therefore, Lloyds needs to enhance its services to build more brand loyalty with its customers. The results show that Lloyds had a higher negative sentiments rating (2.3%) than Superdrug and Boots. This parallels the above finding that Lloyds has fewer customers with a strong positive sentiment. Boots had the highest score for medium (4.1%) and for medium to high negative sentiments (5.9%), which may indicate that while Boots has loyal customers with positive sentiments, a considerable number of customers are also annoyed by Boots.

Table 5: Positive and negative sentiments groupings

Positive Sentiments	Low (1-2)	Medium (3)	Medium to High (3-5)	High (4-5)	Total
Boots	85.0%	10.3%	12.6%	2.3%	97.5%
Lloyds	89.0%	8.8%	9.5%	0.7%	98.5%
Superdrug	84.1%	12.3%	14.0%	1.7%	98.0%
Negative Sentiments					
Boots	91.6%	4.1%	5.9%	1.8%	97.5%
Lloyds	94.2%	2.0%	4.3%	2.3%	98.5%
Superdrug	94.1%	2.1%	4.0%	1.9%	98.0%

Overall, the results show the similar percentages of positive and negative sentiments for each of the retail pharmacy company, although the intensity of the sentiments differs slightly. Retail pharmacy companies need to build stronger relationships with their customers in order to gain stronger positive sentiments, as evidenced by the tweets. As pointed out by Harris and Rae (2010), social media platforms such as Twitter can replace customer annoyance with engagement. That is, by building stronger relationships with customers and by encouraging customers to have more strong positive sentiments, organisations can help to protect their brand reputation through online customer engagement. Finally, posts and comments received from customers indicate personal preferences and opinions, and customers have a variety of experiences with regard to the same kind of products or services. For instance, some customers reported that the waiting time is way too long at the pharmacy, while others posted that they enjoyed their time at the pharmacy since the service was efficient, the deals were great, and the pharmacy staff were friendly and professional.

5.4 The results of social network analysis

Next, we used Leximancer to perform an automatic analysis of the tweets and generate concept maps for understanding the relationships among the key concepts. Figure 7 shows the concept maps generated from Boots, Lloyds and Superdrug. The concept maps show the extracted main concepts and their interrelationships among the three companies (Martin and Rice, 2007; Campbell et al., 2011). The themes in Leximancer are 'heat mapped': that is, large circles indicate the main themes, brighter colours such as red and orange represent greater significance within the text, and dotted lines join different concepts. Here, the concept maps demonstrate the most significant theme in red, the second in orange and the third in yellow. Concepts that are strongly semantically linked will be close to each other and will form clusters (Dann, 2010; He et al., 2016).

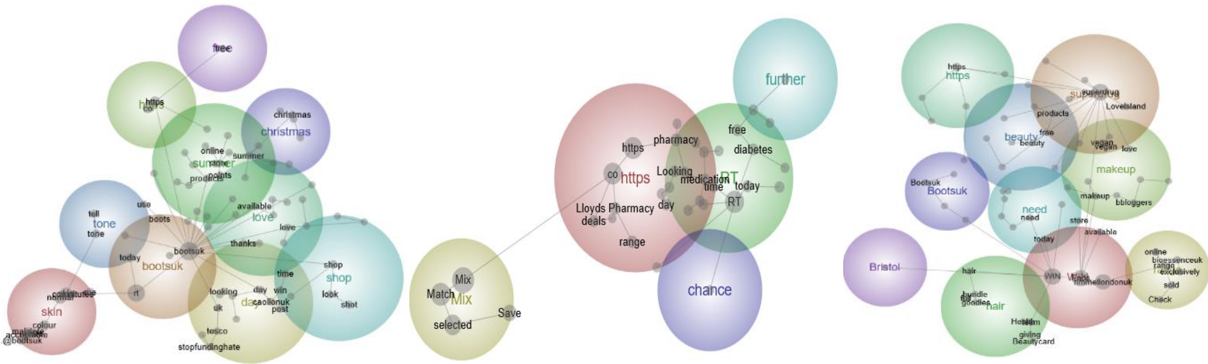


Figure 7: Concept maps generated for Boots, Lloyds and Superdrug

According to the concept map generated for Boots, the main discussions were on 'summer', 'Christmas' and 'skin' colour. As red on the concept map signifies an important theme, this suggests that 'skin' colour is the most important theme. Interestingly, although the data collection time is between June and September, 'Christmas' is one of the main discussion themes among the users, and it provides further information for the purchasing manager for the demand forecasting. 'Summer' concept is related to the comment of the recent marking campaign which provides for improvements to the marketing operation. In addition, shopping for products such as eyelashes and creams were related to each other, which indicates discussions about these products. This is an interesting finding which provides hints for the manager to design the cross-sell and product packages (e.g. eyelash and cream are sold as a bundle). Obviously, the 'thanks' concept indicates some form of customer satisfaction with the company. Therefore, managers in the customer relationship can classify them as a group of loyalty customer. The concept map for Lloyds indicates that the tweets were mainly focused on marketing, such as the 'mix and match' products and product profiling. Importantly, there are indications suggesting that Lloyds had more frequent use of images and video links (represented by 'https'). There are also themes related to further contact for unsatisfactory services and products, which are represented by 'further'. In addition, the themes and overlaps between retweets (appearing as 'RT') and 'further' indicate that Lloyds' customer has a higher tendency to retweet. This is likely because Lloyds at the time was offering to get a free diabetes check to anyone retweeting the company's messages. As for Superdrug, the concept map shows that 'Boots' was often tagged in tweets on the Superdrug Twitter site, which indicates that the user is more likely take the product and services in Boots to compare with Superdrug. Within the 'Superdrug' theme, 'Loveisland' concept appeared very frequently; this is the title of a television programme sponsored by Superdrug. Moreover, vegan products and makeup formed a cluster with 'Superdrug', which suggests these were important products for customers. The 'Bristol' theme indicates that there were favourable discussions of the Bristol store (e.g., giving out free bottled water during the warm summer season). Furthermore, the 'bbloggers' concept appears in the 'makeup' theme, which reflects the fact that Superdrug was using web bloggers in its marketing strategy to promote its new products and services.

6.0 DISCUSSION AND CONCLUSION

Social media enables organisations to involve customers in a relatively inexpensive way and at great levels of efficiency (Aral et al., 2013; Wang et al., 2020). Although many organisations have already applied social media platforms such as Facebook, Twitter, Instagram to enhance customer loyalty and satisfaction, an effective application of social media analytics for improving operations and service management is not always easy (Kaplan and Haenlein, 2010; Zhan et al., 2020). Accordingly, this study proposes a social media analytic framework to illustrate how the social media data from three retail pharmacy organisations can be applied to: a) highlight the most-discussed topics by consumers, b) identify the key areas for improvement based on the most negative customer comments received, and c) to determine the connections among the important concepts and enhance customer loyalty by adding values to consumers. In this way, managers can harvest values from social media to get insights on operations and service improvements and formulate effective marketing strategies.

The findings of this study aim to help retail pharmacy managers to develop a customer-centric business operation. After conducting the data analysis, we identified key areas for improvement for each of the three retail pharmacy organisations. Common areas that need to be improved were related to products and customer services. In particular, Lloyds needs to pay more attention to its product delivery issues, while Boots and Superdrug need to pay more attention to its product availability. Besides, our analysis indicates that poor shopping experience was customer service issues for all three retail pharmacy companies. Thus, it is important to create a pleasant store atmosphere, as this appears to be a strong factor for consumers spending more time and money in-store than they intended (Corley et al., 2010). The next common area that needs to be addressed concerns technology-related issues, especially at Lloyds and Superdrug. For Lloyds, the unstable or erroneous prescription technology needs to be improved. Similarly, problems related to the online website ordering system could cause a loss in sales for Superdrug. Other areas of improvement included marketing issues for Boots (i.e., its marketing campaign had led to negative emotions and had sparked online discussions), the discount card issue for Superdrug which had caused customers to mistrust the discounts or point accumulation system, and, for Lloyds, both the medication availability issue (i.e., Lloyds needs to look at its sales forecasting and the distribution of medications across its stores) and the waiting time issue (i.e., Lloyds might need to address a shortage of workforce in its daily operations).

It is worth pointing out that these key areas for improvement were identified based on the negative comments users shared on the Twitter platform. Many comments were replies to the original posts made by the retail pharmacy organisations themselves. These customers engaged in a discussion, to share their opinions and experiences. Much of the time, customers compared one store with its competitors and provided insightful information to other customers. According to O'Bren and Marakas (2008), approximately 70% of customers who complain about business would be willing to buy from the store again should their concerns be quickly addressed. The present study found that whenever negative comments were published, all three retail pharmacy organisations quickly responded to the posts, in a bid to minimise the impact of negative comments shared on social media.

6.1 Implications for practice

Today, the Coronavirus pandemic has had a huge global impact, rapidly spreading to become an unprecedented and extraordinary public health crisis in the 21st century. On the one hand, social media can and should be utilised by businesses to enhance and sustain the public health response through ethically harvested information. On the other hand, unlike many other business sectors and services, retail pharmacies will remain open during the COVID-19 pandemic to provide essential medicines supply, medical advice, and counselling services to patients and local communities. Nevertheless, the substantial increase in the demand for medicines and the change in public buying behaviours (e.g., panic purchasing over-the-counter) placed a significant amount of stress on retail pharmacy companies. Given these difficult circumstances, the proposed framework in this study can be applied and support retail pharmacy companies to not only respond but also to understand the social dynamics of the increasingly fast and evolving spread of Coronavirus information, the unprecedented consumer demands and also the control measures. Moreover, it can help retail pharmacies to act promptly with an engaged and proactive narrative, which can help retail pharmacies to better prepare for future outbreaks.

Moreover, this study suggests that organisations should consider setting up a database management system to collect, monitor, manage and analyse the content posted on different social media platforms (Capgemini, 2012; Zikopoulos et al., 2013). Notably, the posts and comments made on social media can be removed by organisations and/or its users. To counter this threat, a database management system can be used to store longitudinal social media data. It is also important for organisations to have timely access to data, by increasing the frequency of data integration or adopting advanced technologies that can offer real-time stock updates, such as the application of RFID technologies. However, an organisation's current programme and structure can be disrupted by the adaptation to a new database management system or technologies (Bello-Orgaz et al., 2016).

Furthermore, meeting an organisation's social media objective requires a level of expertise. Indeed, such expertise is critical in the effective management of social media data and promotes an efficient way of carrying out data analysis. Given that a negative word-of-mouth campaign initiated by users can be more persuasive than positive comments (Rohrbeck, 2010; Shu-Chuan and Kim, 2011), organisations need to take a proactive approach to address the impact of negative comments on their businesses. In this regard, the process of balancing costs and benefits makes it necessary for managers to figure out their actual needs from social media outlets and take part in planning. That is, data analytics should be undertaken to fulfil a specific purpose, not for its own sake.

Lastly, organisations need to create an environment that makes it easy for executives, managers and other decision-makers to access the data and the results of the analysis. Specifically, organisations can cultivate their social media platforms, as customers are increasingly embracing social media platforms for information and communication. Given the tendency of customers to use social media to compare products and services that competitors offer, monitoring competitors on social media should be an integral part of strategising (Bello-Orgaz et al., 2016). When organisations monitor and analyse the data posted on their competitors' social media, it provides a chance for them to develop better competitive strategies and business intelligence. The knowledge gained could be useful in identifying market opportunities and challenges by comparing the services and products the organisation provides against those of their competitors.

6.2 Implications for research

Studies have highlighted the challenges of performing social media analysis due to its tremendous volume and mixed data structure and required for more sophisticated results (Gandomi and Haider, 2015; Cui et al., 2018; Meel et al., 2019). Accordingly, this study contributes to social media literature with the development of a social media analytic framework for retail organisations to use social media data in their operations and service improvements. Our analysis shows that social media data can be used to help retailers obtain a real-time overview of customer responses to a marketing event. Moreover, the collection of social media data is relatively inexpensive, and this allows the organisation to capture the sentiments of diverse and large audiences. Therefore, organisations need to monitor, collect and analyse social media data, as this will support service improvement or the development of marketing strategies, and thereby the organisation's competitiveness (Aral et al., 2013; Kaplan and Haenleinm 2010; Singh et al., 2017).

Specifically, the topic modelling for text mining can help managers to determine the most discussed and shared topics among customers regarding various social media platforms. This is vital for retail pharmacy companies as what online users commented and discussed has a significant impact on other customers' future buying decisions (Bharadwaj et al., 2012; Mousazadeh et al., 2015). Especially, the negative tweets are more likely to be related to customer complaints, and part of them are directly and/or indirectly to business operations. By systematically transforming the unstructured data into quantified measurement item in the tweets, the polarity and discussion theme (i.e. concept) of the tweet becomes one of the new measurements of operating performance. This is aligning with the previous studies that applied the similar approach to determine the most related customers in the area, the leading customers, and keyword analysis (He et al., 2016; Laurell and Sandström, 2017; Ibrahim and Wang, 2019). This can generate insights that bring managers' attention to the issues that result in customers' dissatisfaction and behave as a foundation to improve their operations and service management.

6.3 Limitations and future research

As the competition for the market share intensifies, organisations need to prioritise the use of social media data to gain competitive advantages. Based on the results of this study, organisations can gain a better understanding of their strengths and weaknesses, can know more about their competitors and customers, and can improve their operations and service performance to compete more effectively in the marketplace. Nevertheless, this study has limitations, especially concerning data collection. Firstly, the period applied for data collection was relatively short. Ideally, data collected for a longer period will help provide a more comprehensive picture of the use of social media to improve retail pharmacy operations management (Chae, 2015; Schoenherr and Speier-Pero, 2015). Secondly, this study did not conduct interviews among different customers, employees and managers in order to capture the information about their social media experience. Therefore, future studies should be conducted focusing on the social media experience to enhance our proposed framework. Thirdly, this study drew only on Twitter as the social media data source. Thus, it might not be possible to generalise the findings to other social media platforms. In addition, the results may not cover important population subgroups, such as the elderly, who tend less often to have social media accounts. For this reason, future studies should also consider information inputs from individuals who do not use technology and social media. Finally, this study did not consider account users' basic information and profiles, which might have improved the credibility of the data analysis. According to Singh et al. (2017), accurate analysis of real opinion expressed by users on social media can prevent malicious spamming. Therefore, future studies need to consider how customers' rankings of different services and products might be used to produce better-informed business decisions and marketing strategies.

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