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A mixed-method approach for modelling customer-centric mobile phone reverse logistics: application of social media data

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Abstract

Purpose – Recently, reverse logistics (RL) has become more prominent due to growing environmental concerns, social responsibility, competitive advantage and high efficiency by customers because of the expansion of product selection and shorter product life cycle. However, effective implementation of RL results in some direct advantages, the most important of which is winning customer satisfaction that is vital to a firm's success. Therefore, paying attention to customer feedback in supply chain and logistics processes has recently increased so that manufacturers have decided to transform their RL into customer-centric RL. Hence, this paper aims to identify the features of a mobile phone which affect consumer purchasing behaviour and to analyse the interrelationship among them to develop a framework for customer-centric RL. These features are studied based on website analysis of several mobile phone manufacturers. The special focus of this paper is on social media data (Twitter) in an attempt to help the decision-making process in RL through a big data analysis approach.

Design/methodology/approach – A portfolio of mobile phone features that affect consumer's mobile phone purchasing decisions has been taken from website analysis by several mobile phone manufacturers to achieve this objective. Then, interrelationships between the identified features have been established by using big data supplemented with interpretive structural modelling (ISM). Apart from that, cross-impact matrix multiplication, applied to classification analysis, was carried out to graphically represent these features based on their driving power and dependence.

Findings – During the study, it has been observed from the ISM that the chip (F5) is the most significant feature that affects customer's buying behaviour; therefore, mobile phone manufacturers realize that this is to be addressed first.

Originality/value – The focus of this paper is on social media data (Twitter) so that experts can understand the interaction between mobile phone features that affect consumer's decisions on mobile phone purchasing by using the results.

Keywords Logistics, Data analysis, Statistics, Modelling, Supply chain management, Social networks, Interpretive structural modelling (ISM), MICMAC analysis, Mobile phone, Reverse logistics, Twitter data

Paper type Research paper

1. Introduction

With regard to the growing population and ever-expanding technologies, more and more electronic devices are manufactured every day (Balde *et al.*, 2017; Echegaray, 2016; Zink *et al.*, 2014). For instance, according to Gartner, Inc., the sales of mobile phones to end-users in the world totaled 432 million units in the fourth quarter of 2016, which shows a 7% increase compared to a year before. The fourth quarter of 2016 witnessed Apple leapfrogs past Samsung to secure the No.1 global mobile phone vendor position. Overall, in 2016, the

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total cellphone sales to end-users were almost 1.5 billion units, indicating an increase of 5% from 2015 (Kim, 2018). In addition, the latest estimates regarding the number of mobile phones show that it has increased by 250% from 2.21 billion in 2005 to 7.74 billion in 2017 in the world (ITU, 2017). According to studies carried out recently, each year more than 145,000 tons of natural resources – some of which are very rare – have been used to manufacture mobile phones (Christian *et al.*, 2014; Statista, 2020; Valero Navazo *et al.*, 2014) and this amount is growing daily (Echegaray, 2016; Pariatamby and Victor, 2013; Wang and Xu, 2014; Zhang and Xu, 2016) so that just 2% of America's trashes in landfills are related to E-waste, which causes 70% of the total toxic wastes (Slade,2007) and it is increasing four times as fast as other types of wastes (U.S. Environmental Protection Agency,2012). Tools related to information and communication technology (ICT) (e.g. personal computers, mobile phones and printers) were responsible for 7% of E-waste in 2014 (Kuehr *et al.*, 2015; Guarnieri *et al.*, 2016); and each year, billions of dollars of natural resources are wasted in mobile phone industry (Ahmadi *et al.*, 2020; Tan *et al.*, 2017; Zink *et al.*, 2014). Undoubtedly, e-waste is a great challenge in modern communities (Long *et al.*, 2016) and it includes some materials (e.g. Mercury, Lead and Arsenic) that can be harmful not only to wildlife but also to humans. Fortunately, environmental concerns are attracting more attention in the 21st century. In this regard, conventions, international laws and state laws have limited countries from polluting the environment and depleting natural resources (Sarath *et al.*, 2015). In addition, the cost of raw materials is competing with that of recycling returned products. Therefore, manufacturers in different industries have recently started paying due attention to reverse logistics (RL) (Dat *et al.*, 2012; Hagelüken and Corti, 2010).

The mobile phone industry is the most innovative and rapidly changing industry in the world. According to Cisco, there will be 10 billion mobile-connected devices by 2017 (Kelly, 2013). Short life cycles and rapid advances in new technologies are putting used mobile phones at the forefront of reverse supply chain implementations (Geyer and Blass, 2010). There are almost 10 to 12 key physical parts in a standard mobile phone, some parts of which such as display, camera, battery and charger can be easily disassembled and re-manufactured for the primary or secondary markets (Ellen Macarthur Foundation Report, 2012). The 500 to 1,000 components existing in a standard cellphone are made of different substances and materials (Life Cycle Environmental Issues of Mobile Phones, 2005). Over 30 metals such as silver, gold and exceptional earth metals have been used in a cellphone and the potential recycling rate is 50% in half of them. According to U.S. Environmental Protection Agency (2016), as from each 1 million recycled cellphones, 772 lbs. of silver, 35,274 lbs. of copper, 33 lbs. of palladium and 75 lbs. of gold are recyclable, it is essential for cellphone manufacturers to pay special attention to RL.

RL includes the recovery of items after they are disposed of by consumers, with the aim of making the most of the recovered products by activities such as recycling, reusing and remanufacturing (Rubio and Jiménez-Parra, 2014). Andel (1997) is of the opinion that the effective implementation of RL results in direct advantages, the most important of which is to improve customer satisfaction, which shows that decisions made in RL are directly related to customer satisfaction to which producers need to pay attention.

Winning customers' satisfaction is critical to a firm's success because it is an antecedent of customer retention/loyalty (Shokouhyar *et al.*, 2018; Szymanski and Henard, 2001). Higher customer satisfaction results in increased transactions (Bolton and Lemon, 1999), willingness to purchase additional services (Arabi *et al.*, 2018; Anderson and Bernth-Peterson, 1997) and reduced-price elasticity (Arabi *et al.*, 2018; Anderson, 1996) and transaction costs (Anderson and Bernth-Peterson, 1997). Therefore, attention to customer feedback in supply chain and logistics processes has recently increased and manufacturers plan to transform their supply chains (SCs) (forward and reverse) into consumer-centric SCs (Ahmadi *et al.*, 2020; Laari *et al.*, 2016; Taghikhah *et al.*, 2019).

Manufacturers use different methods such as "market and competitor monitoring", "market research", "direct/indirect interviews", "consumer feedback in retail stores" and "CRM methods" to move towards a customer-centric SC (Ross, 2005; Stefanou *et al.*, 2003; Zondag and Ferrin, 2014). Retailers are incapable of attracting large audiences and receive feedback by using these methods because most customers prefer not to discuss their complaints/praise in stores for different reasons like an inconvenience, lack of time, distance to the retailer and brand disinterest (Ashley *et al.*, 2011; Reimers and Clulow, 2009). Therefore, data samples are small; that is, the data set is probably inaccurate (Jin and Agrawal, 2003; Kattan and Cooper, 1998).

With the introduction of online social media (SM), platforms such as Twitter, Facebook and Tumblr, remarkable data have been generated, reflecting the true opinions of customers (Ahmadi *et al.*, 2020; Wolny and Mueller, 2013). According to statistics released in the first four months of 2019, 330 million Twitter users were on twitter (Clement, 2019). SM data are qualitative and unstructured in nature, often large in volume, variety and velocity (He *et al.*, 2013) relatively inexpensive and effective in collecting the opinions of large and different audiences (Katal *et al.*, 2013). Effective analysis of SM data can add useful insights into the feelings and behaviours of consumers (Blasi *et al.*, 2020; Kühl *et al.*, 2019).

The outcome of operation management tools and techniques is normally based on limited data collected from different sources such as surveys, interviews and experts' opinions. Decision-making could be accurate if such analyses are supplemented by SM data. Hence, this study tries to incorporate SM data using interpretive structural modelling (ISM) and MICMAC analysis to establish a customer-centric RL. The involvement of information from SM data will give consumers a sense of empowerment (Mishra *et al.*, 2017). To achieve this goal, cellphone features that influence customer purchasing behaviour are extracted. Such features not only affect the RL but also influence one another. Therefore, it is essential to study the mutual interaction among these features. A critical study of cellphone features affecting consumer purchasing behaviour and their mutual relationship can provide decision-makers with vital information. ISM is a suitable technique for the identification and establishment of relationships between different variables (Mandal and Deshmukh, 1994). This study identifies the features of cellphones influencing consumers' purchasing behaviour based on analyzing the websites of several cellphone manufacturers and studies their relationship with RL by experts. After that, Twitter's social media data are used to make a model for a customer-centric reverse supply chain in ISM. Using social media information would give consumers a sense of empowerment and would give insights to managers so that they can prioritize their implementation efforts better. The main goals of this paper are:

- To identify the features of cellphone that affect consumer purchasing' behaviours and their relationship with RL.
- To incorporate social media data using ISM and MICMAC analyses to develop a framework for customer-centric RL.

The other sections of the paper are as follows: Section 2 highlights the review of literature related to RL and social media (Twitter), Section 3 describes the methodology adopted in this research, Section 4 presents the research discussion and implications and the conclusions and future research directions are to be dealt with in Section 5.

2. Literature review

Our literature review is examined in two sections: logistics and social media (Figure 1). The following is a description of them.

2.1 Reverse logistics

The idea of RL dates back to a long time ago, but its knowledge has been expanded over time (Kokkinaki *et al.*, 2001; Ravi, 2014). The term "reverse distribution channel" for recycling has already existed in the literature since the 1970s (Guiltinan and Nwokoye, 1975; Ginter and Starling, 1978), but the term "reverse logistics" was first introduced. In the context of the broader SC, RL is defined as:

> "The process of planning, implementing and controlling the efficient, cost-effective flow of raw materials, in-process inventory, finished goods and related information from the point of consumption to the point of origin for the purpose of recapturing value or proper disposal" (Waites, 2015; Rogers and Tibben-Lembke, 1998).

In recent years, due to growing environmental concerns, competitive advantage, promises of financial potential, legal reasons, social responsibility and high efficiency by customers resulting from the expansion of product selection and shorter product life cycle, RL has become more prominent in the business community and academia, spanning such diverse areas as recycling, remanufacturing, information technology, warehousing, operations and environmental sustainability (Shokouhyar *et al.*, 2018; Dowlatshahi, 2000, 2012; Venkatesh, 2010). Thus, the growing importance of research in RL has also been highlighted by many authors (see, for example, Islam and Huda, 2018 and Mahadevan, 2019). The reverse supply chain is predominantly known as RL in most of the literature. However, in this paper, reverse SC and RL are interchangeably used although logistics is part of the main SC (Li, 2014).

2.1.1 Related studies on reverse logistics. Hammes *et al.* (2020) proposed a model for the evaluation of RL performance in civil construction to assist the practice of return activities in developing countries. Initially, a bibliographic search was performed to find indicators for the model. The reverse flow in the civil construction was mapped based on works published in Brazil and Colombia. From this mapping, a 12-indicator model was elaborated to approach supply logistics, internal logistics operations and the waste management of the construction companies to evaluate the performance of this sector. Moreover, these indicators were prioritized through the AHP method. Kazancoglu *et al.* (2020) have developed a system dynamics model to analyse and comprehend the green performance of RL activities by predicting the environmental impact of RL activities. The proposed model has been validated by a case study in the context of a food supply chain. In the company

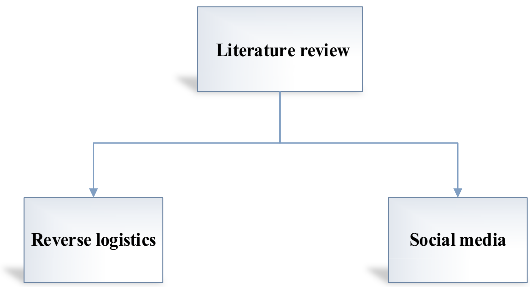


Figure 1.
Literature review framework

where the case study is carried out, the environmental effects of RL activities have been analysed. These activities in a food supply chain in terms of CO_2 (carbon dioxide), NO_x (nitrogen oxide), SO_2 (sulfur dioxide) and PM (particulate matter) emissions have been predicted through a system dynamics model for the years 2020 to 2024. Chaves *et al.* (2020) have determined the most frequently used performance measures for the evaluation of RL in Brazilian companies. Furthermore, they sought to verify whether a correlation exists between certain performance measure dimensions (cost, asset management, customer service and productivity), company size (micro, small, medium and large) and their sectors of the economy. Han and Trimi (2018) have identified the criteria that should be used in designing and evaluating social commerce based on RL processes by firms. They have tested the effectiveness of the identified criteria by using them to evaluate the RL practices of three major global firms that use social commerce platforms. Peña-Montoya *et al.* (2020) proposed an adapted maturity model to measure maturity levels of RL aspects at small- and medium-sized enterprises in regions from Colombia to contribute to sustainable solid waste management. Dev *et al.* (2020), under the paradigm of industry 4.0, designed an RL model and examined how product diffusion dynamics in the market affect the economic and environmental performances of an inventory and production planning (I&PP) system. Islam and Huda (2018) have reviewed the literature on RL and the closed-loop supply chain of electrical and electronic waste equipment. For this purpose, 157 articles, published between 1999 and May 2017, have been studied. As a result, research gaps in the literature that indicate future research opportunities have been identified. Yan and Yan (2019) have presented two remanufacturing RL network models; namely, the open-loop model and the closed-loop model. The former features a location selection with two layers. For this model, a mixed-integer linear programme is built to minimize the total costs of the open-loop RL system. For the latter, a special demand function considering the relationship between new and remanufactured products is developed. Zarbakhshnia *et al.* (2019) have designed and programmed a green forward and RL network through a mixed-integer linear programming model. The model is applied to a multi-stage, multi-product and multi-objective problem whereby the first objective is to minimize the cost of operations, processes, transportation and fixed costs of the establishment. The second objective is to minimize the amount of CO2 emissions based on the gram unit, while the third is to optimize the number of machines in the production line. Liao (2018) developed a generic mixed integer nonlinear programming model (MINLP) for RL network design. This is a multi-echelon RL model which maximizes total profit by handling products returned for repair, remanufacturing, recycling, reuse or incineration/landfill. A hybrid genetic algorithm (GA) is proposed to solve the problem. The designed model is validated and tested by using a real-life example of recycling the bulk waste in Taoyuan City, Taiwan. Sensitivity analyses are conducted on various parameters to illustrate the capabilities of the proposed model. John *et al.* (2018) developed a mathematical model for the network design of a multi-product, multi-echelon RL system. Different recovery options such as remanufacturing, repairing and recycling are considered in this study. An integer linear programming formulation was used to model and solve the problem. Two commonly used consumer electronic goods, mobile phones and digital cameras are considered for validation. Alshamsi and Diabat (2017) have designed an RL network by using a genetic algorithm. Transportation decisions such as whether to use in-house or outsourced vehicles are often based on cost-effectiveness. The problem is formulated for the case of a household appliance in the Gulf Cooperation Council (GCC) region. In total, 68 cities are considered, leading to a very large number of variables and constraints. Thus, a heuristic approach; namely, a Genetic Algorithm (GA), is chosen to solve the problem. The main contribution of this paper is to develop a very efficient GA capable of solving a large scale problem in a short time. Kilic *et al.* (2015) have designed an RL system for WEEE in Turkey which is one of the fast-developing countries in the world. In total, 10 scenarios are taken into account regarding different collection rates via a mixed-integer linear programming model. Different types of storage sites and recycling facilities are considered within the model differing from the existing studies. The optimum locations of storage sites and recycling facilities are obtained for each scenario satisfying the minimum recycling rates stated by the European Union directive for each product category. Yu and Solvang (2016) suggested a novel idea for designing and planning an inverted general logistics network and formulated it through multi-purpose mixed-integer programming. The RL system is an independent network and comprises three echelons for collection, remanufacturing, recycling, energy recovery and disposal of used products. The mathematical model not only takes into account the minimization of system operating costs but also considers minimization of carbon emissions related to the transportation and processing of used products and the minimum rate of resource utilization is also required to minimize the waste of resources in landfill. Illustration, sensitivity analysis and numerical experimentation are given to show the applicability and computational efficiency of the proposed model. This work provides an alternative approach to account for both the economic and environmental sustainability of an RL system. Chakraborty *et al.* (2018) developed a causal model among the identified issues and sub-issues for setting up a reverse supply chain in an Indian semiconductor manufacturing industry and then they evaluated the critical issues based on the causal relations. Adabavazaeh and Nikbakht (2019) analysed reverse supply chain critical success factors in the air industry using ISM. Ravi and Shankar (2017) analysed the interaction among major variables of RL seen in automobile industries. Mangla *et al.* (2016) evaluated the important success factors (CSF) associated with RL implementation in manufacturing industries in India. investigated the complex relationship among factors affecting RL for the pharmaceutical industry in India. Mahadevan (2019) presented the research carried out on the development of a conceptual framework termed “Reverse Collaboration Framework (RCF)” to provide supply chain (SC) visibility and information sharing to practitioners in RL operations. Wang *et al.* (2019) have proposed a demand-matching oriented Multiple Criteria Decision-Making (MCDM) method to identify the best collection mode for components used for RL. Agrawal *et al.* (2016) explored different options in RL using graph theory and matrix approach and they came up with an approach to choose the best alternative. A case of a mobile manufacturing firm is discussed for the illustration of this approach. The firm has to select the best disposition alternative among four identified alternatives such as products returned for repair or reuse and resell as new or repair or refurbish and resell or re-manufacture and sell or recycle. Asees and Ali (2019) have examined the impact of sustainable practices, i.e. environmental, economic and social sustainability on RL recovery options. The results of this study show that waste management, impact on biodiversity and economic growth are the most important factors in designing sustainable recovery options RL. Agrawal and Singh (2019) explored the RL in the context of the Indian electronics industry and examine the effect of disposition decisions on Triple Bottom Line (TBL) i.e. economic, environmental and social performance of RL. Mahindroo *et al.* (2018) analysed the impact of a conceptualized information system(IS) framework on achieving RL strategic outcomes under the individual moderating influence of resource commitment (RC) and return frequency. The results show that IS capability, IS for logistics, IS partnership quality and IS for value addition lead to RL strategic benefits. Sirisawat and Kiatcharoenpol (2018) focused on the classification of RL barriers and ranking both barriers and solutions to RL implementation in electronics industry. Ali *et al.* (2018) examined the contextual relationship and interactions among barriers to implement RL practices in the computer supply chain of Bangladesh. Bouzon *et al.* (2018) evaluated the inter-relationship among RL barriers from the perspectives of the most important stakeholders in the Brazilian context using the grey decision-making approach. Prakash and Barua (2016) evaluated and ranked the barriers to RL implementation so that companies could design strategies to deal with them based on priority. Bouzon *et al.* (2016) identified and evaluated RL barriers in the Brazilian context using the fuzzy Delphi method and AHP. Bouzon *et al.* (2016a) evaluated barriers to RL implementation in the Brazilian context using the grey decision-making approach.

2.2 Social media

Jabeur *et al.* (2018) defined social media as fundamentally electrical communication procedures through which users can make online communities and share thoughts, feelings, information, messages and other content forms in diverse formats including text, pictures and videos. The term "social media" is currently used quite often. Due to the emergence of social media as an instant way to exchange ideas and a main source of information, they have become increasingly attractive to users. The number of users, whit online post-text messages, pictures and videos, has grown in recent years. In 2020, more than 3.6 billion people used social media worldwide, which is a significant increase compared to 2017, which was about 2.86 billion people (Tankovska, 2021). Thus, firms encountered a rapid change in environment as customers and employees began using social media on a massive scale; and these competitive stresses compelled firms to present content on diverse social media channels as expected by customers (Chae, 2015; He *et al.*, 2013). A firm should use social media to gain the benefits of doing so (Chae, 2015; He *et al.*, 2013); in addition, social media bridge the gap between producers and consumers (Markova and Petkovska-Mirčevska, 2013). For instance, social media help firms promote their brands and market their products to consumers thereby enhancing external communication, awareness and thought leadership (Markova and Petkovska-Mirčevska, 2013). Therefore, in a changing world in the business world, social media are valuable and managers and decision-makers need to pay special attention to them. According to a global survey (January 2020), Facebook (94 %), Instagram (76%), LinkedIn (59 %), Twitter (53 %) and YouTube (53 %) are the most frequently used social media among marketers worldwide (Statista Research Department, 2021). In this paper, we pay attention to one particular social media platform, Twitter because, among different social media technologies and ever since its inception in 2006, it has become the fastest-growing social platform, ahead of Facebook and Google (Ahmadi *et al.*, 2020). Over 75% of the Fortune Global 100 owns one or more Twitter accounts at the corporate level and for their specific brands and over 270 active Twitter users generate 500 million tweets per day. Customers follow products, services and brands and discuss them on Twitter (Malhotra *et al.*, 2012). Another important reason is that, unlike Facebook data, Twitter data could be considered "open". Thus, research and business communities can access Twitter data using Twitter Application Programming Interface (API) (Twitter, 2013), which has offered them opportunities to access the data in an unprecedented scale and size and to analyse such data for challenging problems in diverse domains. In this research, we used streaming API for a limited period of time.

2.1.1 Related studies on social media based on Twitter. Bodaghi and Oliveira (2020) studied dozens of rumors on Twitter to find new insights into user characteristics and macro patterns in the process of rumor spreading. They investigated 56,852 tweets from 43,919 users. Hassan *et al.* (2020) measured the early impact of research articles through the sentiments expressed in tweets about them. They used the SentiStrength tool and improved it by incorporating new opinion-bearing words into its sentiment lexicon pertaining to scientific domains. Then, they classified the sentiment of 6,482,260 tweets linked to 1,083,535 publications covered by Altmetric.com. Tang *et al.* (2020) discovered similarities and differences in the construction industry in China and the USA by using data analytic tools on data crawled from social media platforms. By using the platform-provided APIs, all Weibo messages of interested users were collected in the period from October 7, 2009, to April 14, 2016. By using the Web search-based crawler, all the tweets of interested users were collected in the period of 05.16.2008~03.10.2016. Radi and Shokouhyar (2021) have used Social Media Analysis to understand the perception of consumers towards the sustainability efforts of two major companies in the mobile phone industry. They have suggested a dictionary-based framework, including Content analysis, Descriptive Analysis and Sentiment analysis to extract the features that correspond to the three dimensions of TBL. Yang and Stewart (2019) examined the Houston Police Department (HPD)'s public engagement efforts using Twitter during Hurricane Harvey, which was a large-scale urban crisis event. This study harvested a corpus of over 13,000 tweets using Twitter's streaming API, across three phases of the Hurricane Harvey event: preparedness, response and recovery. Both text and social network analysis (SNA) techniques were used including word clouds, *n*-gram analysis and eigenvector centrality to analyse data. Palmer and Udawatta (2019) investigated "Green Building" as a topic on Twitter. Green Building construction is identified as one of the methods that promote sustainable construction. In this study, for the period under consideration (1 September 2016 to 30 August 2017), 64,236 tweets containing the phrase "green building" were recorded. Pourebrahim *et al.* (2019) analysed data from Twitter during Sandy Hurricane. The results suggest that Twitter is a highly valuable source of disaster-related information particularly during the power outage. With a substantial increase in the number of tweets and unique users during the Sandy Hurricane, a large number of posts contained first-hand information about the hurricane showing the intensity of the event in real-time. More specifically, a number of images of damage and flooding were shared on Twitter through which researchers and emergency managers can retrieve valuable information to help identify storm damages and plan relief efforts. Singh *et al.* (2019) used Twitter analytics for analyzing the startup ecosystem of India. In this paper, descriptive analysis and content analytics techniques of social media analytics were used to examine 53,115 tweets from 15 Indian startups across different industries. The study also used techniques such as the Naïve Bayes Algorithm for sentiment analysis and the Latent Dirichlet allocation algorithm for topic modelling of Twitter feeds to generate insights for the startup ecosystem in India. Becken *et al.* (2019) examined whether the electronic word of mouth originating from Twitter posts offers a useful source for assessing destination sentiment. Moreover, they examined what caveats need to be considered when interpreting the findings because destination monitoring is crucial to understand performance and identify the key points of differentiation and visitor satisfaction is an essential driver of destination performance. Using a geographically informed filtering process, a collection of tweets posted from within the Gold Coast destination was created and analysed. Meta-data were analysed to assess the population of Twitter users and sentiment analysis, using the Valence Aware Dictionary for Sentiment Reasoning algorithm, was performed. Zhang *et al.* (2018) assessed and compared perceptions about chemotherapy of patients and health-care providers through analysis of chemo-related tweets. Chemotherapy-specific tweets were extracted from the historical tweet set and the content of these tweets was analysed using a topic model, sentiment analysis and word co-occurrence network. Pai and Alathur (2018) performed sentiment analysis using Twitter data to measure the perception and use of various mobile health applications among citizens. The methodology followed in this research is qualitative with the data extracted from a social networking site "Twitter" through the tool RStudio. Thompson *et al.* (2018) explored how two social media platforms were used by the Grand Slam tennis events to achieve branding and relationship marketing goals. A content analytic design was used to examine Twitter and Facebook posts from the official accounts during and post-, each respective event. Garant (2017) explored the effectiveness of using text mining to analyse the consumer-generated content from online hotel reviews. Specifically, this study focuses on demonstrating the helpfulness of such tools in the case of Original Sokos Hotel Vaakuna Helsinki and Scandic Marski in Finland. By analyzing the current trends and patterns of online reviews of the two hotels, the objective of the study is to understand the extent to which text mining can improve marketing decisions and thus bring value to consumers. He *et al.* (2017) proposed knowledge management (KM) framework for leveraging big social media data to help interested organizations to integrate Big Data technology, social media and KM systems to store, share and leverage their social media data. Specifically, this research focuses on extracting valuable knowledge on social media by contextually comparing social media knowledge among competitors. This paper analysed 882,751 Twitter messages related to five large companies in the retail industry (Costco, Walmart, Kmart, Kohl's and The Home Depot) on generating new knowledge.

The field of supply chain management and RL has been relatively slow in studying social media and big data for research and practice (Chae, 2015). Schmidt *et al.* (2020) examined the relationship between supply chain glitches and stock market returns by examining tweets related to supply chain glitches. They analysed data on 213 supply chain glitches for 150 firms across 5 years and over 2 billion tweets on publicly traded firms. Sharma *et al.* (2020), from a strategic perspective, explored the major issues that companies have faced, as the advent of the coronavirus and the strategic options that companies are considering. In this paper, Twitter data from NASDAQ 100 firms are used. Tseng *et al.* (2019) improved sustainable supply chain capabilities using social media in a decision model. They applied the fuzzy synthetic evaluation and decision-making trial evaluation laboratory to address linguistic preferences and provide a strategic approach for the proposed attributes. Iftikhar and Khan (2018) presented a framework for the improvement of demand forecasting in the supply chain industry using social media analytics. The proposed framework used the sentiment, trend and word analysis results from social media big data in an extended Bass Emotion Model along with historical sales data to predict product demand. The forecasting framework is used in a case study to validate the framework that would assist in improving demand forecasting in a supply chain. Singh *et al.* (2018) proposed a big-data analytics-based approach that considers social media (Twitter) data for the identification of supply chain management issues in food industries. Mishra *et al.* (2017) have identified factors influencing consumer's beef purchasing decisions with the help of the literature and social media Big Data. Chan *et al.* (2016) developed a hierarchical model and tested it for a decision-making process in which social media data are used for new product development. Chae (2015) contributed to the supply chain management community by proposing a novel, analytical framework (Twitter Analytics) for analyzing supply chain tweets, highlighting the current use of Twitter in supply chain contexts and further developing insights into the potential role of Twitter for supply chain practice and research. Data collection was conducted between February 5 and April 10, 2013 and the final data set includes 22,399 tweets with the hashtag #supply chain and their meta-data. He *et al.* (2013) described an in-depth case study, which applies text mining to analyse unstructured text content on Facebook and Twitter sites of the three largest pizza chains: Pizza Hut, Domino's Pizza and Papa John's Pizza. Their research results help companies understand how to perform a social media competitive analysis and transform social media data into knowledge for decision-makers and e-marketers.

Some of the studies carried out in RL and social media (Twitter) were enumerated. By reviewing the literature on the subject, it was noticed that:

- Relatively limited studies have been conducted in the field of supply chain management and RL about studying social media and big data for research and practice.
- The studies of RL that relate end-user's opinions from social media (Twitter) to RL decisions is a relatively new concept.
- Research on the application of social media data in RL, especially in the field of mobile phones, is in its preliminary stage.
- The simultaneous use of quantitative and qualitative techniques in these studies is very limited.

Therefore, in this paper, we seek to bridge these research gaps by providing a model for customer-centric RL using customer feedback, to improve the RL decision-making process.

3. Methodology

This research mainly aims to develop a structural model of cellphone features that affect the purchasing decision of consumers and to prioritize them to achieve a customer-centric reverse supply chain based on opinions of customers extracted from social media (Twitter). The ISM tool and MICMAC analysis are used to establish the interrelationship between the features that affect the consumer's decision to purchase a cellphone and to identify the driving and dependence power of each feature. The results of this study are to guide the policymakers, managers and supply chain designers to review their strategies for the implementation of RL processes. Hence, in this section, initially, the features that affect the consumer's decision of purchasing a cellphone and how it relates to RL are described. Then, consumers' opinions are extracted from social media (Twitter), which are rich in nature and provide unbiased opinions unlike consumer interviews, surveys, etc. (Conceptual Analysis). Cluster analysis is carried out on the data collected from Twitter to find out the relation among identified features (Relational Analysis). Finally, ISM and MICMAC analysis are used to provide a theoretical framework with the factors interlinked to each other at different levels. The proposed framework is presented in Figure 2.

The steps of the proposed framework are as follows:

- Identifying the mobile phone features that influence the purchasing behaviour of mobile phone customers, by reviewing websites of several cellphone manufacturers and applying the opinions of experts;
- Determining the relationship between identified features and inverse logistics with the help of expert opinion;
- Using keywords to extract all tweets related to mobile phone products from August 1, 2019 to October 31, 2019 and storing them in the data warehouse;
- Applying primary filters to extracted tweets to identify tweets related to Apple cellphones;
- Extracting the keywords related to features identified by using the content analysis of Apple's website;
- Finding tweets related to each of the features identified in step 1;

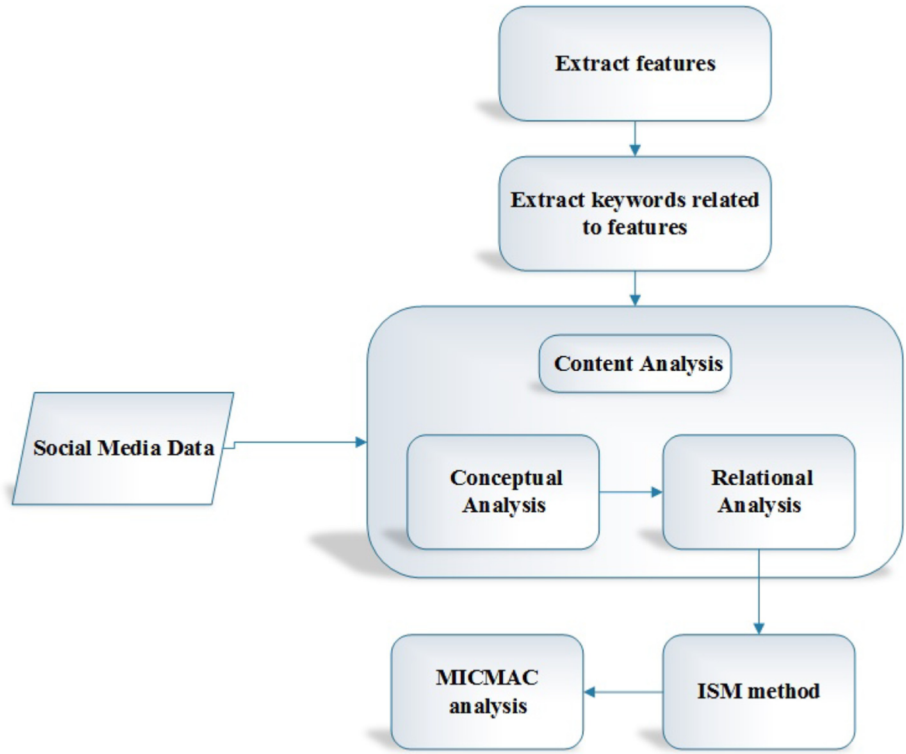


Figure 2.
Proposed framework

- Clustering the tweets obtained in the previous step into 18 clusters;
- Determining the relationship between features, using the Pearson correlation coefficient and distance between the clusters in accordance with incidence frequency and similarity;
- Holding a brainstorming session among mobile phone experts to form a structural self-interaction matrix; and
- Implementation of ISM and MICMAC analysis

3.1 Mobile phone features influencing the consumer's decision of buying a mobile phone and their relationship with reverse logistics

To identify the cellphone features that influence the purchasing behaviour of cellphone customers, firstly, websites of several cellphone manufacturers were checked and 26 features were extracted. Then, cellphone experts were requested to classify and merge these features on the basis of the features of the iPhone and eventually 18 features were obtained. They were also requested to determine the relationship between these features and RL, which results in Table 1. Some of the features were directly and some were indirectly related to RL. Direct communication means the selected feature has a direct effect on RL decision-making and indirect communication means customer satisfaction or dissatisfaction is a relevant feature leading to the return of the product or the customer's motivation. Features directly related to RL also have physical components, some of which have both internal and external parts, some have only internal parts and some have only external parts, like a camera with two internal parts (CCD, processor, . . .) and the exterior (lens, optical zoom, . . .). In the following, an overview of customer feedback on 18 identified features will be provided and suggestions will be made for decision-making in RL.

(1) *Capacity:* This module can be used in different models of mobile phones. Due to the increased capabilities and quality of content such as high-resolution photos, as well as 4 K movies and over 30 fpt videos stored on mobile phones, they require more storage. Therefore, users are reluctant to use 64 GB capacity and less. Additionally, given that, newer Apple operating systems such as ios13, come with higher capabilities and require more space than older models to install on the device. Therefore, the effective space for the user is less than its nominal amount and the user cannot use all the declared space. Users are also unhappy with models with less than 64 GB of storage and offer the company a recycle solution without any additional consideration such as return to the supplier or reclaim materials.

(2) *Screen:* This feature consists of two parts, internal and external. Users do not directly comment on the internal part. The major dissatisfaction with users was

Table 1.
Smartphone features and their relationship to reverse logistic classified by expert

No.	Smartphone features (first step)	iPhone features (second step)*	Relation to the RL
1	Price	Price	Indirectly
2	Capacity	Capacity	Directly
3	Screen	Screen	Directly
4	Design	Design, size and weight	Directly
5	Size	merged into design	Merged into design
6	Weight	merged into design	Merged into design
7	Resistance	Resistance	Directly
8	Chip	Chip	Directly
9	Camera	Camera, video recording, front camera, video calling, audio calling, audio playback and video playback	Directly
10	Video recording	merged into camera	Merged into camera
11	Front camera	merged into camera	Merged into camera
12	Cellular	Cellular	Directly
13	Security	Security	Indirectly
14	Video calling	merged into camera	Merged into camera
15	Audio calling	merged into camera	Merged into camera
16	Audio playback	merged into camera	Merged into camera
17	Video playback	merged into camera	Merged into camera
18	Artificial intelligence systems	Siri	Indirectly
19	Battery	Battery	Directly
20	Headphones	Headphones	Directly
21	Sensors	Sensors	Directly
22	Connector	Connector	Directly
23	Warranty	Warranty	Indirectly
24	Operating systems	iOS	Indirectly
25	Trade-in programme	Apple trade-in	Indirectly
26	Featured accessories	Featured accessories	Directly

Note: *Some items merged

in two areas. Firstly, comparing it with other competitors of any other brands and mobile phone models; and secondly, the LCD has no impact resistance on strike. The iPhone 5 Series and iPhone SE, of course, have a small screen. The recycling policy is one based on user opinion. Besides, users are well satisfied with the quality and LCD resistance of the iPhone series 8 and beyond and the manufacturer has been able to satisfy customers. Apart from that, users are also satisfied with the full-screen LCD on iPhone X models, but this new change has made LCD edges more vulnerable, it is recommended to recycle the exterior parts of the iPhone 5 series, iPhone SE, iPhone 6, iPhone 6 *s* and iPhone 8 models.

(3) *Design:* All models of the iPhone 5 series, iPhone SE, iPhone 6 *s* and iPhone 6 have been criticized for their small screen sizes. Some users have also mentioned the high weight of the iPhone 6 *s*. Meanwhile, the large screen of iPhone 6 Plus and iPhone 6 *s* Plus have satisfied users. Therefore, it is recommended that the factory adopt a reuse policy for these larger screens. In addition, the high weight along with the location of the cameras protruding out of the iPhone's back has led users to complain about the design of the iPhone 11 series. Thus, it is suggested that Apple take this into consideration in designing future products.

(4) *Resistance:* Apple's 2016 iPhone models are not waterproof, dustproof and impact resistant, causing users to be unhappy with their phones and damage to the internal components against moisture, dust and impact. The users of iPhone 7 and 8 Series models have also complained about the impact of the handset being hit and dropped, which has led to severe user dissatisfaction. These damages include breaking and scratching the glass behind the phone along with their screen. Of course, as mentioned, there is relative satisfaction with the LCD of the iPhone 8 Series, but not against impact. However, in the iPhone X series onwards, the home button is removed. Therefore, iPhone's vulnerability has increased significantly due to the full-screen LCD, causing a lot of customer dissatisfaction; but overall, customers are satisfied with this feature of the iPhone 8 Series. According to users' sentiment analysis, Apple has fixed most of the defects in the iPhone 11 Pro and iPhone 11 Pro Max and gained relative satisfaction from customers.

(5) *Chip:* Users comment on this feature more in terms of the mobile phones' speed while working with it. Some customers, however, have explicitly referred to the type of chip and its performance. They give their opinions in the form of comparison with other models within the same brand or another brand. The manufacturer is upgrading its software capabilities every year, which requires more powerful processors (mainly chips) and more resources to run its software applications smoothly. Most users are not satisfied with 2015 and earlier models. Apple has used a powerful chip called the Fusion chip series on iPhone 7 and later models. It should be noted that the chip architecture of all the models under consideration in this paper is 64-bit. There is relative consumers' satisfaction with the iPhone 7 Plus and later models. Due to the slowdown in many mobile phone operations, customers are not satisfied with the iPhone 5, iPhone 6, iPhone 6 Plus, iPhone 6 *s* and iPhone 7 chips.

(6) *Camera:* Most users have talked about the usability and quality of cameras for taking photos and videos. However, they did not talk specifically about the internal components of the cameras such as charged coupled device (CCD) and lens. Hence, as mentioned before, suggestions and discussions based on users' opinions are applied only to the external parts of the "camera" feature. Users made more

comments related to photography than a video recording. The rear-facing cameras on iPhone 5 series models have very low resolution and poor night photography and photo shooting capability. Their front-facing cameras have even lower quality, which has made users unhappy. The photo shooting quality has been improved to 12 megapixels in the iPhone SE and the iPhone 6 series models, but other features such as video recording speed (frames per second), camera zoom (optical/digital), night mode shooting and poor camera quality have been criticized by many users. As a result, customers' sentiments on the camera feature have been negative. Most of the criticism of the iPhone 8 model is related to the poor zooming quality for photos and videos. The iPhone 7 Plus model incorporates an optical zoom in the mobile phone, which gives users relative satisfaction. However, a thicker lens on the back of the camera is needed for the optical zoom capability, which often displeases customers. This has been a subject of much criticism for the iPhone 8 series and later models. However, in general, customers are relatively satisfied with the iPhone X and iPhone 11 series models.

(7) *Cellular:* There are a few comments on this feature, which is one of the parts that does not change much from one model to the newer ones, but lack of support for all LTE frequencies on the iPhone 5 and iPhone 5c models has made users unhappy with these features. Other capabilities such as Bluetooth 50 or LTE Advanced versions have not been widely criticized or applauded by users.

(8) *Battery:* This feature has the most dissatisfaction within all iPhone models. Customer satisfaction with this feature was only gained in the iPhone X, iPhone 8 Plus, iPhone XS, iPhone XS Max, iPhone 11 Pro and iPhone 11 Pro Max models. Other models gave a very unpleasant experience to the users. Battery dissatisfaction has been with battery life and a long time to recharge. Besides, short battery life has been the subject of much criticism from users in many iPhone models. Often, dissatisfaction with this feature has been so high that users have compared it with criticisms in price among mobile phones because of its weakness. These criticisms have been sharpened on newer mobile phones like the iPhone 11. Users are looking for abilities such as fast charging and longer battery life. According to Apple, a normal battery is designed to retain up to 80% of its original capacity at 500 complete charge cycles when operating under normal conditions (Apple, 2021). Due to consumer dissatisfaction, it seems it is time for Apple to change its battery production policies.

(9) *Headphones:* After the removal of the 3.3 mm headphone jack in 2016, Apple received a lot of criticisms, which have still left users dissatisfied. Of course, with the advent of air pods that same year, there was a slight reduction in criticisms, but paying extra for these accessories has greatly reduced user satisfaction so much so that expressing that criticism has displeased users in all iPhone models.

(10) *Sensors:* This feature also attracts a small amount of user feedback and is far from the eyes of users due to its internalization, but most users' comments were based on their successful experiences while using it; for example, using a compass in the forest or desert. Most criticisms have been of the inaccuracy of compass when placed near metals. This part has not changed much like the Cellular and SIM card feature over time and only after the iPhone 6 model barometer capability has been added.

(11) *Connector:* Users are very satisfied with the use of the lightning connector and have criticized very little. Only some users have requested that lightning to

Micro-USB converter should be inserted in the iPhone package when purchased. This feature is common to all iPhone models studied.

(12) *Featured iPhone Accessories:* Some users use this feature, but the major dissatisfaction is with the lack of phone accessories over the past three years of iPhone models. For example, accessories for the iPhone 7 will no longer be available. This feature includes a wide range of equipment including iPhone case, air pods, wireless chargers, HomeKit, Gaming and Toys and many more that are being added continuously over the years. For example, the latest model of air pods with wireless charging capability and the air pods pro have recently been added to the list. Customers who use this feature are very happy with them. The following are the features that indirectly affect the RL decision (not having a physical component).

(13) *Price:* Price plays a crucial role in the assessment of products by consumers (Marian *et al.*, 2014). It could be perceived as an amount of money spent by consumers for a particular transaction (Lichtenstein *et al.*, 1993). It is usually considered a determinant of quality; i.e. high price products are often associated with better quality (Erickson and Johansson, 1985; Völckner and Hofmann, 2007). Criticism of the high price of Apple's phones, especially its new ones, has led to consumer dissatisfaction. The company does not make its market available for anyone, especially in its new mobile phones. With the launching of the new iPhone models, the price of the previous models is reduced and users are not satisfied with the iPhone X and later prices due to the comparison of the performance with its price in other brands. Many people tend to have suggestions for replacing their older iPhone with a newer one or getting a discount on the new model price, but it is not yet fully available to its loyal customers all over the world and only in certain areas will the payment be made in the form of an Apple gift card, after a certain amount of time has elapsed so that the company can calculate the right price to charge Apple gift card to pay the customer.

(14) *Security:* This is a basis for authentication and access to all parts of all iPhones, especially their personal and financial parts. This was possible on the iPhone 5 and earlier models when users were authenticated through 4 or 6-digit codes. However, fingerprints were used for authentication for the iPhone 5 *s* and later, up until the iPhone 8 Plus model. Subsequently, face recognition technology (even in very dim light or no light) has been used via a camera dedicated to 3 D face detection. This camera can identify a person while asleep or awake. Users have a lot of dissatisfaction with the use of fingerprints for identification and authentication. For many users, accessing their mobile was impossible, as their hands or the sensors were not properly cleaned; or, during cold seasons, users could not access their phones while wearing gloves. Apple's face recognition feature is satisfying and most users are satisfied with the feature. This feature works even if some parts of the face are covered (e.g. by sunglasses or a beard) (Apple, 2021).

(15) *Siri:* The use of artificial intelligence (AI) in mobile phones makes it very easy to work with. It is an intelligent assistant that has been integrated into Apple's operating system since 2010. It has been added to its capabilities in newer versions of iOS, providing users satisfaction. Capabilities that gain the most customer satisfaction include phone and text actions, schedule events and reminders, handle device settings and more.

(16) *Warranty:* Apple's Warranty programme has been heavily criticized by customers. Most users expect Apple to repair/replace in the form of a warranty plan when the battery is depleted and the screen is crushed and they claimed that this should happen in warranty plan because the impact on the mobile phone's screen is not so severe and the battery life has been reduced to half in less than a year. However, Apple has not included these items in its warranty plan, which has caused a lot of users' dissatisfaction. In addition to preventing such issues, users are suggesting to each other the use of mobile phone protective equipment such as a case and LCD projector which impose a cost on the customers. Besides, one of the major causes of customer dissatisfaction with a warranty plan has been the length of time some services have been provided outside the US.

(17) *17-iOS:* Apple's operating system (iOS) has gained the most users' satisfaction. The operating system has played a key role in public satisfaction in Apple iPhones because its primary task is to communicate seamlessly and flawlessly between hardware and software. The operating system capabilities have also been gradually added from earlier versions. In addition to overall satisfaction and being user-friendly, some users have stated that a large number of revisions to Apple's operating systems have made them unhappy. For example, the time gap between versions 13 and 13.1 was less than 2 weeks and the same was true for versions 10, 11 and 12. Users of the iPhone 5 and iPhone 5*s* also tend to use the newer capabilities of the newer iPhones' iOS such as dark/light appearance.

(18) *Apple Trade-in:* Apple has described this feature: "It is our trade-in and recycling programme that is good for you and the planet. If your trade-in device is eligible for credit, you can offset the purchase price of a new one. If it is not eligible for credit, you can recycle it for free" (www.apple.com/shop/trade-in). According to Apple's official reports, the company's plans for accepting returned products and converting them into raw materials have improved day by day. For the iPhone 11 and later models, all parts are 100% recyclable to their raw materials (Apple, 2021) and Apple encourages customers to return these mobile phones for cash. Apple is among the first companies to pay for returned products. These products have been checked and users are paid in the form of an Apple gift card (Apple Website, 2020). Users are fully satisfied with the Apple trade-in programme and have suggested that Apple develop more trade-in plans for older iPhones. Currently, the test/review period for the trade-in plan is 2–3 weeks and this programme is applicable only in the US (Apple Website, 2020).

3.2 Social media data and cluster analysis

Twitter's social media data were used to capture real-time consumer responses, behaviours, emotions, views and feelings about purchasing iPhones. For this purpose, firstly, keywords of "smartphone", "cellphone" and "mobile phone", as well as "Apple", "Samsung" and "Huawei" (case insensitive and their words in other languages) were used. All the tweets related to cellphone products were extracted from August 1, 2019 to October 31, 2019 and were stored in the data warehouse. The API communication protocol sends data to us in JSON format and the transferred data have four sections for each tweet. The first main tweet, the second retweet of the main tweet, the third quotes the main tweet and the fourth quotes the second part. Each part is known as a tweet object and has common attributes. In this paper, each of the received tweets is divided into 4 tweets with the above sections and is stored in a specific data warehouse. The analysis showed that the number of original

Tweets received through the API was 36,394,927, out of which 8,210,429 were Retweets (22.6%), which normally reflect the widespread developments in the cellphone industry. The number of quoted tweets was 23,626,746 or 64.9% of the total number, which is usually the case when a customer faces a situation similar to another customer or a customer adds an item to a complaint or a comment. The results are illustrated in Table 2.

Tweets in English were not just analysed and geographical constraints for the research were not comprehensive. Figure 3 shows the 10 languages most used in extracted tweets. English, Japanese and Portuguese is the top three, with English being the most used language.

Then, they were further referenced so that those related to only our domain of study i.e. "Identify Features of Apple cellphones that affect the shopping behaviour of customers" are selected. In this study, Apple's cellphones since 2012 will be analysed. These cellphones include iPhone 5, iPhone 5 *s*, iPhone SE, iPhone 6, iPhone 6 Plus, iPhone 6 *s*, iPhone 6 *s* Plus, iPhone 7, iPhone 7 Plus, iPhone 8, iPhone 8 Plus, iPhone X, iPhone XR, iPhone XS, iPhone XS Max, iPhone 11, iPhone 11 Pro and iPhone 11 Pro Max. At the time of this study, Apple was only releasing iOS (iPhone operating system) for this model of its cellphones (Apple, 2021). Therefore, the first filter on all the tweets was collected through Apple's cell phone models since 2012.

Then, the words corresponding to the 18 features identified in Section 3.1 were extracted by using the content analysis of Apple's Web site and the results are presented in Table 3. By applying these identified words, the tweets related to the subject under study were filtered. Consequently, the number of tweets associated with

Type	Description	No. of tweets	Percentage of total	No. of tweets filtered whit "iPhone" keywords
TO	Original tweet	36,394,927	49.0	18,737,060
TO-RSO	retweet of original tweet	8,210,429	11.0	4,051,890
TO-QSO	quote of original tweet	23,626,746	31.8	12,062,310
TO-RSO-QSO	quote of retweet of original tweet	6,054,933	8.2	3,026,802
Total		74,287,035	100.0	37,878,062

Table 2.
Number of tweets and tweet objects

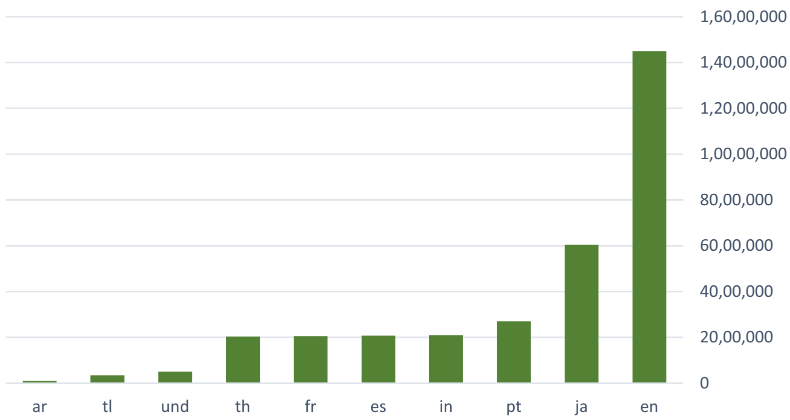


Figure 3.
Top 10 most used languages in tweets (und means unidentified text by Twitter)

each feature was obtained and the results are shown in Tables 4 and 5. After that, on the basis of these results, the tweets were grouped into 18 clusters as described above. The relationship between these clusters is studied by using the total linkage clustering method. Pearson correlation coefficient is used to determine the relationship between features and the distance between the clusters is determined in accordance with incidence frequency and similarity. The findings are illustrated in Table 6. The pairs of features that have a score of 0.9 or above are considered interrelated and the remaining pairs of features or clusters are not related to one another. The result of the cluster analysis is transferred to ISM to define the features and interrelationships between the dependent, independent and linkage features. The detailed description of the ISM is shown in the subsections.

Table 3. Features and their related keywords (extracted from apple's website and verified by IT experts)

No.	Feature	Minor Related Topics
1	Capacity	Memory
2	Screen	LCD, Display, Ultra Wide, Widescreen, Liquid Retina, Pixel Resolution, Multi-Touch, Contrast Ratio, TrueDepth and Brightness
3	Design	Size, Height, Width, Depth, Inch, Weight, Textured Matte Glass, Stainless Steel, Aluminum, Colour, Curved Design, Rounded Corners and Home Button
4	Resistance	Splash Resistance, Water Resistance, Dust Resistance and IP68
5	Chip	Bionic Chip, Neural Engine, Fusion Chip and Chipset
6	Camera	Telephoto, Dual Camera, Triple Camera, Aperture, Night Mode, Image Stabilization, Digital Zoom, Optical Zoom, Portrait Mode, Smart HDR, FPS, 4k Video Recording, HD video Recording, Time Lapse, Retina Flash, Animoji, Memoji, Face Time Video and Face Time Audio
7	Cellular	GSM, EDGE, UMTS, HSPA+, DC-HSDPA, CDMA, LTE, Wifi, Bluetooth, GPS, NFC, Carrier and Wireless
8	Battery	Power, Battery Life, Rechargeable, Lithium-Ion Battery, Wireless Charging, Adapter, Fast-Charge, Qi Wireless Chargers, USB-C Power Adapters, Lifespan, Battery Performance, Energy-Saving and Battery Health
9	Headphones	EarPods and Lightning Connector
10	sensors	Three-Axis Gyro, Accelerometer, Proximity Sensor, Ambient Light Sensor and Barometer
11	Connector	Lightning
12	Featured iPhone Accessories	AirPods, Wireless Chargers, Silicone Case, Leather Case and Featured Accessories
13	Price	Purchase
14	Security	Face ID, Facial Recognition, Secure Authentication and Privacy
15	Siri	Intelligent Suggestions and Voice
16	Waranty	Repair, AppleCare+plan, Apple Repair Centre and Genuine Parts
17	iOS	Update, Control Centre, Auto-Brightness, General, Accessibility, Low Power Mode, Animati, Background Activity, Location Services, Lock Screen, Home Screen, Airplane Mode, Find My iPhone, Dark Mode, Augmented Reality, Reminders and Settings
18	Apple Trade-in	Trade-In Recycling, Reused, Environment, Planet, Chemicals, Nickel, Humanly, Repair, Testing Lab, Daisy Robot, Cobalt, Carbon Emission, Landfill and Refurbished

Table 4. Number of tweets for iPhone models and their related direct feature

Year introduced	Type/direct features	Capacity	Screen	Design	Resistance	Chip	Camera	Cellular	Battery	Headphones	Sensors	Connector	Featured iPhone accessories	Total
2012	iPhone 5	19,240	15,248	26,568	2,474	2,088	30,310	7,812	18,955	41,856	5,736	20,890	4,840	196,017
2013	iPhone 5c	7,724	12,309	28,992	26,595	543	21,710	15,335	5,494	3,320	8,388	10,150	5,795	146,355
2013	iPhone 5 *s*	19,868	11,484	20,991	60,245	12,123	17,674	1,234	15,016	4,944	22,185	15,984	820	202,568
2016	iPhone SE	17,065	24,960	27,808	6,714	16,032	26,312	4,740	11,416	9,936	12,096	1,588	5,124	163,791
2014	iPhone 6	19,002	52,716	6,818	15,642	2,785	21,318	11,352	11,450	58,780	17,516	11,060	2,310	230,749
2014	iPhone 6 Plus	27,002	7,422	6,492	48,800	11,494	17,964	1,218	7,736	22,900	62,330	13,076	14,230	240,664
2015	iPhone 6 *s*	19,355	7,040	34,600	13,128	25,560	60,465	8,445	36,125	7,432	24,474	6,849	10,556	254,029
2015	iPhone 6 *s* Plus	16,896	42,945	9,560	59,484	4,124	12,072	6,038	21,015	52,632	10,860	7,518	2,956	246,100
2016	iPhone 7	6,456	4,635	7,682	11,565	5,838	16,546	13,590	32,316	8,198	8,350	27,085	5,622	147,883
2016	iPhone 7 Plus	15,696	22,770	17,872	51,390	5,196	35,868	5,661	8,436	6,447	1,305	20,180	6,423	197,244
2017	iPhone 8	7,116	5,463	46,835	18,950	3,555	46,350	11,560	44,370	13,866	16,865	26,485	10,560	251,975
2017	iPhone 8 Plus	45,545	17,718	22,308	17,016	5,244	38,988	7,764	26,709	22,334	8,800	20,308	5,062	237,796
2017	iPhone X	26,960	52,276	63,925	47,928	3,288	14,990	7,680	39,399	14,594	33,065	9,936	18,335	332,376
2018	iPhone XR	42,520	39,087	30,796	14,224	4,932	26,745	29,360	34,524	9,297	7,995	24,196	4,116	267,792
2018	iPhone XS	59,555	18,177	13,818	36,625	5,648	3,400	18,676	20,187	21,002	31,980	34,436	11,946	275,450
2018	iPhone XS Max	30,231	22,008	10,312	25,707	9,440	22,544	6,834	44,380	44,490	3,052	27,336	912	247,246
2019	iPhone 11	17,250	10,912	11,080	62,215	900	36,216	20,332	66,748	37,456	21,030	31,915	9,471	325,525
2019	iPhone 11 Pro	4,938	45,354	47,766	14,336	2,062	75,655	25,384	19,884	11,788	10,312	23,019	8,343	288,841
2019	iPhone 11 Pro Max	19,644	70,535	15,535	4,316	1,170	42,316	18,520	30,400	30,340	16,565	34,845	10,176	294,362
2012–2019	iPhone	422,063	483,059	449,758	537,354	122,022	567,443	221,535	494,560	421,612	322,904	366,856	137,597	4,546,763

Year introduced	Type/indirect features	Price	Security	Siri	Warranty	iOS	Apple trade-in	Total
2012	iPhone 5	10,850	5,472	14,844	17,784	7,389	130	56,469
2013	iPhone 5c	24,665	2,180	11,132	20,848	18,036	1,476	78,337
2013	iPhone 5 *s*	15,455	25,233	7,730	12,712	20,185	765	82,080
2016	iPhone SE	64,865	12,459	3,260	4,144	20,660	9,120	114,508
2014	iPhone 6	18,248	4,550	28,794	10,176	28,227	11,095	101,090
2014	iPhone 6 Plus	23,648	10,815	14,146	7,408	7,820	2,575	66,412
2015	iPhone 6 *s*	35,720	10,154	5,178	11,820	6,484	2,324	71,680
2015	iPhone 6 *s* Plus	27,122	4,785	11,710	6,462	4,440	20,472	74,991
2016	iPhone 7	33,120	8,664	15,710	6,321	23,244	8,640	95,699
2016	iPhone 7 Plus	23,832	58,085	15,027	13,328	30,680	855	141,807
2017	iPhone 8	41,740	20,598	14,256	18,495	10,527	2,488	108,104
2017	iPhone 8 Plus	45,870	5,500	7,732	30,198	37,175	2,152	128,627
2017	iPhone X	75,620	22,956	12,385	21,532	5,493	1,960	139,946
2018	iPhone XR	10,110	36,044	21,722	14,960	21,540	8,500	112,876
2018	iPhone XS	27,400	12,252	13,660	7,002	15,320	21,828	97,462
2018	iPhone XS Max	26,622	5,236	46,308	18,888	13,336	2,481	112,871
2019	iPhone 11	16,402	19,335	23,616	26,268	32,848	471	118,940
2019	iPhone 11 Pro	69,330	10,305	46,168	30,395	5,019	2,073	163,290
2019	iPhone 11 Pro Max	22,464	7,200	17,416	39,360	62,070	2,436	150,946
2012–2019	iPhone	613,083	281,823	330,794	318,101	370,493	101,841	2,016,135

Table 5.
Number of tweets for iPhone models and their related indirect feature

3.3 Application of interpretive structural modelling

ISM is a well-established methodology for identifying relationships among specific items, which define a problem or an issue (Mandal and Deshmukh, 1994). For any complex problem under consideration, a number of factors may be related to an issue or problem. However, the direct and indirect relationships between the factors describe the situation far more accurately than the individual factor taken into isolation. Therefore, ISM develops insights into collective understandings of these relationships (Attri *et al.*, 2013). In ISM methodology, various features directly or indirectly affecting the system under consideration are structured in a comprehensive fundamental model. Providing a clear understanding of the importance of the number of elements involved in the system is the specialty of this model. It provides the rank and order on the intricacy of the relationship among the features of a system (Agrawal *et al.*, 2019). The main features of this technique, with respect to the study of the subject literature, are as follows: The ISM uses expert opinion to establish relationships between the different features which make it interpretive. It is a modelling technique because the associated relationship, the overall structure and the analysis of direct and transitive linkages are represented by a digraph model. It helps in depicting a complex system in a simple form and it is developed to transform imprecise and weakly expressed models of different systems into clear and straightforward models and hence helps in providing answers to “what” and “how” in theory building. The structural model provides the interpretation of both the links and nodes (Agrawal *et al.*, 2019). Moreover, the advantages of using this technique can be mentioned below (Raj *et al.*, 2008):

- The revision and modification are quite easy.
- It requires fewer computational exercises when 10–15 features are involved in the system.
- The technique can be used for a number of real-life conditions.
- ISM also has several limitations like any other technique (Jena *et al.*, 2017):

S.No.	Variable I	Variable I I	P.C.C. Score
1	Capacity	Chip	0.93
2	Capacity	Camera	0.96
3	Capacity	Battery	0.94
4	Capacity	Featured iPhone accessories	0.91
5	Capacity	Price	0.98
6	Capacity	Warranty	0.94
7	Capacity	iOS	0.93
8	Capacity	Apple trade-in	0.95
9	Screen	Design	0.96
10	Screen	Resistance	0.94
11	Screen	Chip	0.96
12	Screen	Camera	0.97
13	Screen	Battery	0.92
14	Screen	Sensors	0.97
15	Screen	Price	0.93
16	Screen	Warranty	0.94
17	Screen	Apple trade-in	0.97
18	Design	Resistance	0.93
19	Design	Camera	0.94
20	Design	Battery	0.93
21	Design	Sensors	0.92
22	Design	Connector	0.91
23	Design	Featured iPhone accessories	0.96
24	Design	Price	0.95
25	Design	Apple trade-in	0.96
26	Resistance	Camera	0.97
27	Resistance	Price	0.96
28	Chip	Camera	0.94
29	Chip	Cellular	0.96
30	Chip	Battery	0.93
31	Chip	Sensors	0.92
32	Chip	Price	0.91
33	Chip	Security	0.94
34	Chip	Warranty	0.96
35	Chip	iOS	0.97
36	Camera	Battery	0.93
37	Camera	Sensors	0.94
38	Camera	Featured iPhone accessories	0.96
39	Camera	Price	0.95
40	Camera	Security	0.93
41	Camera	Warranty	0.94
42	Camera	iOS	0.95
43	Camera	Apple trade-in	0.97
44	Cellular	Battery	0.96
45	Cellular	Siri	0.98
46	Battery	Connector	0.95
47	Battery	Featured iPhone accessories	0.93
48	Battery	Price	0.97
49	Battery	iOS	0.93
50	Headphones	Price	0.92
51	Headphones	Warranty	0.91
52	Sensors	Price	0.96

(*continued*)

Table 6.
Pearson correlation test of the cluster analysis (partial results)

S.No.	Variable I	Variable I I	P.C.C. Score
53	Sensors	Security	0.94
54	Connector	Featured iPhone accessories	0.92
55	Connector	Warranty	0.97
56	Price	Security	0.91
57	Price	iOS	0.95
58	Security	iOS	0.93
59	Siri	iOS	0.94
60	iOS	Apple trade-in	0.92

Table 6.

Notes: P.C.C: Pearson correlation coefficient; s.no.: serial number

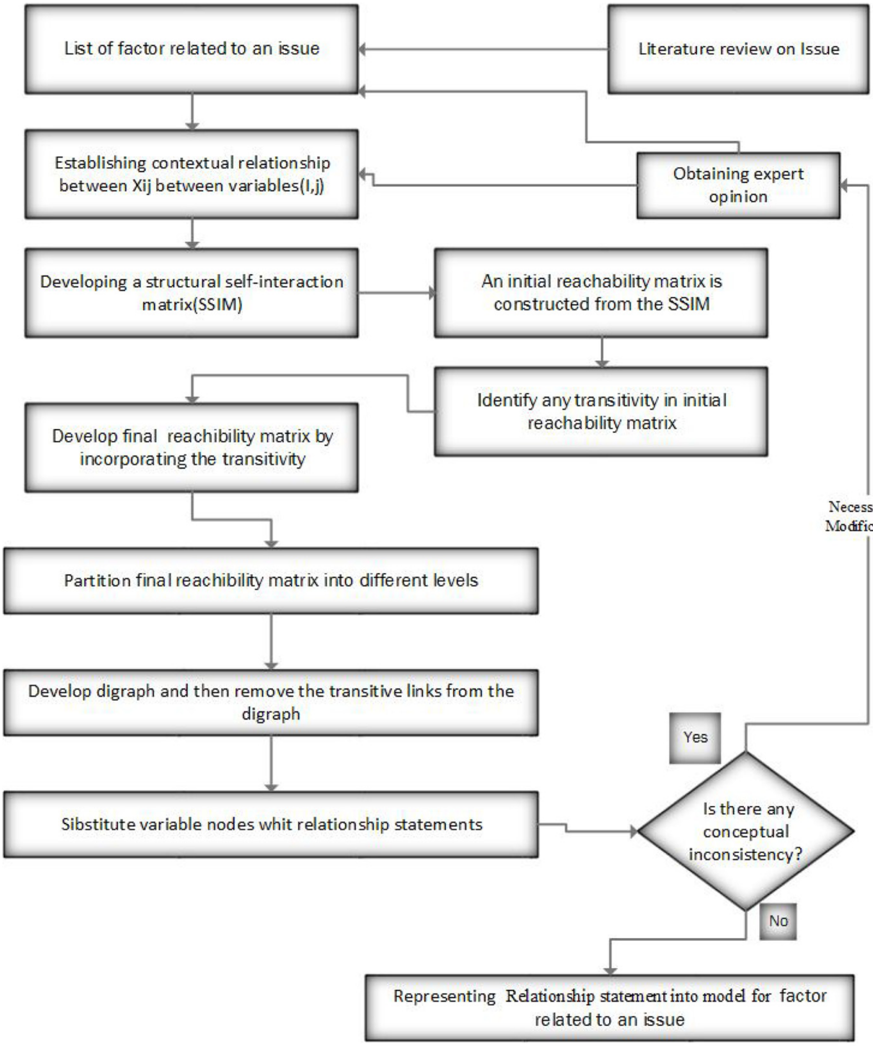
- The contextual relationship between the elements is highly dependent on the knowledge and experience of individuals.
- ISM provides a feeble interpretation of links; therefore, other individuals cannot get a similar interpretation of the model.

The ISM approach has been widely applied in various fields. For example, Tan *et al.* (2019) have used ISM to identify the Barriers to Building Information Modelling (BIM) implementation in China's prefabricated construction. Kaswan and Rathi (2019) have applied ISM techniques to analyse and model the enablers of Green Lean Six Sigma implementation. Agrawal *et al.* (2019) applied the ISM approach to analyse barriers in implementing the digital transformation of the supply chain. Avinash *et al.* (2018) have used ISM to understand the interaction among the barriers of biodiesel production from waste cooking oil in India. Ullah and Narain (2018) proposed a model showing the hierarchical relationship among various enablers of mass customization by using the ISM approach. Mishra *et al.* (2017) used ISM for a customer-centric beef supply chain. Maheshwari *et al.* (2018) have used ISM to advertise effectiveness in the Indian mobile phone industry. Gopal and Thakkar (2016) have used ISM and MICMAC analysis to investigate the critical success factors (and their contextual relationships) responsible for sustainable practices in the supply chains of the Indian automobile industry. Kumar *et al.* (2016) have used ISM to identify barriers for implementing the green lean six sigma product development process. Haleem *et al.* and Sindhu *et al.* (2016) have used ISM and fuzzy MICMAC to identify and analyse the barriers to solar power installation in the rural sector in India. Mani *et al.* (2016) have developed an ISM model to investigate the barriers (and their contextual relationships) to the adoption of social sustainability measures in Indian manufacturing industries and Mathiyazhagan *et al.* (2013) have used ISM to identify the barriers in implementing green supply chain management in Indian SMEs manufacturing auto components.

ISM starts with an identification of features relevant to the problem or issue and then extends with a group problem-solving technique. Then, a contextually relevant subordinate relation is chosen. Having decided on the element set and the contextual relation, a structural self-interaction matrix (SSIM) is developed based on a pair-wise comparison of features. In the next step, the SSIM is converted into a reachability matrix and its transitivity is checked. Once transitivity embedding is complete, a matrix model is obtained. Then, the partitioning of the elements and extraction of the structural model, called ISM, is derived (Agrawal *et al.*, 2019). Figure 4 demonstrates various steps involved in ISM methodology (Khaba and Bhar, 2017).

Different steps leading to the creation of an ISM model are explained below:

(1) STEP 1 – Identifying Mobile phone features influencing the consumer's decision for buying mobile phones
Identifying the elements relevant to the problem could be done by a survey or group problem-solving technique (Attri *et al.*, 2013). In Section 3.1, the characteristics of mobile features affecting customer shopping behaviour in the cellphone (Apple) industry were identified with a total of 18 features.



Source: Modified from Mandal and Deshmukh, 1994

Figure 4.
Flowchart for preparing ISM

(2) STEP 2 – Developing a structural self-interaction matrix (SSIM)
Although the Pearson correlation coefficient test has revealed the association between factors, it is not clear what kind of association or relationship they have among themselves. To identify the relationship, the opinions of 17 experts in the field of mobile phones have been collected. In this study, experts with more than 10 years of work experience were selected. The results obtained from Big Data analysis have been circulated to the experts and a session was organized to establish the relationships between each pair of features. The brainstorming session was conducted for several hours and then the final consensus was reached on the SSIM matrix as shown in Table 7. To express the relationships between different features (i.e. Capacity, Screen, design, Resistance, Chip, Camera, Cellular, Battery, Headphones, Sensors, Connector, Feature iPhone Accessories, Price, Security, Siri, Warranty, iOS, Apple Trade-in) that affect customer shopping behaviour in the mobile phone (Apple), four symbols were used to denote the direction of the relationship between parameters i and j (here $i < j$): V – Construct i helps achieve or influences j, A Construct j helps achieve or influences i, X – Constructs i and j help achieve or influence each other and O – Constructs i and j are unrelated.

For a better understanding of each symbol, an example is given here:

- Screen (feature2) helps achieve or influences Battery (feature 8) (V);
- Sensors (feature 10) helps achieve or influences camera (feature 6) (A); and
- Connector (feature 11) and Siri (feature 15) are unrelated (O).

(3) STEP 3 - Developing reachability matrix
The SSIM is transformed into an initial reachability matrix by replacing the symbols "V", "A", "X" and "O" by binary digits 1 and 0 as per the following principles (Barve *et al.*, 2008):

Features	18	17	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2
1. Capacity	V	A	V	O	O	V	V	O	O	O	V	O	A	A	O	O	O
2. Screen	V	O	V	O	O	V	O	O	A	O	V	O	V	A	V	V	
3. Design	V	O	O	O	O	V	V	V	V	O	V	O	V	O	V		
4. Resistance	O	O	O	O	O	V	O	O	O	O	O	O	A	O			
5. Chip	O	V	V	O	V	V	O	O	V	O	V	V	V				
6. Camera	V	A	V	O	V	V	V	O	A	O	V	O					
7. Cellular	O	O	O	V	O	O	O	O	O	O	V						
8. Battery	O	A	O	O	O	V	V	A	O	O							
9. Headphones	O	O	V	O	O	V	O	O	O								
10. Sensors	O	O	O	O	V	V	O	O									
11. Connector	O	O	V	O	O	O	V										
12. Featured iPhone accessories	O	O	O	O	O	O											
13. Price	O	A	O	O	A												
14. Security	O	A	O	O													
15. Siri	O	A	O														
16. Warranty	O	O															
17. ios	V																
18. Apple trade-in																	

Table 7.
Structural self-interactional matrix (SSIM)\

- For (i, j) entry, if it is V in SSIM, then corresponding (i, j) entry in reachability matrix becomes "1" and (j, i) becomes "0".
- For (i, j) entry, if it is A in SSIM, then corresponding (i, j) entry in reachability matrix becomes "0" and (j, i) becomes "1".
- For (i, j) entry, if it is X in SSIM, then corresponding (i, j) entry in reachability matrix becomes "1" and (j, i) becomes "1".
- For (i, j) entry, if it is O in SSIM, then corresponding (i, j) entry in reachability matrix becomes "0" and (j, i) becomes "0".

Hence, the initial reachability matrix for the 18 dimensions of Factors Influencing Customer Buying Behaviour in the mobile phone (Apple) industry is developed using the aforementioned rules, as illustrated in Table 8.

We used the "transitivity principle" to develop the final reachability matrix (Dubey and Ali, 2014; Dubey *et al.*, 2015). This principle can be clarified by using the following example: if "a" leads to "b" and "b" leads to "c", the transitivity property implies that "a" leads to "c". This property assists to eliminate the gaps among the features if any (Dubey *et al.*, 2015). By following the above criteria, the final reachability matrix is created and is shown in Table 9. Table 9 also shows the driving and dependence power of each variable. The driving power for each variable is the total number of features (including itself), which it may help to achieve. On the other hand, dependence power is the total number of features (including itself), which may help in achieving it. As per Dubey and Ali (2014), driving power is calculated by adding up the entries for the possibilities of interactions in the rows, whereas the dependence is determined by adding up such entries for the possibilities of interactions across the columns. The driving power and dependence power will be used later in the classification of features into four groups including autonomous, dependent, linkage and drivers (Agrawal *et al.*, 2019; Singh *et al.*, 2007).

Features	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. Capacity	1	0	0	0	0	0	0	1	0	0	0	1	1	0	0	1	0	1
2. Screen	0	1	1	1	0	1	0	1	0	0	0	0	1	0	0	1	0	1
3. Design	0	0	1	1	0	1	0	1	0	1	1	1	1	0	0	0	0	1
4. Resistance	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0
5. Chip	1	1	0	0	1	1	1	1	0	1	0	0	1	1	0	1	1	0
6. Camera	1	0	0	1	0	1	0	1	0	0	0	1	1	1	0	1	0	1
7. Cellular	0	0	0	0	0	0	1	1	0	0	0	0	0	0	1	0	0	0
8. Battery	0	0	0	0	0	0	0	1	0	0	0	1	1	0	0	0	0	0
9. Headphones	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	1	0	0
10. Sensors	0	1	0	0	0	1	0	0	0	1	0	0	1	1	0	0	0	0
11. Connector	0	0	0	0	0	0	0	1	0	0	1	1	0	0	0	1	0	0
12. Featured iphone accessories	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
13. Price	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
14. Security	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0
15. Siri	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
16. Warranty	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
17. ios	1	0	0	0	0	1	0	1	0	0	0	0	1	1	1	0	1	1
18. Apple trade-in	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

Table 8.
Initial reachability matrix

Table 9.
Final reachability matrix

Features	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	DRP
1. Capacity	1	0	0	0	0	0	0	1	0	0	0	1	1	0	0	1	0	1	6
2. Screen	1*	1*	1	1	0	1	0	1	0	1*	1*	1*	1	1*	0	1	0	1	13
3. Design	1*	1*	1	1	0	1	0	1	0	1	1	1	1	1*	0	1*	0	1	13
4. Resistance	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	2
5. Chip	1	1	1*	1*	1	1	1	1	0	1	1*	1*	1	1	1*	1	1	1*	17
6. Camera	1	0	0	1	0	1	0	1	0	0	0	1	1	1	0	1	0	1	9
7. Cellular	0	0	0	0	0	0	1	1	0	0	0	1*	1*	0	1	0	0	0	5
8. Battery	0	0	0	0	0	0	0	1	0	0	0	1	1	0	0	0	0	0	3
9. Headphones	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	1	0	0	3
10. Sensors	1*	1	1*	1*	0	1	0	1*	0	1	1*	1*	1	1	0	1*	0	1*	13
11. Connector	0	0	0	0	0	0	0	1	0	0	1	1	1*	0	0	1	0	0	5
12. Featured iphone accessories	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1
13. Price	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1
14. Security	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	2
15. Siri	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1
16. Warranty	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1
17. ios	1	0	0	1*	0	1	0	1	0	0	0	1*	1	1	1	1*	1	1	11
18. Apple trade-in	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
19. Capacity	7	4	4	7	1	6	2	10	1	4	5	11	14	7	4	10	2	8	

Notes: 1*: Shows transitivity, DNP: Dependence power, DRP: Driving power, F: Feature

(4) STEP 4 – Level partitions

The reachability matrix obtained in the previous step was partitioned into different levels. The reachability and antecedent set for each feature (Warfield, 1974) were found from the final reachability matrix (Table 9). The reachability set for a said feature consists of itself and the other features which it may help to achieve. The antecedent set consists of the features themselves and the other features that may help in achieving it. The intersections of both these sets were also derived for all features. If the reachability set and the intersection set for a given feature is the same, then that feature is considered to be in level I and is given the top position in the ISM hierarchy (Kannan and Haq, 2007). With this partition, iteration 1 is completed. After the first iteration, the features forming level I are discarded and with the remaining features, the above-stated procedure is continued in iteration 2. These iterations are continued until the level of each feature has been found. These identified levels help in constructing the digraph and the final model (Table 10). Table 11 depicts the level of each feature that affects the mobile phone purchasing behaviour.

(5) STEP 5 – Formation of the ISM model

Partitioning of the reachability matrix through a number of iterations resulted in the identification of the level of each factor influencing customer buying behaviour in the ISM hierarchy. The structural model is to be prepared using these level partitions while discarding the transitivities, as explained in the ISM methodology (Patil and Warkhedkar, 2016). Figure 5 represents an interpretive structural model for iPhone features, which define the inter-relationships among them through structured Delphi rounds.

Features	Reachability set	Antecedent set	Intersection set	Level
Iteration1				
F1	1,8,12,13,16,18	1,2,3,5,6,10,17	1	
F2	1,2,3,4,6,8,10,11,12,13,14,16,18	2,3,5,10	2,3,10	
F3	1,2,3,4,6,8,10,11,12,13,14,16,18	2,3,5,10	2,3,10	
F4	4,13	2,3,4,5,6,10,17	4	
F5	1,2,3,4,5,6,7,8,10,11,12,13,14,15,16,17,18	5	5	
F6	1,4,6,8,12,13,14,16,18	2,3,5,6,10,17	6	
F7	7,8,12,13,15	5,7	7	
F8	8,12,13	1,2,3,5,6,7,8,10,11,17	8	
F9	9,13,16	9	9	
F10	1,2,3,4,6,8,10,11,12,13,14,16,18	2,3,5,10	2,3,10	
F11	8,11,12,13,16	2,3,5,10,11	11	
F12	12	1,2,3,5,6,7,8,10,11,12,17	12	I
F13	13	1,2,3,4,5,6,7,8,9,10,11,13,14,17	13	I
F14	13,14	2,3,5,6,10,14,17	14	
F15	15	5,7,15,17	15	I
F16	16	1,2,3,5,6,9,10,11,16,17	16	I
F17	1,4,6,8,12,13,14,15,16,17,18	5,17	17	
F18	18	1,2,3,5,6,10,17,18	18	I
Iteration2				
F1	1,8	1,2,3,5,6,10,17	1	
F2	1,2,3,4,6,8,10,11, 14	2,3,5,10	2,3,10	
F3	1,2,3,4,6,8,10,11, 14	2,3,5,10	2,3,10	
F4	4	2,3,4,5,6,10,17	4	II
F5	1,2,3,4,5,6,7,8,10,11, 14, 17	5	5	
F6	1,4,6,8, 14	2,3,5,6,10,17	6	
F7	7,8	5,7	7	
F8	8	1,2,3,5,6,7,8,10,11,17	8	II
F9	9	9	9	II
F10	1,2,3,4,6,8,10,11, 14	2,3,5,10	2,3,10	
F11	8,11	2,3,5,10,11	11	
F14	14	2,3,5,6,10,14,17	14	II
F17	1,4,6,8, 14, 17	5,17	17	
Iteration 3				
F1	1	1,2,3,5,6,10,17	1	III
F2	1,2,3, 6, 10,11	2,3,5,10	2,3,10	
F3	1,2,3, 6, 10,11	2,3,5,10	2,3,10	
F5	1,2,3, 5,6,7, 10,11,17	5	5	
F6	1, 6	2,3,5,6,10,17	6	
F7	7	5,7	7	III
F10	1,2,3, 6, 10,11	2,3,5,10	2,3,10	
F11	11	2,3,5,10,11	11	III
F17	1, 6,17	5,17	17	
Iteration 4				
F2	2,3, 6, 10	2,3,5,10	2,3,10	
F3	2,3, 6, 10	2,3,5,10	2,3,10	
F5	2,3, 5,6, 10, 17	5	5	
F6	6	2,3,5,6,10,17	6	IV
F10	2,3, 6, 10	2,3,5,10	2,3,10	
F17	6,17	5,17	17	

(*continued*)

Table 10.
Level partitioning of reachability matrix

Features	Reachability set	Antecedent set	Intersection set	Level
Iteration 5				
F2	2,3, 10	2,3,5,10	2,3,10	V
F3	2,3, 10	2,3,5,10	2,3,10	V
F5	2,3, 5, 10, 17	5	5	
F10	2,3, 10	2,3,5,10	2,3,10	V
F17	17	5,17	17	V
Iteration6				
F5	5	5	5	VI

Table 10.

Features	Reachability set	Antecedent set	Intersection set	Level
12	12	1,2,3,5,6,7,8,10,11,12,17	12	I
13	13	1,2,3,4,5,6,7,8,9,10,11,13,14,17	13	I
15	15	5,7,15,17	15	I
16	16	1,2,3,5,6,9,10,11,16,17	16	I
18	18	1,2,3,5,6,10,17,18	18	I
4	4,13	2,3,4,5,6,10,17	4	II
8	8,12,13	1,2,3,5,6,7,8,10,11,17	8	II
9	9,13,16	9	9	II
14	13,14	2,3,5,6,10,14,17	14	II
1	1,8,12,13,16,18	1,2,3,5,6,10,17	1	III
7	7,8,12,13,15	5,7	7	III
11	8,11,12,13,16	2,3,5,10,11	11	III
6	1,4,6,8,12,13,14,16,18	2,3,5,6,10,17	6	IV
2	1,2,3,4,6,8,10,11,12,13,14,16,18	2,3,5,10	2,3,10	V
3	1,2,3,4,6,8,10,11,12,13,14,16,18	2,3,5,10	2,3,10	V
10	1,2,3,4,6,8,10,11,12,13,14,16,18	2,3,5,10	2,3,10	V
17	1,4,6,8,12,13,14,15,16,17,18	5,17	17	V
5	1,2,3,4,5,6,7,8,10,11,12,13,14,15,16,17,18	5	5	VI

Table 11.
Combined result of level partitions for features

3.4 Matrix of cross-impact multiplications applied to classifications analysis

The term MICMAC is the abbreviation of "Matrice Impacts croises-multiplication appliqué au classment" (matrix of cross-impact multiplications applied to classifications) (Hasan *et al.*, 2013). The multiplication properties of matrices serve as a basis for the MICMAC principle, which states that if variable i directly affects variable j and if variable j directly affects variable k, then any action on the variable i will have repercussions on variable k (Abbasi and Arya, 2000). The MICMAC analysis determines the dependence and driving powers of system elements and the analysis depends on the multiplication properties of matrices (Mandal and Deshmukh, 1994; Jothimani *et al.*, 2016). The driving power of an element is calculated from the reachability matrix by adding the number of "1's" in the rows and its dependence power is calculated by adding the number of "1's" in the columns. On the basis of their driving and dependence power, the features are classified into four categories (Figure 6). The first cluster describes a weak driving power and weak dependence of features. As these features are relatively disconnected from the system and have only a few

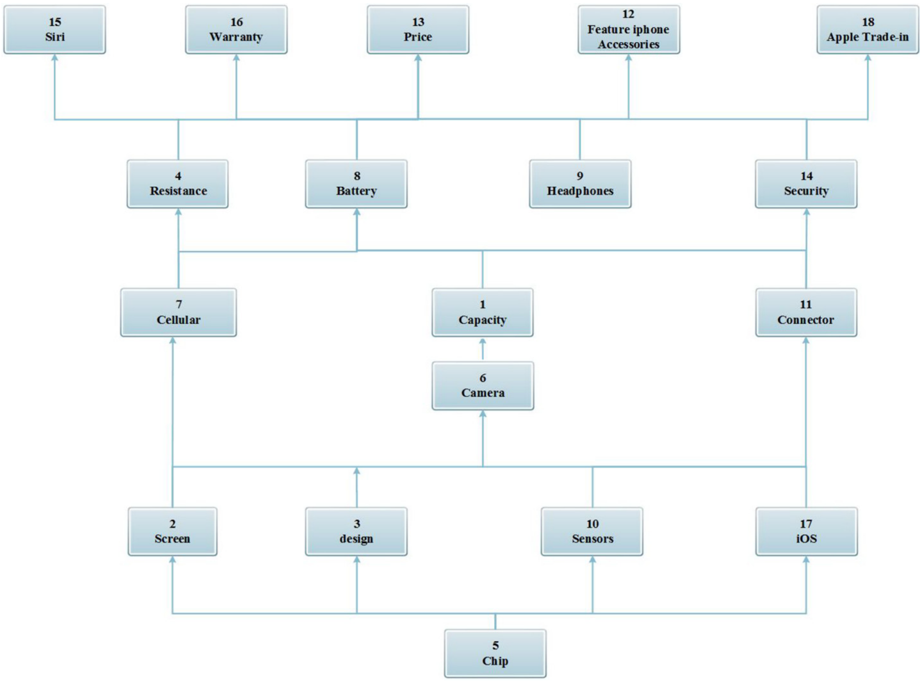


Figure 5. Interpretive structural model for features

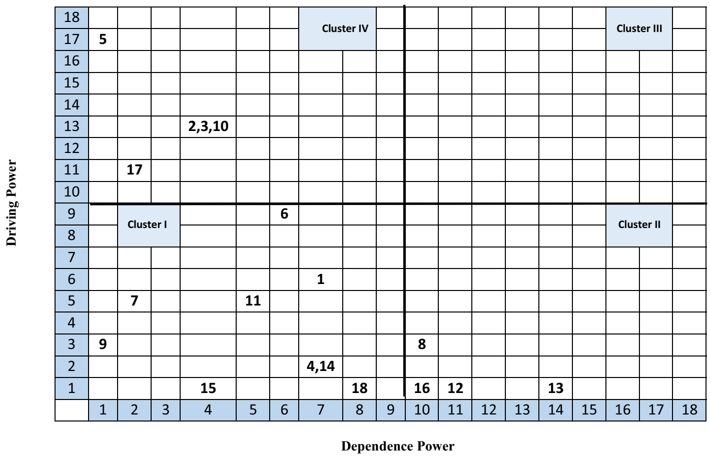


Figure 6. Driving power and dependence diagram

links that may or may not be strong, they are termed autonomous features. The second cluster focuses on the dependent features that have a weak driving power, but strong dependence. In the system hierarchy, they are considered the topmost features. Implementation of these enablers depends on the other variables of the system. The next cluster includes features with a strong driving power and strong dependence. Any action on these enablers will have an effect on others and will receive a feedback effect on them. The last cluster, i.e. four, comprises the features that have a strong driving power and weak dependence, rightly termed as driver features. These are called the key features of the system. It is observed that if the feature has a strong driving power, it will obviously fall into Cluster 3 or Cluster 4 (Grzybowska, 2012; Majumdar and Sinha, 2018).

4. Discussion and implication

In recent years, due to increasing environmental concerns, competitive advantage, promising financial potential, legislative reasons and social responsibility, attention to RL issues has grown among researchers and practitioners. According to Andel (1997), it is believed that the effective implementation of RL leads to several direct advantages, one of the most important of which is improving customer satisfaction. Satisfying customers is critical to a firm's success. Higher customer satisfaction leads to increased transactions (Bolton and Lemon, 1999), willingness to purchase additional services (Anderson and Bernth-Peterson, 1997), as well as reduced price elasticity (Anderson, 1996) and transaction costs (Anderson and Bernth-Peterson, 1997). For this reason, in recent years, attention to customer feedback in supply chain and logistics processes has increased and manufacturers intend to transform their supply chains (SCs) (forward and reverse) into consumer-centric SCs (Laari *et al.*, 2016; Taghikhah *et al.*, 2019). To move towards a customer-centric reverse supply chain, it is necessary to gather customer feedback. With the advent of online social media (SM), platforms such as Twitter, Facebook and Tumblr, a significant number of data have been generated that reflect the genuine opinions of customers (Wolny and Mueller, 2013). This paper highlights the features of mobile phones influencing consumer purchasing behaviour and presents their relationship with reverse logistics and then puts them into an ISM to develop a customer-centric RL model.

Examining the literature review, we found that previous studies in the field of RL have been conducted on several key topics; namely, RL network design (Yan and Yan (2019); Zarbakhshnia *et al.*, 2019; Liao, 2018; John *et al.*, 2018; Alshamsi and Diabat, 2017; Yu and Solvang, 2016; Kilic *et al.*, 2015); Model for the evaluation of RL performance (Hammes *et al.*, 2020; Kazancoglu *et al.*, 2020; Chaves *et al.*, 2020; Han and Trimi, 2018; Peña-Montoya *et al.*, 2020); Investigation of critical success factors in RL implementation (Chakraborty *et al.*, 2018; Adabavazaeh and Nikbakht, 2019; Mangla *et al.*, 2016); Identification of different options in RL and choosing the best option (Wang *et al.*, 2019; Agrawal *et al.*, 2016); RL for sustainability (Asees and Ali, 2019; Agrawal and Singh, 2019); Investigation of the barriers to RL implementation (Sirisawat and Kiatcharoenpol, 2018; Ali *et al.*, 2018; Bouzon *et al.*, 2018; Prakash and Barua, 2016; Bouzon *et al.*, 2016; Bouzon *et al.*, 2016a) and few studies in supply chain management and RL have been conducted using Twitter social media data (Schmidt *et al.*, 2020; Sharma *et al.*, 2020; Tseng *et al.*, 2019; Iftikhar and Khan, 2018; Singh *et al.*, 2018; Mishra *et al.*, 2017; Chan *et al.*, 2016; Chae, 2015; He *et al.*, 2013). We also found that research on the use of customer feedback in RL decisions is very limited (Mishra *et al.*, 2017). Therefore, in this research, by presenting a proposed framework in the methodology section, we try to improve the decision-making process in the field of RL by using the opinions of customers on Twitter social media. Due to its short life cycle and rapid advances in new technologies, it has placed mobile phones at the forefront of reverse supply chain implementations (Geyer and Blass, 2010), therefore, to implement the proposed framework, a case study has been conducted on the mobile phones of one of the largest mobile phone manufacturers; namely, Apple.

This study supports the findings of cellphone features affecting customer purchasing behaviour. Firstly, the websites of several cellphone manufacturers were examined and 26 features were extracted. Then, mobile experts were requested to classify and integrate the features on the basis of the iPhone's features and finally, 18 features were obtained. After that, social media data (Twitter) related to these 18 features about Apple phones were collected from 2012 to 2019 and were classified into 18 clusters. The relationship between these clusters was studied by using the total linkage clustering method. Pearson correlation was also used to determine the relationship between features. The results of cluster analysis were given to experts so that they can define the features and the interrelationships between them. Then, they developed a relational matrix as the first step in developing ISM. This method not only creates a link/interrelationship among the features but also addresses the most influential or as the major features to customer purchasing behaviour and then approaches the least important ones. The features have been accordingly linked and further classified as autonomous, independent and dependent features.

As illustrated in Figure 6, features capacity (F1), resistance (F4), camera (F6), cellular (F7), headphones (F9), connector (F11), security(F14), Siri (F15) and Apple Trade-in (F18) are in autonomous features in this study (cluster I). Autonomous variables generally appear as weak drivers, as well as weak dependent and are relatively disconnected from the system. These variables do not have much influence on other variables of the system. Features battery (F8), Featured iPhone Accessories (F12), price (F13) and warranty (F16) are weak drivers, but they strongly depend on other features (cluster II). They are seen at the top level of the hierarchical model (Figure 5) and are strongly dependent on other features. These features represent desired objectives for any organization and are classified as dependent features. There is no linkage feature, which has a strong driving power and strong dependence (cluster III). Thus, it can be inferred that among all the 18 features chosen in this study, no feature is unstable. These are of unstable nature as any changes occurring to them will have an effect on other measures and a boomerang effect on themselves as well (Barve *et al.*, 2008; Verma *et al.*, 2011). Features chip (F5), Screen (F2), design (F3), sensors (F10) and iOS (F17) are independent features having high driving power (cluster IV). These features will help organizations to achieve their desired objectives and are classified as independent features or drivers and need immediate action because they drive the other features.

This study has also tried to find levels for different features. From the model, it is observed that Features featured iPhone Accessories (F12), price (F13), Siri (F15), warranty (F16) and Apple Trade-in (F18) are at the top. Resistance (F4), battery (F8), headphones (F9) and security (F14) are at the second level; and Capacity (F1), cellular (F7) and connector (F11) are at the third level. The camera (F6) is at the fourth level. The remaining features are at the lower levels. In addition, it has been observed from the ISM that chip (F5) is at the bottom of the model, which indicates that it affects other features; therefore, it is the most significant feature that affects customer buying behaviour; hence, mobile phone manufacturers realize that this is to be addressed first. The paper, specifically by using social media data, develops a model to explore mobile phone features that affect customer buying behaviour and yet, it presents a generalized approach to be used in other manufacturing industries.

The results of this study are to guide the policymakers, managers and supply chain designers to review their strategies for the implementation of RL processes. The revealing of the interaction of various mandatory factors to achieve a consumer-centric supply chain would assist in improving vertical and horizontal collaboration within the supply chain. Consequently, an efficient strategy would be developed by taking the drivers into account for increasing the market share of a business firm, having an advantage over their rivals and developing a consumer-centric supply chain. This mechanism will assist in appropriate partner selection within the supply chain to improve sustainability. In addition, the results of the analysis of tweets about Apple mobile phones can be effective in increasing profitability and improving the decision-making process in Apple; or another example, an analysis of tweets about design features shows that all models of the iPhone 5 series, iPhone SE, iPhone 6 *s* and iPhone 6 have been criticized for their small screen sizes. Some users have also mentioned the heavyweight of iPhone 6 *s*. Meanwhile, the large screen of iPhone 6 Plus and iPhone 6 *s* Plus have satisfied users. Therefore, it is recommended that the factory adopt a reuse policy for these larger screens. In addition, the high weight along with the location of the cameras protruding out of the iPhone's back has led users to complain about the design of the iPhone 11 series. Thus, it is suggested that Apple take this into consideration in designing future products.

5. Conclusions and future research directions

In competitive markets, consumers are very selective. To be sustainable in this competitive scenario, manufacturers must examine customers' purchasing behaviour and the factors affecting its effectiveness. They need to see how these factors are related to each other and which factors belong to the category of driver, dependent, link and independence. This helps manufacturers minimize waste, simplify the supply chain, improve its efficiency and make it more consumer-oriented. One way to reach customer feedback is using social media operating systems. Manufacturers use social media to promote their services and to connect with their customers. This study tries to incorporate social media data by using ISM and MICMAC analysis in an attempt to establish a customer-centric RL. The involvement of information from social media data will give consumers a sense of empowerment (Mishra *et al.*, 2017). To achieve this goal, cell phone features influencing customers' purchasing behaviour is extracted. These features affect the RL and influence each other. Thus, it is necessary to study the mutual interaction among these features. A critical study of features of cellphone affecting consumer purchasing behaviour and their mutual relationship can give decision-makers crucial information.

In this study, firstly, the websites of several cellphone manufacturers were examined to identify the features that affect the consumers' decision for purchasing a cellphone. Then, cluster analysis on consumers' information from Twitter was conducted in the form of big data. It helps in finding how the features which determine the consumers' cellphone purchasing preferences are influenced. Then, experts' opinion, ISM and MICMAC analysis are used to classify18 features into linkage, dependent, driver and independent features and their interrelationships are explored. During the study, it was observed from the ISM that chip (F5) was the most significant feature that affects customer purchasing behaviour; therefore, cellphone manufacturers understand that this is to be addressed first. Furthermore, the results of the analysis of tweets about Apple mobile phones can be effective in increasing profitability and improving the decision-making process in Apple. Based on the findings, recommendations were given for making consumer-centric RL. Future investigations can be carried out to develop a theoretical mechanism for consumer-centric RL by assimilating some more aspects. In this regard, the methods illustrated in this research could provide a useful reference for other economies that aim to investigate the interrelationships between factors influencing consumer buying behaviour to form customer-oriented reverse logistics. Based on the findings, recommendations were given for making consumer-centric RL. Future investigations can be carried out to develop a theoretical mechanism for consumer-centric RL by assimilating some more aspects.

The developed theoretical model is limited to the identification of features of mobile phones influencing consumer purchasing behaviour. In the future, similar studies can be conducted in other areas or sectors as well. Furthermore, the developed model can be tested according to different research fields. The features considered here may be incomplete or their inter-relationship may be diverse according to the expert's opinion. The use of 18 features may be increased or reduced considering the need of the industry or sector. Moreover, apart from the ISM technique, other techniques may also be engaged with larger sample size. The model proposed in this paper can be further statistically validated by using SDM and SEM. Although the study involves ISM and MICMAC approaches, the results can also be compared with other approaches such as analytical network process (ANP) and analytical hierarchical process (AHP) or fuzzy analytic network process (FANP). Moreover, the identified features could be further ranked by using interpretive ranking process (IRP) to develop consumer-centric mobile phone reverse logistics. In the future, an improved list of keywords can be used to further analyse the topic. In addition, Twitter analytics can be used for data gathered over a longer period of time and can be applied to other industries. Analytics could also be performed by using search API instead of streaming API.

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