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Toward customer-centric mobile phone reverse logistics: using the DEMATEL approach and 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 advantages and high efficiency by customers because of 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 (SC) and logistics processes has recently increased, so 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 consumers' purchasing behavior and to analyze the causality and prominence relations among them that can help decision-makers, policy planners and managers of organizations to develop a framework for customer-centric RL. These features are studied based on analysis of product review sites. This paper's special focus is on social media (SM) data (Twitter) in an attempt to help the decision-making process in RL through a big data analysis approach.

Design/methodology/approach – This paper deals with identifying mobile phone features that affect consumer's mobile phone purchasing decisions. Using the DEMATEL approach and using experts' insights, a cause and effect relationship diagram was generated through which the effect of features was analyzed.

Findings – Eighteen features were categorized in terms of cause and effect, and the interrelationships of features were also analyzed. The threshold value is calculated as 0.023, and the values lower than that were eliminated to obtain the digraph. F6 (camera), F13 (price) and F5 (chip) are the most prominent features based on their prominent score. It was also found that the F5 (chip) has the highest driving power (1.228) and acts as a causal feature to influence other features.

Originality/value – The focus of this article is on SM data (Twitter), so that experts can understand the interaction between mobile phone features that affect consumer's decision on mobile phone purchasing by using the results. This study investigates the degree of influence of features on each other and categorizes the features into cause and effect groups. This study is also intended to help organizational decision-makers move toward a reverse customer SC.

Keywords DEMATEL, Twitter data, Reverse logistics, Mobile phone

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; Zink *et al.*, 2014). For instance, according to Statistic which is a German company specializing in market and consumer data, in the first quarter of 2021, around 1.53 billion smartphones were sold worldwide which shows a 12% increase compared to the total number of smartphones sold to consumers in 2020. Overall, mobile phones sales have risen from 296 million in 2010 to 1.37 billion in 2020, which indicating an increase of 360% (O'Dea, 2021). According to studies carried out recently, each year more than 145 thousand tons of natural resources – some of which are very rare – have been used to manufacture mobile phones (Christian *et al.*, 2014;

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Statista, 2020), and this amount is growing daily (Echegaray, 2016; Zhang and Xu, 2016). Tools related to information and communication technology (e.g. computers, mobile phones) were responsible for 7% of e-waste in 2014 (Baldé *et al.*, 2015; Guarnieri *et al.*, 2016); and each year, billions of dollars of natural resources are wasted in mobile phone industry (Geyer and Blass, 2010; Zink *et al.*, 2014). Undoubtedly, e-waste is a great challenge in modern communities (Long *et al.*, 2016). It includes some materials (e.g. Mercury, Lead, 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). Besides, 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) (El Baz *et al.*, 2018).

The mobile phone industry is probably the most innovative and rapidly changing in the technological world, both in market size and in models and suppliers (Zeng and Hou, 2019; O'Dea, 2020). Global smartphone shipments are projected to add up to around 1.48 billion units in 2023. By the end of 2020, 44.9% of the world's population is projected to own a smartphone (O'Dea, 2020). Short life cycles and rapid advances in new technologies are putting used mobile phones at the forefront of reverse supply chain (RSC) implementations (Geyer and Blass, 2010). There are almost 10–12 key physical parts in a standard mobile phones. Some parts, such as display, camera, battery and charger, can be easily disassembled and remanufactured for primary or secondary markets (Ellen Macarthur Foundation Report, 2012). The 500–1,000 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 the US Environmental Protection Agency (2016), from each 1 million recycled cellphones, 772 lb of silver, 35,274 lb of copper, 33 lb of palladium and 75 lb of gold are recyclable. Another fact about the cellphone is that the owners often do not throw them away. In addition, cellphones have better resell and recycling values than the other types of *e*-waste (Noman and Amin, 2017). Therefore, it is essential for cellphone manufacturers to pay special attention to RL.

RL is the process of transferring goods from their typical destination(s) through an RL system to capture value or proper disposal (Rogers and Tibben-Lembke, 1999). Therefore, an RL system involves the management of the flow of products or parts destined for remanufacturing, recycling or disposal by effective use of resources (Dowlatshahi, 2000). 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 (CS), which shows that decisions made in RL are directly related to CS to which producers need to pay attention.

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

Manufacturers use different methods like "market and competitor monitoring," "market research," "direct/indirect interviews," "consumer feedback in retail stores" and "CRM methods" in order to move toward 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 inconvenience, lack of time, distance to the retailer and brand disinterest (Ashley *et al.*, 2011). Therefore, data samples are small, and 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 customers' true opinions (Wolny and Mueller, 2013). According to statistics released in the first four months of 2019, 330 million Twitter users were on Twitter (Tankovska, 2021). SM data are qualitative, unstructured in nature and often large in volume, variety and velocity (He *et al.*, 2017). Also, SM data are 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 consumers' feelings and behaviors (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 the DEMATEL method in order to establish a customer-centric RL. The involvement of information from SM data will give consumers a sense of empowerment (Mishra *et al.*, 2017). In order to achieve this goal, cellphone features that influence customers' purchasing behavior are extracted. The features incorporated in a mobile handset are the most important factors considered by consumers while purchasing the mobile phone. However, all features of mobile phones are not equally important (Kim, 2018). 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 consumers' purchasing behavior and their mutual relationship can provide decision-makers with vital information. DEMATEL is most commonly accepted and refereed among academia to build a relationship among various criteria (Gardas *et al.*, 2018). This method is applied in this study to measure the mutual effects of the features. This study identifies the features of cellphones influencing consumers' purchasing behavior based on analyzing several cellphone manufacturers' websites and studies their relationship with RL by experts. After that, Twitter's SM data help experts in the DEMATEL method move toward a customer-centric RSC. Using SM information would give consumers a sense of empowerment and give insights to managers to prioritize their implementation efforts better. The main goals of this paper are as follows:

(1) To identify the features of cellphone that affect consumers' purchasing behavior and their relationship with RL.

(2) Integrate SM data with the DEMATEL method to help organizational decision-makers move toward a reverse customer SC.

The other sections of the paper are as follows. Section 2 highlights the review of literature related to RL and SM (Twitter), Section 3 describes the methodology adopted in this research, Section 4 presents the calculation and results, Section 5 presents the finding and discussion, Section 6 presents the practical implications and the conclusions and future research directions are to be dealt with in Section 7.

2. Literature review

In this section, we briefly investigate three significant literature elements: RSC and logistics, CS and SM. In RL, much attention is given to material and money streams and the associated increases in CS and profit, alongside decreases in returned products and waste (Kurilova-Palisaitiene *et al.*, 2018). To the best of our knowledge, the information stream rarely has been considered in RL decision-making processes. While consumers' opinions have been paid more attention recently in SC (Ren *et al.*, 2019), consumers are not very comfortable giving their opinions about retail stores. Therefore, most researchers use SM as an acceptable alternative (Kühl *et al.*, 2019). The focus of this review is extracting and analyzing the mobile phone features that affect consumer's mobile phone purchasing decisions through online reviews and then understanding the interaction between features by using SM data (Twitter) and the DEMATEL method.

2.1 Reverse logistics

Over the past few years, due to growing environmental concerns, competitive advantage, promises of financial potential, legal reasons, technological changes, innovation, globalization, social responsibility and high efficiency by customers resulting from the expansion of product selection and shorter product life cycle, RL has enticed the attention to industrial managers and researchers (Yadollahinia *et al.*, 2018; Ali *et al.*, 2018). As a result, the concept of RL has been accepted and widely practiced in manufacturing industries all over the world (Islam and Huda, 2018). 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 like "reverse distribution channel" for recycling has already existed in the literature since the 1970s (Guiltinan and Nwokoye, 1975; Ginter and Starling, 1978). The term "reverse logistics" was first introduced by Stock (1992). Rogers and Tibben-Lembke (1998) defined RL 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" (Ali *et al.*, 2018). Also, RL is defined as "all activities associated with a product/service after the point of sale, the ultimate goal to optimize or make more efficient aftermarket activity, thus saving money and environmental resources" (Mohamed *et al.*, 2015). Apparently, researchers consider the RL process as a conception that helps reduce manufacturing costs, generate additional profits and constrain environmental pressures which aims at remanufacturing, manufacturing reveres. It plays the big part in minimizing waste, stopping pollution and conserving energy, which achieves environmental, social and economic sustainability (Alnoor *et al.*, 2018; Lau and Wang, 2009). Furthermore, the RL process could provide a company with an appropriate competitive feature through obtaining market share in addition to the ability to meet customer demands and value.

The literature relevant to the concept of RL deals with a variety of issues which include barriers to RL implementation (Sirisawat and Kiatcharoenpol, 2018; Ali *et al.*, 2018; Bouzon *et al.*, 2016), critical success factors (Adabavazaeh and Nikbakht, 2019; Ravi and Shankar, 2017; Mangla *et al.*, 2016), outsourcing (Agrawal *et al.*, 2016; Tavana *et al.*, 2016; Li and Olorunniwo, 2008), performance evaluation (Hammes *et al.*, 2020; Chaves *et al.*, 2020; Han and Trimi, 2018), design of an RL network (Yan and Bo, 2019; John *et al.*, 2018; Yu and Solvang, 2016), return policies (Cortés and Alarcón, 2018; de Campos *et al.*, 2017; Agrawal *et al.*, 2016), sustainable practices (Asees Awan and Ali, 2019; Agrawal and Singh, 2019), selection of third-party partner (Chen *et al.*, 2021; Govindan *et al.*, 2019; Guarnieri *et al.*, 2015) and impact of factors on RL (Mahindroo *et al.*, 2018; Asees Awan and Ali, 2019). Furthermore, studies on RL have been done in many sectors such as the carpet industry (Biehl *et al.*, 2007), retail industry (Bernon *et al.*, 2011), bottling sector (González-Torre *et al.*, 2004), paper industry (Ravi and Shankar, 2006), glass sector (González-Torre and Adenso-Diaz, 2006), mobile phone industry (Ahmadi *et al.*, 2020; John *et al.*, 2018), pharmaceuticals industry (Narayana *et al.*, 2019; Ali *et al.*, 2018), construction sector (Hammes *et al.*, 2020), food industry (Kazancoglu *et al.*, 2020; Mishra *et al.*, 2017), semiconductor manufacturing industry (Chakraborty *et al.*, 2018), air industry (Adabavazaeh and Nikbakht, 2019), automobile industry (Ravi and Shankar, 2017) and electronics industry (Agrawal and Singh, 2019; Sirisawat and Kiatcharoenpol, 2018). To the best of our knowledge, studies in the field of RL that involve customer feedback in the decision-making process are relatively few. This has motivated the present research to address this gap.

2.2 Reverse logistics bridge for customer satisfaction

Customers express their views descriptively, which often indicates their level of satisfaction/dissatisfaction with their experiences. Firms that cannot satisfy their customers are likely to lose market share to rivals who offer better products and services at lower prices (Enaworu *et al.*, 2018). Conversely, successful firms are usually "rewarded with more business from customers and with more capital from investors" (Anderson *et al.*, 2004). CS is often considered the key to a company's success and long-term competitiveness (Hennig-Thurau and Klee, 1997). CS has been defined by Oliver (1997) as "a judgment that a product or service feature, or the product or service itself, provided a pleasurable level of consumption-related fulfillment, including levels of under- or over-fulfillment". Based on this definition, satisfaction can be thought of as an evaluation based on a comparison between performance and expectations. Azhar *et al.* (2019) stated that if the product/service performance is lower than the consumer's expectation, the consumer will be dissatisfied; if the performance is as expected, the consumer will be delighted. Satisfaction or delight creates an emotional bond between the consumer and the brand rather than a mere rational preference that can affect period of loyalty of a customer and decision to continue the relationship with the company (Ahmadi *et al.*, 2020; Enaworu *et al.*, 2018; Ndubisi and Wah, 2005). Therefore, due to reduced consumer acquisition, costs and price sensitivity affects organizational profitability and performance (Reichheld and Teal, 1996; Abdullateef and Salleh, 2013). This is why companies try to increase CS. RL is a way that can help companies increase CS and loyalty (Abbas and Farooquie, 2013). Therefore, attention to customer feedback in SC and logistics processes has recently increased, and manufacturers plan to transform their SCs (forward and reverse) into consumer-centric SCs (Taghikhah *et al.*, 2019; Laari *et al.*, 2016). Some research has investigated the role of CS in the RSC (Tomic and Brkic, 2019; Asian *et al.*, 2019; Jermsittiparsert *et al.*, 2019; Chavez *et al.*, 2016). Some authors have also tried to adjust customer-centric SC by considering CS (Anastasiadis *et al.*, 2021; Zondag and Ferrin, 2014). Other researchers have worked on improving CS to minimize inventory, waste, cost and pollution while maximizing profit and SC sustainability (Bautista-Lazo and Short, 2013; Garai and Roy, 2020). Most authors have used traditional approaches (e.g. distributing questionnaires, asking questions face to face) to gather the data needed to calculate CS. However, as SM usage, big data and data analysis techniques have grown, researchers' interest in using SM data has increased. For instance, Tseng *et al.* (2019) used SM and CS in a decision-making model to improve sustainable SC capabilities. Agrawal *et al.* (2016) worked on disposition decisions in RL through graph theory and a matrix approach in which a mobile manufacturing firm was discussed. In this research, customer-centric RL has been achieved mostly by considering CS for disposition decisions in RL.

2.2.1 The role of consumer satisfaction in the decision-making of reverse logistics. The ability to respond quickly and effectively and to satisfy customer needs has become a defining characteristic of competitiveness and of manufacturing success. Firms operating in an increasingly dynamic and competitive marketplace should place greater emphasis on the development and maintenance of CS in order to gain superior performance. Because CS fully mediates customer integration–performance connection and is considered one of the most important indicators of company performance, it is necessary for manufacturers to understand the important role of CS in manufacturing success (Sadikoglu and Zehir, 2010; Jamal and Naser, 2002; Fournier and Mick, 1999). By providing high value to their customers, firms can achieve high levels of CS (Stank *et al.*, 2003; Zhang *et al.*, 2003). According to Kim (2006), CS is a reflection of operational elements related to efficient cost structures, quality products, speed and responsiveness. It has been even indicated that it is now conventional wisdom in manufacturing strategy that competitive strategy enhances business performance (Rosenzweig *et al.*, 2003). Therefore, policymakers, managers and SC designers must pay close attention to this issue in their decisions and continuously capture the feedback of customers related to the product or service they have purchased and, if CS starts decreasing, take necessary corrective and preventive actions (Sharma *et al.*, 1999; Lee *et al.*, 1999). If corrective actions implemented effectively (Brandt and Reffett, 1989), are supposed to continuously improve the quality of products or services that will enhance CS (Tummala and Tang, 1996; Lee *et al.*, 1999). One way to increase the effectiveness of corrective actions is to use customer feedback throughout the SC. If companies can extract and analyze customers' opinions of the products or services offered, they can take corrective actions in the RL decision-making process tailored to the customer wants and needs, which in turn increases CS and loyalty and yields a steady stream of future cash flows (Reichheld and Sasser, 1990). These cash flows are more steady and certain, in part, because high levels of CS tend to reduce price inelasticity (Garvin, 1988). Furthermore, since there are a greater number of purchases from the same buyers attributable to increased loyalty, learning effects reduce transaction costs (Fornell, 1992) and the number of failures. Heikkila (2002) suggests that understanding the customer's situation and need together with the right product offering contributes to improving the demand chain, which further leads to superior SC efficiency and high CS. Therefore, in general, it is necessary for decision-makers and policymakers of companies to increase CS by implementing customer opinions during RL decisions and implement RL practices in accordance with customer demands and suggestions.

2.3 Social media

While consumers' opinions have been paid more attention recently in RL (Ren *et al.*, 2019), most customers prefer not to discuss their complaints/praise in stores for different reasons such as inconvenience, lack of time, distance to the retailer and brand disinterest (Ashley *et al.*, 2011; Reimers and Clulow, 2009). Therefore, manufacturers and retailers are incapable of attracting large audiences and receive feedback by using traditional methods like market and competitor monitoring, market research, direct/indirect interviews, CRM methods and consumer feedback in retail stores (Stefanou *et al.*, 2003). Due to the emergence of SM, platforms such as Twitter, Facebook and Tumblr, as an instant way to exchange ideas and a main source of information, 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 SM worldwide, which is a significant increase compared to 2017, which was about 2.86 billion people (Tankovska, 2021); therefore, remarkable data have generated, reflecting the true opinions of customers (Tseng *et al.*, 2019; Wolny and Mueller, 2013). Besides, SM bridge the gap between producers and consumers (Markova and Petkovska-Mirčevska, 2013). For instance, SM 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 of business, SM 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 SM among marketers worldwide (Statista Research Department, 2021).

Different SM platforms (e.g. blogs, Facebook, LinkedIn, Twitter and YouTube) have different functions. This paper focuses on one particular form of SM, Twitter, for the following reasons:

(1) One potential communication media for sharing knowledge and interactive communication process is SM and in particular, Twitter, one of the most widely used SM tools (Mills *et al.*, 2019), that compared with other SM platforms like

Facebook and TripAdvisor, Twitter data could be considered "open". Twitter provides application programming interface (API) that allows practical industrial applications and academic research to collect Twitter data using different types of queries, including keywords and user profiles in real time (Alotaibi *et al.*, 2020; Kühl *et al.*, 2019; Chae and Park, 2018), and to capture an approximately 1% random sample of all tweets and follow the tweets of up to 5,000 users (Mills *et al.*, 2019; Chae and Park, 2018). In this research, we used streaming API for a limited period.

(2) In recent years, Twitter data have become one of the most popular information sources for practical applications and academic research in many fields (Chae, 2015). There are numerous examples of practical applications of Twitter data, ranging from brand management (Malhotra *et al.*, 2012), explore consumers' opinions (Rathore and Ilavarasan, 2017; Martini *et al.*, 2013), stock forecasting (Arias *et al.*, 2014), improve marketing decisions (Garant, 2017), discovering similarities and differences between different industrials. (Tang *et al.*, 2020), health field (Zhang *et al.*, 2018), knowledge management (He *et al.*, 2017), identification of patterns (Bodaghi and Oliveira, 2020), to crisis management (Yang and Stewart, 2019). It is evident from prior research that Twitter is among the most preferred SM platforms in the SC and logistics context (Radi and Shokouhyar, 2021; Singh *et al.*, 2018; Chae, 2015).

(3) While Facebook is said to be the most widespread social networking platform, many professionals are opposed to using it for work-related practices; instead, various sources propose that Twitter is more appropriate (Antheunis *et al.*, 2013; Ellison *et al.*, 2007). Many large companies such as Walmart and Papa John's Pizza have used Twitter to assist customers, to share specials and to interact with customers (He *et al.*, 2017). Twitter is also dominant in attracting and retaining customers in business (Culnan *et al.*, 2010).

(4) Among the various web/application-based SM platforms and ever since its inception in 2006, it is a leader in terms of activity, especially regarding customer engagement and speed of development, ahead of Facebook and Google+ (Ahmadi *et al.*, 2020; De Filippo and Serrano-López, 2018). Over 75% of the Fortune Global 100 own one or more Twitter accounts at the corporate level and for their specific brands (Malhotra *et al.*, 2012). As of the first quarter of 2019, Twitter averaged 330 million monthly active users (Tankovska, 2021), which posted 500 million tweets each day, viewable by more than 300 million individuals (Mills *et al.*, 2019). This information is extremely valuable for marketing purposes (Mostafa, 2013).

(5) Twitter users are 38% more likely to post opinions about brands and products than other SM users (Salman, 2021).

(6) The unique "retweet" feature in Twitter allows the forwarding of a tweet by posting it again and again, thus facilitating rapid dissemination of information to a larger audience (Thelwall *et al.*, 2011). Additionally, using "reply" or the "@" symbol allows Twitter members to address a post to another Twitter user, thus facilitating effective discussions and targeted collaborations (Gupta *et al.*, 2012).

(7) Twitter can be a reliable source of information in analyzing consumers' attitudes and redesigning companies' marketing and advertising campaigns (Samoggia *et al.*, 2020; Simeone and Russo, 2017).

In the field of SC management and RL, few studies in SM and big data for research and practice have been conducted (Chae, 2015). Tan *et al.* (2015) have presented a big data analytic framework to improve the SC innovation capabilities; Chae (2015) developed a novel analytical framework for assimilating the potential role of Twitter for SC practice and research; Mishra and Singh (2018) have utilized Twitter data to develop waste minimization strategies by backtracking the SC; Chan *et al.* (2016) have developed a hierarchical model for new product development in which SM data are used. Singh *et al.* (2018) have used SM (Twitter) data for the identification of SC management issues in food industries; Iftikhar and Khan (2018) presented a framework for the improvement of demand forecasting in the SC industry using SM analytics; Tseng *et al.* (2019) improved sustainable SC capabilities using SM in a decision model; Schmidt *et al.* (2020) examined the relationship between SC glitches and stock market returns; Ahmadi *et al.* (2020) have proposed a framework that demonstrates how to analyze positive/negative feedback from consumers to form the most effective disposition decision strategies for managers in RL; Sharifi and Shokouhyar (2021) have presented a framework that focuses on data mining techniques to investigate consumer attitudes toward refurbished phones by one of the RSC practices: refurbishment. On the other hand, by examining the literature review, it becomes clear that the role of SM in research related to CS is a relatively new concept and has received more attention in recent years. For example, Gu and Ye (2014) have measured the impact of management responses on CS using data retrieved from a major online travel agency in China; Mishra *et al.* (2017) have identified factors influencing consumer's beef purchasing decisions with the help of literature and SM big data; Istanbulluoglu (2017), by using data collected from consumers who complained on Facebook or Twitter, has explored how the response times of multiple company responses on SM influence CS; Ramanathan *et al.* (2017) have investigated how retail network leverage the potential of SM reviews along with unique service operations to satisfy customers; Singhal and Khattri (2018) have explored and investigated how SM influence consumers behavior and their purchase decision in Indian travel and tourism industry; Al-Obeidat *et al.* (2019) developed a novel sentiment analysis framework with a sentiment scaling technique, making use of data mining strategies toward obtaining, identifying and analyzing fast fashion SM data, for the identification of consumer; Radi and Shokouhyar (2021) have utilized Social Media Analysis to understand the perception of consumers toward sustainability efforts of two major companies in the mobile phone industry; Tsai and Bui (2021) have examined the impact of travel information sourced from SM on consumers' purchase intentions with word of mouth (WOM praise and WOM activities) as a mediating factor.

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

(1) Relatively limited studies have been conducted in the field of SC management and RL about studying SM and big data for research and practice.

(2) The RL studies that relate end users' opinions from SM (Twitter) to RL decisions are relatively new concepts.

(3) Research on the application of SM data in RL, especially in the field of mobile phones, is in its preliminary stage.

(4) 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 to improve the RL decision-making process and move toward customer-centric RL.

3. Methodology

This research mainly aims to prioritize and then analyze interdependence between the cellphone features that affect consumers' purchasing decisions achieve a customer-centric

RSC based on customers' opinions extracted from SM (Twitter). DEMATEL method is applied to evaluate features that affect the consumer's decision to purchase a cellphone and explore the causal and effect relationship among features. This study aims to guide the policymakers, managers and SC designers to review their strategies to implement RL processes. Hence, in this section, initially, the features that affect the consumer's decision to purchase a cellphone and how it relates to RL are described. Then, consumers' opinions are extracted from SM (Twitter), which is rich in nature and provides unbiased opinions unlike consumer interviews, surveys, etc. Cluster analysis is carried out on the data collected from Twitter in order to find out the relation among identified features. Finally, the interrelationship among the features and the intensity of influencing each other is examined by the DEMATEL method. The proposed framework is presented in Figure 1.

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

Over the years, many researchers have focused on the questionnaire survey methods to get the factors influencing the purchase decision of mobile phone (Asif *et al.*, 2017; Sata, 2013; Dziwornu, 2013; Mokhlis and Yaakop, 2012; Yang *et al.*, 2007; Karjaluoto *et al.*, 2005). These studies focus more on family's recommendation, friend's recommendation, brand and TV advertising and are less focused on mobile phone features such as battery, capacity, design, etc. Furthermore, to the best of our knowledge, no research has been conducted to identify mobile phones' features that affect customers' buying behavior. Since the collection and analysis of questionnaire data are tedious, this work used the online review of mobile phone to address this challenge. Product review sites are a vast pool of public opinion messages that gather customer experience on mobile phone. Analyzing these reviews helps mobile phone manufacturers to develop better models that meet market requirements.

The steps of methodology for identifying the features of mobile phones that affect customers' buying behavior are mentioned as following:

(1) The user reviews of the mobile phone were extracted from websites like Amazon, gadgets, gsmarena, bgr, androidpit, Flipkart, Paytm and overdrive with the help of ParseHub software which is a scrapping tool designed to work on websites with JavaScript and Ajax.

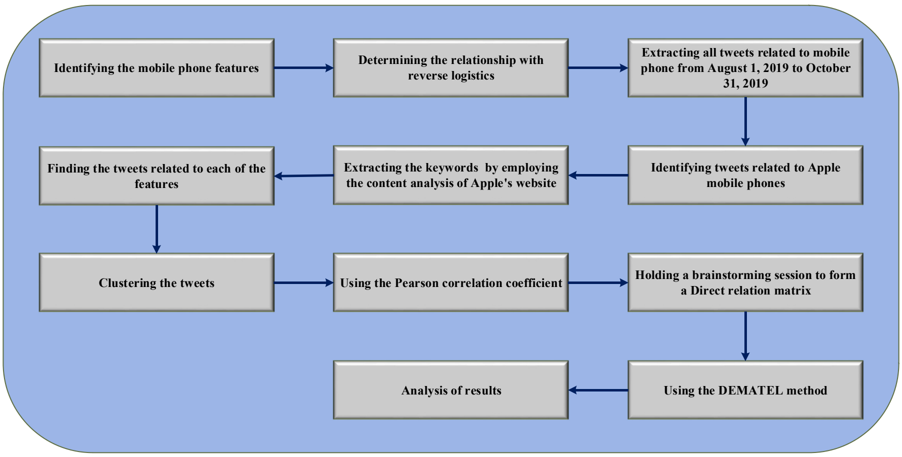

Figure 1.
Proposed framework

(2) Since text data are the most unstructured form of data, it requires lots of cleaning, which depends on the nature of the data. For this study, the user review may contain lots of hashtags, URLs that were removed in this step. Further normalization of the data was also done in this step.

(3) Finally, sentiment analysis was used to extract online customer reviews and generating a list of most frequently used words from online reviews from written text. For performing sentiment analysis, "RStudio" version 1.1.423 was used.

Many researchers have examined online customer reviews by using advanced machine learning and sentiment classification approaches for product attributes extraction (Jin *et al.*, 2019; Kumar, 2018; Wang *et al.*, 2018; Ghani *et al.*, 2006). In order to choose the correct mobile phone features in this list, we formed an eight-member expert group and details about the experts are as follows: two sales managers have experience over 12 years in sales and other strategic decision-making in the modular electronic productions; two product development engineers with an experience over 10 years in mobile phone product design; two researchers-cum-academicians have conducted various industrial case studies in the area of the electronics industry and two senior production managers in a leading mobile phone manufacturing company. A brainstorming session was organized among the expert group to identify the mobile phone features from the list of most frequently used words, and finally, 26 features were obtained. Then, a group of expert requested to classify and merge these features based on our case study, which is mobile phones that are manufactured in Apple company, and eventually 18 features were obtained (Table 1). 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-named features mean that they are directly associated with inverse logistics, meaning that feature directly affects RL decision-making. These features contain one or more 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, etc.) and the exterior (lens, optical zoom, etc.); In other words, direct-named features depend only on physical components. Another example is resistance. This feature is dependent only on physical components and belongs to this group. Other features that do not have physical components are indirect such as price, security, etc.

The following is a brief description of the identified features:

(1) *Capacity*: Due to the increased capabilities and quality of content such as high-resolution photos as well as 4K movies and over 30fpt videos stored on mobile phones, customers require more storage. The amount of storage capacity available is described as gigabytes (GB), and iPhone storage on current devices ranges from 32 GB to 512 GB.

(2) *Screen*: This feature consists of two parts, inner and outer. The outer part is often unique to each mobile phone model, and the inner part, called the driver, is responsible for generating the corresponding signals for display on the outer part. High-pixel resolution, image quality, energy consumption, weight and thickness, correct color display, screen size, the performance of the touch screen and high response speed are the main topics of interest to users in this feature.

(3) *Design*: Design is one of the important features that smartphone users consider when buying smartphones. User-friendly design makes the customer want to buy, and design that does not match the user's taste disappoints the customer from the brand. In designing, factors such as color, size, type of material used and the location of the phone's external components are considered by users.

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, 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, 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 program	Apple trade-in	Indirectly
26	Featured accessories	Featured accessories	Directly

Note(s): *Some items merged

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

(4) *Resistance*: Due to the daily use of mobile phones, this device is always exposed to shock, moisture, chemicals and heat. Therefore, it is necessary for mobile phone manufacturers to consider certain standards to increase mobile phones' resistance. Scratch resistance of various parts of the phone such as the body, camera lens glass, LCD and sometimes shiny or matte metal parts of the phone further satisfies the end consumer.

(5) *Chipset*: Smartphones are usually built on top of a silicon chipset (also known as system-on-chip or SOC) that serves as the foundation of the device hardware. A smartphone chipset provides a core set of functions ranging from cellular, Wi-Fi and Bluetooth communication to general computing, power management, memory, storage interface and peripheral interfaces.

(6) *Camera*: Camera quality when shooting is one of the factors affecting CS in purchasing (Uddin *et al.*, 2014). Today, customers consider the quality of

photography and video recording not only as one of the essential needs of a mobile phone but also as a competitive factor among mobile phone manufacturers.

(7) *Cellular*: Cellular data is a term that means connecting to the Internet using a cellular phone network. Internet connection problems, such as disconnection or disruption, can dissatisfy users because most mobile features and applications are dependent on the Internet connection (Ding *et al.*, 2013; Pathak *et al.*, 2012).

(8) *Battery*: Due to the increasing use of mobile phones in daily work, users expect mobile phones battery has a long life. In addition, the speed of recharging the battery is very important for users. Battery overheating while charging or long-term use of mobile phones is another issue with this feature (Eftekhari, 2017).

(9) *Headphones*: Proper design, good sound quality and extra noise reduction are important factors that customers pay attention to when buying. Apple's current product line consists of EarPods, wired earbuds available with a 3.5 mm headphone or Lightning connector, AirPods Pro, AirPods with Charging Case, AirPods with Wireless Charging Case, AirPods Max and, wireless Bluetooth earbuds and wireless Bluetooth over-ear headphones.

(10) *Sensor*: Sensor is a device, module, machine or subsystem device that responds to a physical stimulus (such as heat, light, sound, pressure, magnetism or a particular motion) and transmits a resulting impulse (as for measurement or operating a control). The main sensors that help inject intuitive and impressive interface technology in the iPhone include a proximity sensor, accelerometer, ambient light sensor, moisture sensor, three-axis gyroscope, location sensor (GPS), barometer sensor, fingerprint sensor and facial recognition sensor.

(11) *Connector*: Having a standard USB cable is very important for users, but Apple has tended to meet all its mobile phones' communication needs with its lightning cable. A lightning connector is an eight-pin connector developed by Apple Inc. in 2012 for its series of iOS devices. The lightning connector is used to provide communication with the computer and supply power to Apple handheld devices.

(12) *Featured iPhone accessories*: Mobile phone accessories are additional accessories that can be used in order to gain more functionality from a smartphone. These include cases, stands, Bluetooth accessories, etc.

(13) *Price*: Price plays a crucial role in assessing products by consumers (Marian *et al.*, 2014). Price 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).

(14) *Security*: Since mobile phones are becoming a computer in medium, security issues have arisen due to the many applications which run on mobile phones (Clarke and Furnel, 2007). The proliferation of application and data has increased the user needs to protect the data which exist in mobile devices (Kremić and Subaşi, 2011).

(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. Siri supports a wide range of user commands, including performing phone actions, checking basic information, scheduling events and reminders, handling device settings, searching the Internet, navigating areas,

finding information on entertainment and is able to engage with iOS-integrated apps.

(16) *Warranty*: The warranty is a contractual agreement between a manufacturer (seller) and a consumer (buyer), requiring the manufacturer to address any failures that occur during the warranty period (Oumlil, 2008). The warranty is an important part of the marketing mix for many consumer durables. It provides extra value to purchasers of durable products by insuring against product failure (Reisenwitz and Gupta, 2011).

(17) *iOS*: iOS is a mobile operating system developed by Apple. It was originally named the iPhone OS but was renamed to the iOS in June 2009. Originally developed for the iPhone, it has always extended to support other Apple, Inc. devices such as the iPod touch, iPad and Apple TV. Apple Inc. does not license iOS for installation on third-party hardware (Jain and Sharma, 2013).

(18) *Apple Trade-in*: By using this feature, customers can recycle any Apple device (including devices from Apple-owned brands) at any Apple Store and on apple.com for free. When the device is delivered to the company, it will be thoroughly inspected to determine whether components can be recycled or reused. Apple company 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 Inc, 2020).

3.2 Social media data and cluster analysis

3.2.1 Data collection. Twitter's SM data were employed to capture real-time consumer responses, behaviors, emotions, views and feelings about purchasing iPhones. For this purpose, first, cellphone-related hashtags, such as #smartphone, #cellphone, #mobile phone, #Apple, #Samsung, #Huawei, #Nokia and so on, were used as the keywords in Twitter Streaming API to collect cellphone products–related tweets between August 1, 2019, and October 31, 2019, with the support of NCapture 10. This API method allows acquiring 1% of publicly available Twitter data. Twitter data are also available through data providers (e.g. GNIP, DataSift), also known as Twitter Firehoses, which can deliver 100% of Twitter data based on criteria. This is an ideal, but very costly, option. The final data set includes 74,287,035 tweets. In data collection processing, hashtags were case-insensitive, and their translated words in other languages were included. Also to maximize accuracy, tweets in English were not just analyzed, and geographical constraints for the research were not comprehensive. 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 four tweets with the above sections and is stored in a specific data warehouse.

3.2.2 Descriptive analytics (DA). Twitter data contain a large amount of information, including tweets and metadata (e.g. user information). DA focuses on descriptive statistics, such as the number of tweets, distribution of different types of tweets and the number of hashtags. To perform DA, we used Python languages and multiple statistical and data mining techniques. The analysis showed that the total number of tweets received through the API was 74,287,035, of which 36,394,927 were original tweets (49%); The number of retweets was 8,210,429 (22.6%), which normally reflect the widespread developments in the cellphone industry. The number of quoted tweets was 23,626,746, or 31.8% of the total number, which is usually when a customer faces a situation similar to another customer, or a customer adds an item to a complaint or a comment. Also, the analysis showed English, Japanese and

Portuguese are the top three, with English being the most used language. Figure 2 shows the 10 languages most used in extracted tweets.

Afterward, we filtered out tweets with the word of desired brand through coding, which in our case study is "Apple," and 37,878,062 tweets were considered to be processed and analyzed in the proposed framework. The results are illustrated in Table 2.

3.2.3 Select keywords to identify topic-related tweets for final analysis. To reach the relevant tweets to only our domain of study, i.e. "identify features of Apple cellphones that affect customers' shopping behavior", we used two sets of keywords to filter tweets using Python languages. The initial filter was based on Apple mobile phone models produced from 2012 to 2019. These cellphones include iPhone 5, iPhone 5c, iPhone 5s, iPhone SE, iPhone 6, iPhone 6 Plus, iPhone 6s, iPhone 6s 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. In the next step, based on the content analysis of Apple's website and documents, the issues related to the 18 features identified in Section 3 were identified, the results of which are shown in Table 3. The second step was to filter the tweets using these identified topics. Table 3 was used to categorize tweets stored in our data warehouse appropriately. Each keyword was also used as a hashtag to filter tweets. For example, words/patterns/topics such as "LCD", "Display", "Ultra Wide," "Widescreen," "Liquid Retina," "Pixel Resolution," "Multi-Touch," "Contrast Ratio," "True Depth," "Brightness," etc. were often used on web pages and documents with the "Screen" feature. Finally, by applying these filters, 6,580,898 tweets were obtained for content analytics (CA).

3.2.4 Content analytics (CA). Section 3.2.3 described the process of filtering tweets in two steps based on two categories of keywords, which finally, 6,580,898 tweets were obtained. SM data are primarily texts and thus "unstructured" in nature and sophisticated for further

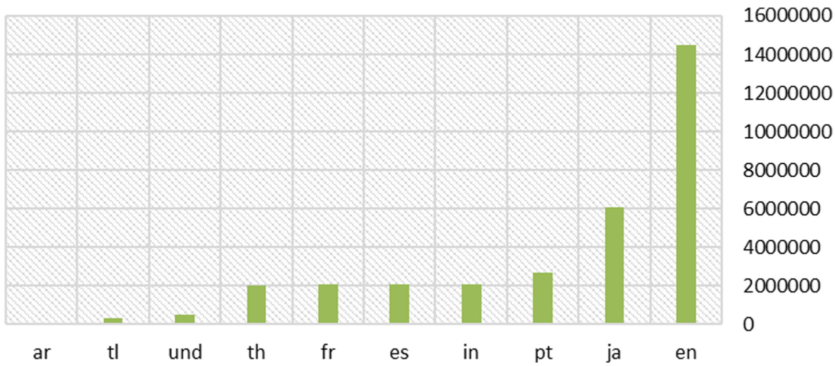

Figure 2.
Ten most used languages in tweets (und means unidentified text by twitter)

Table 2.
Number of tweets and tweet objects

Type	Description	Number of tweets	Percentage of total	Number 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

	Feature	Minor related topics
1	Capacity	Memory
2	Screen	LCD, display, ultra wide, widescreen, liquid retina, pixel resolution, multi-touch, contrast ratio, true depth, brightness
3	Design	Size, height, width, depth, inch, weight, textured matte glass, stainless steel, aluminum, color, curved design, rounded corners, home button
4	Resistance	Splash resistance, water resistance, dust resistance, IP68
5	Chip	Bionic chip, neural engine, fusion chip, 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, face time audio
7	Cellular	GSM, EDGE, UMTS, HSPA+, DC-HSDPA, CDMA, LTE, WiFi, bluetooth, GPS, NFC, carrier, 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, battery health
9	Headphones	EarPods, lightning connector
10	Sensors	Three-axis Gyro, accelerometer, proximity sensor, ambient light sensor, barometer
11	Connector	Lightning
12	Featured iPhone accessories	Air pods, wireless chargers, silicone case, leather case, featured accessories
13	Price	Purchase
14	Security	Face ID, facial recognition, secure authentication, privacy
15	Siri	Intelligent suggestions, voice
16	Warranty	Repair, AppleCare plan, apple repair center, Genuine parts
17	iOS	Update, control center, auto-brightness, general, accessibility, low power mode, animations, background activity, location services, lock screen, home screen, airplane mode, find my iPhone, dark mode, augmented reality, reminders, settings
18	Apple trade-in	Trade in, recycling, reused, environment, planet, chemicals, nickel, humanly, repair, testing lab, daisy robot, cobalt, carbon emission, landfill, refurbished

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

processing. Therefore, these unstructured data need to be analyzed first to extract useful information (Sharifi and Shokouhyar, 2021). Therefore, firstly by using text mining techniques such as tokenization, n-grams, stemming and removing stop words (unnecessary words) (Weiss *et al.*, 2005), cleaning and preprocessing text was performed. Those transformed texts can be used for text summarization, keyword analysis, word frequency analysis and text clustering, using machine learning algorithms such as clustering and association analysis. Detailed discussions of these topics can be found in the Natural language processing (NLP) and sentiment analysis literature (Feldman, 2013; Bird *et al.*, 2009; Pang and Lee, 2008). In this study, the term frequency analysis (TFA) adopting NVivo software (version 10) was used to do a content analysis of the tweets. NVivo is a software developed by QSR International for qualitative data analysis, such as content analysis and narrative analysis (Phillips and Lu, 2018). The software allows researchers to collect, organize and analyze these varied data types. Documents can be imported from Microsoft Word (.doc and .docx), portable document format (.pdf), rich text (.rtf) and plain text (.txt) formats. A cool new feature of version 10 supports the use of Web pages, SM (Facebook, LinkedIn, and Twitter), YouTube and Survey Monkey to directly import data. This wide range of data importation makes this software attractive to researchers using various methods of data collection (Castleberry, 2014). Because in this study, in the total linkage clustering (TLC) method, the distance between clusters is determined in accordance with incidence frequency and similarity of occurrence; therefore, the TFA was used to obtain the number of tweets associated with each feature. Also, the TFA was applied to guarantee a bottom-up approach to guarantee the maximum adherence to the analysis of WOM. The TFA included tweets, retweets and quotes. The TFA defined a preliminary dictionary. This was consolidated with keyword-in-context analysis (KWIC). KWIC allowed to fully understand the words used in TFA and possibly confirm or exclude the unclear or misused words.

The data coding process is a key feature of qualitative research. In NVivo software, the coding process is called "nodes." Nodes can represent anything that the researcher wants them to be and grant easy organization and reorganization of themes in the data. In this study, 19 nodes were defined initially based on the model of Apple mobile phones under review (from 2012 to 2019), and with the help of NVivo software, tweets were extracted and organized related to each model. After identifying and categorizing the tweets related to all Apple mobile phone models, we performed the second step of the coding process. In this step, based on the 18 features identified, we defined 18 nodes and extracted and categorized the tweets related to each feature in each Apple mobile phone model. Three researchers reviewed coded results. Coding reliability was checked by giving three trained researchers the results and asking them to confirm the categories' machine-coded allocations. A high level of reliability was reached (92%). Coding reliability is aimed at evaluating whether a coding exercise yields the same data within a tolerable margin of error. The higher the reliability is, the more trustworthy and reproducible is the data set (Hayes, 2020; Mikhaylov *et al.*, 2012). Any inconsistencies pointed out by any researcher were then reviewed until consensus was reached. The categories' creation followed to analyses tweets' contents according to the most common key topics included in the tweets.

The results of the concept analysis showed that the most direct feature tweets are related to the iPhone X (number of tweets 332,376), and the most indirect feature tweets are related to the iPhone 11 Pro (number of tweets 163,290). Among the direct features, the camera has the highest number of tweets (567,443), and for indirect, the price (613,083) has the highest number. 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 TLC method. TLC is one of several methods of agglomerative hierarchical clustering. At the beginning of the process, each element is in a cluster of its own. The clusters are then sequentially combined into larger clusters until all elements end up being in the same cluster. In this method, the link between two clusters contains all element pairs, and the distance between clusters equals the distance between those two elements (one in each cluster) that are farthest away from each other. In this study, the distance between the clusters is determined in accordance with incidence frequency and similarity of occurrence. Pearson correlation coefficient (PCC) is employed to determine the relationship between features. PCC measures the strength and direction (decreasing or increasing, depending on the sign) of a linear relationship between two variables (Ahlgren *et al.*, 2003). The closer the correlation coefficient is to +1, the stronger the positive correlation. The closer the correlation coefficient is to −1, the stronger the negative correlation. If the correlation coefficient is zero, the two variables are independent, i.e. they are uncorrelated (Bae and Lee, 2012). Table 6 shows PCCs between features. For example, we found a strong positive correlation between capacity (variable **I**) and iOS (variable **II**) with PCC of 0.93. Another example is a stronger correlation between iOS (variable **II**) and price (variable **I**) with PCC of 0.95, but iOS (variable **I**) and design (variable **II**) have a PCC of 0.18 that is a weak positive correlation. Also iOS (variable **I**) and sensors (variable **II**) have a PCC equal to zero that shows the two features are independent. In this study, the pairs of features having PCC 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

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 5s	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 6s	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 6s 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

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

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 5s	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 6s	35,720	10,154	5,178	11,820	6,484	2,324	71,680
2015	iPhone 6s 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

analysis is transferred to the DEMATEL method. The detailed description of the DEMATEL method is shown in the subsections.

3.3 Application of DEMATEL method

DEMATEL is a common method for modeling relationships between variables (Gandhi *et al.*, 2016). In this method, the cause–effect relationships between variables are determined by using the knowledge of experts, and then directional relationships are drawn between them, which is helpful to determine the direction of actions for addressing the problem in real-world situations (Kaur *et al.*, 2018; Awasthi and Grzybowska, 2014). One of the key advantages of DEMATEL over other models is the ability to generate possible findings with minimum information (Sivakumar *et al.*, 2018; Wu and Lee, 2007). Compared with other modeling methods, the DEMATEL model enables researchers to understand the conceptual correlations between the variables used within the problem structure and helps determine the effects of their interrelationships (Yadav *et al.*, 2020). This method not only converts the interdependency relationships into a cause and effect cluster via matrixes but also discovers the critical factors of an intricate system of factors with the aid of an impact relation diagram (Si *et al.*, 2018).

All stages for developing a DEMATEL-based model have been discussed as follows (Kaur *et al.*, 2018; Sivakumar *et al.*, 2018; Shieh *et al.*, 2010):

Step 1: Compute the average matrix – Each respondent was asked to evaluate the direct influence between any two features by a scale ranged from 0 (no influence) to 5

S. No.	Variable I	Variable II	PCC score	S. No.	Variable I	Variable II	PCC score
1	Capacity	Chip	0.93	31	Chip	Sensors	0.92
2	Design	Camera	0.94	32	Battery	iOS	0.93
3	Capacity	Battery	0.94	33	Chip	Security	0.94
4	Capacity	Featured iPhone accessories	0.91	34	Screen	Sensors	0.97
5	Camera	Battery	0.93	35	Chip	iOS	0.97
6	Camera	Price	0.95	36	Camera	Sensors	0.94
7	Capacity	Apple trade-in	0.95	37	Camera	Featured iPhone accessories	0.96
8	Screen	Design	0.96	38	Capacity	iOS	0.93
9	Design	Featured iPhone accessories	0.96	39	Sensors	Security	0.94
10	Screen	Chip	0.96	40	Camera	Warranty	0.94
11	Capacity	Camera	0.96	41	Chip	Price	0.91
12	Design	Connector	0.91	42	Sensors	Price	0.96
13	Screen	Camera	0.97	43	Screen	Battery	0.92
14	Camera	iOS	0.95	44	Camera	Apple trade-in	0.97
15	Capacity	Warranty	0.94	45	Capacity	Price	0.98
16	Chip	Warranty	0.96	46	Cellular	Battery	0.96
17	Screen	Price	0.93	47	Cellular	Siri	0.98
18	Design	Battery	0.93	48	Headphones	Price	0.92
19	Screen	Apple trade-in	0.97	49	Battery	Featured iPhone accessories	0.93
20	Design	Resistance	0.93	50	Design	Sensors	0.92
21	Chip	Cellular	0.96	51	Siri	iOS	0.94
22	Screen	Warranty	0.94	52	Battery	Connector	0.95
23	Battery	Price	0.97	53	Headphones	Warranty	0.91
24	Design	Price	0.95	54	Connector	Featured iPhone accessories	0.92
25	Chip	Camera	0.94	55	Security	iOS	0.93
26	Design	Apple trade-in	0.96	56	Connector	Warranty	0.97
27	Resistance	Camera	0.97	57	Price	Security	0.91
28	Screen	Resistance	0.94	58	Camera	Security	0.93
29	Resistance	Price	0.96	59	Price	iOS	0.95
30	Chip	Battery	0.93	60	iOS	Apple trade-in	0.92

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

(very high influence). The entry "a_{ijk}" signifies the degree to which the expert conceives that feature i affects feature j. If "k" is the number of respondents and "n" is the number of features, then for each respondent, an $n \times n$ nonnegative matrices are established as $A_k = [a_{ijk}]$. To incorporate all opinions from H respondents, the average matrix average matrix $A = [a_{ij}]$ can be constructed as follows (Gandhi *et al.*, 2016):

$$a_{ij} = \frac{1}{H}\sum_{k=1}^{H} a_{ijk} \quad 1 \le k \le H \tag{1}$$

Step 2: Calculate the normalized overall direct-relation matrix – Normalize overall direct-relation matrix can be accomplished by equation (2). This must be noted that the sum of each column in the normalized relation matrix must be less than one for the feasibility of the DEMATEL method (Singh and Sarkar, 2020).

$$X = [x_{ij}]_{n\times n} = \frac{A}{\max\sum_{j=1}^{i} a_{ij}}.\text{where } 0 \le x_{ij} \le 1 \quad \text{and } 1 \le i \le n \tag{2}$$

Step 3: Calculation of the total relation matrix – The total relation matrix T is found using Equation 3, where I is denoted as an identity matrix.

$$T = [t_{ij}]_{n\times n} = X[I - X]^{-1} \tag{3}$$

Step 4: Calculation of sum of rows and columns based on total relation matrix T – The sum of rows (R) and columns (D) of total relation matrix are computed by Equations (4) and (5), respectively. "D" indicates the degree of influence exerted on other factors, and "R" represents the degree of influence received from other factors. (D + R) expresses the degree of the central role that factor "i" plays in the numerical (Tzeng *et al.*, 2007). (D–R) means the influence strength, which can be divided into dispatchers or receivers (Zhang *et al.*, 2019).

$$R = [r_{ij}]_{n\times 1} = \left[\sum_{j=1}^{n} t_{ij}\right]_{n\times 1} \tag{4}$$

$$D = [d_{ij}]_{1\times n} = \left[\sum_{i=1}^{n} t_{ij}\right]_{1\times n} \tag{5}$$

Step 5: Set up a threshold value – Matrix T provides information on how one factor affects another, it is necessary for a decision-maker to set up a threshold value to filter out some negligible effects. Researchers have proposed different methods for setting the threshold value. The most common ones being discussion with experts, averaging the values of the T matrix, adding two standard deviations to the mean and maximum mean de-entropy algorithm (Kaur *et al.*, 2018). In this paper, average of the values of the T matrix is chosen as threshold value by the decision-maker that is obtained from the following equation (Singh *et al.*, 2020; Sivakumar *et al.*, 2018; Kaur *et al.*, 2018):

$$\alpha = \frac{\sum_{j=1}^{n}\sum_{i=1}^{n} t_{ij}}{n^2} \tag{6}$$

where, n represents the total number of elements in the matrix T.

Step 6: Preparation of a causal diagram – ($R + D$) is projected on the horizontal axis for the causal and effect graph while the vertical axis is depicted by (R – D). Positive (R – C) indicates that the feature will be a dispatcher, a negative (R – C) shows that the feature will be a receiver (Singh and Bhanot, 2020; Zhang *et al.*, 2019).

4. Calculation and results

The interrelationship of identified features is established with the application of the proposed framework. Although the PCC test has revealed the association between features, it is not clear what kind of association or relationship they have among themselves. In order to identify the relationship, the opinions of eight experts in the field of mobile phone 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. It had been discussed with experts to use a scale from 0 to 5 to demonstrate a pairwise relationship between features. The scale value was described in Section 3.3. The experts have been asked to provide a response by pairwise correlation in the matrix. In Table 7, the overall direct relationship matrix is computed using Equation (1) as mentioned above in Section 3.3. Table 7 has been developed by entering the average value of all a_{ijz} entries collected from all the experts (Gandhi *et al.*, 2016; Sivakumar *et al.*, 2018).

Further, as shown in Table 8, the initial normalized matrix is calculated using Equation (2). By using Equation (3), total relationship matrix is calculated and represented in Table 9.

For attaining a reflection of the noteworthy connection, the inner dependence matrix is established by rejecting the least significant relationship. So, to construct the causal digraph, the threshold value (α) is calculated. For this purpose, Equation (7) is used. The threshold value in the total relation matrix represents how one feature affects other feature; thus the threshold value allows to differentiate between the significant and insignificant results (Gandhi *et al.*, 2016) (see Table 10).

The α value is computed as 0.023, and the values lower than α were eliminated for obtaining the interrelationships of features. The inner dependency matrix was derived by excluding items lower than the threshold value in the total relation matrix (Table 11). This indicates that only the significant relationships were retained. Also, in order to increase the reliability of the calculated threshold value, sensitivity analysis was performed by $\pm 10\%$ threshold value (0.0207 – 0.0253). Therefore, the inner dependence matrix was reconstituted, and it was observed that there is no significant change in the results.

5. Finding and discussion

This paper highlights the features of mobile phones influencing consumers' purchasing behavior. It presents their relationship with RL and then used them in the DEMATEL method to move toward a customer-centric RSC. Examining the literature review, we found that previous studies in the field of RL have been conducted on several key topics, and few studies in SC management and RL have been conducted using Twitter SM data. 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 customers' opinions on Twitter SM. Due to its short life cycle and rapid advances in new technologies, it has placed mobile phones at the forefront of RSC implementations (Geyer and Blass, 2010); therefore, in order 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 customers' purchasing behavior. First, the product review sites were examined, and 26 features were extracted. Then, mobile experts were requested to classify and integrate the features based on the iPhone's features, and finally 18 features were obtained. After that, SM 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 TLC method. Pearson correlation was also employed 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 direct relation matrix as the first step in developing the DEMATEL method.

The results are presented in Table 10. Based on (D-R) values, features were divided into two groups: (1) cause group and (2) effect group. All those features having (D-R) > 0 were classified as a cause feature and have influenced the others directly. In other words, it can be implied that these causal group features are autonomous and will drive the other features. While, the features with (D-R) < 0 were categorized in the effect category and influenced

Table 7.
Overall direct relationship matrix

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18
F1	0	0	0.5	0	0.5	0.5	0	4	0	0	0	3	4.5	0	0	3.5	0	4
F2	0	0	4.5	4	0	4.5	0	3.5	0	0	0	0	4	0	0	4	0	4.5
F3	0	2	0	4	0	4	0.5	3.5	0	1.5	2.5	4	4.5	0	0	0	0	4
F4	0	0	1	0	0	0	0	0	0	1	0	0	4	0	0	1.5	0	0
F5	3.5	4.5	0	0	1	3.5	4	3.5	0	3	0	0	4	3.5	0	4	3.5	0
F6	3	0	1.5	4	0	0	0	4	0	0	0	6	4.5	2	0	4	0	3.5
F7	0	0	0	0	0	0	0	3.5	0	0	0	0	0	0	4	0	0	0
F8	0	0	1	0	0	0	0	0	0	0	0	3.5	4	0	0	1.5	0	0
F9	0	0	0.5	0	0	0	0	0	0	0	0	0	4.5	0	0	3.5	0	0
F10	0	4.5	3	0	0.5	2.5	0	0	0	0	0	0	4	4.5	0	1	0	0
F11	0	0	0	0	0	0	0	2	0	0	0	3.5	0	0	0	3	0	0
F12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F13	1	0	0	0	0.5	2	0	0	0	0	0	0	0	0	0	0	0	0
F14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F15	0	0	0	0	0	0	0	0.5	0	0	0	0	0	0	0	0	0	0
F16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F17	4	0	0	0	0	2.5	0	3.5	0	0	0	0	4.5	4	3.5	0	0	2.5
F18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 8. Initial normalized matrix

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18
F1	0.000	0.000	0.012	0.000	0.012	0.012	0.000	0.094	0.000	0.000	0.000	0.071	0.106	0.000	0.000	0.082	0.000	0.094
F2	0.000	0.000	0.106	0.094	0.000	0.106	0.000	0.082	0.000	0.000	0.000	0.000	0.094	0.000	0.000	0.094	0.000	0.106
F3	0.000	0.047	0.000	0.094	0.000	0.094	0.012	0.082	0.000	0.035	0.059	0.094	0.106	0.000	0.000	0.000	0.000	0.094
F4	0.000	0.000	0.024	0.000	0.000	0.000	0.000	0.000	0.000	0.024	0.000	0.000	0.094	0.000	0.000	0.035	0.000	0.000
F5	0.082	0.106	0.000	0.000	0.024	0.082	0.094	0.082	0.000	0.071	0.000	0.000	0.094	0.082	0.000	0.094	0.082	0.000
F6	0.071	0.000	0.035	0.094	0.000	0.000	0.000	0.094	0.000	0.000	0.000	0.141	0.106	0.047	0.000	0.094	0.000	0.082
F7	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.082	0.000	0.000	0.000	0.000	0.000	0.000	0.094	0.000	0.000	0.000
F8	0.000	0.000	0.024	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.082	0.094	0.000	0.000	0.035	0.000	0.000
F9	0.000	0.000	0.012	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.106	0.000	0.000	0.082	0.000	0.000
F10	0.000	0.106	0.071	0.000	0.012	0.059	0.000	0.000	0.000	0.000	0.000	0.000	0.094	0.106	0.000	0.024	0.000	0.000
F11	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.047	0.000	0.000	0.000	0.082	0.000	0.000	0.000	0.071	0.000	0.000
F12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F13	0.024	0.000	0.000	0.000	0.012	0.047	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F15	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.012	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F16	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F17	0.094	0.000	0.000	0.000	0.000	0.059	0.000	0.082	0.000	0.000	0.000	0.000	0.106	0.094	0.082	0.000	0.000	0.059
F18	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 9.
Total relation matrix

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18
F1	0.006	0.002	0.015	0.004	0.014	0.021	0.001	0.099	0.000	0.002	0.001	0.084	0.122	0.002	0.000	0.090	0.001	0.098
F2	0.012	0.006	0.117	0.117	0.002	0.125	0.002	0.106	0.000	0.007	0.007	0.039	0.144	0.007	0.000	0.116	0.000	0.129
F3	0.012	0.052	0.017	0.111	0.002	0.111	0.012	0.104	0.000	0.039	0.060	0.126	0.150	0.010	0.001	0.029	0.000	0.112
F4	0.003	0.004	0.026	0.004	0.002	0.009	0.000	0.004	0.000	0.025	0.002	0.004	0.102	0.003	0.000	0.038	0.000	0.004
F5	0.105	0.118	0.027	0.025	0.028	0.118	0.097	0.133	0.000	0.074	0.002	0.038	0.165	0.106	0.016	0.135	0.085	0.040
F6	0.075	0.003	0.042	0.099	0.003	0.012	0.001	0.106	0.000	0.004	0.002	0.161	0.140	0.048	0.000	0.109	0.000	0.095
F7	0.000	0.000	0.002	0.000	0.000	0.001	0.000	0.084	0.000	0.000	0.000	0.007	0.008	0.000	0.094	0.003	0.000	0.000
F8	0.003	0.001	0.024	0.003	0.001	0.007	0.000	0.003	0.000	0.001	0.001	0.086	0.099	0.001	0.000	0.037	0.000	0.003
F9	0.003	0.001	0.012	0.002	0.001	0.007	0.000	0.002	0.000	0.001	0.001	0.003	0.109	0.000	0.000	0.084	0.000	0.002
F10	0.010	0.112	0.087	0.027	0.014	0.087	0.002	0.027	0.000	0.005	0.005	0.024	0.131	0.112	0.000	0.047	0.001	0.028
F11	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.047	0.000	0.000	0.000	0.086	0.005	0.000	0.000	0.072	0.000	0.000
F12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F13	0.028	0.002	0.003	0.005	0.013	0.050	0.001	0.009	0.000	0.001	0.000	0.010	0.011	0.004	0.000	0.009	0.001	0.007
F14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F15	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.012	0.000	0.000	0.000	0.001	0.001	0.000	0.000	0.000	0.000	0.000
F16	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F17	0.102	0.001	0.006	0.007	0.003	0.067	0.000	0.100	0.000	0.001	0.000	0.026	0.135	0.098	0.082	0.019	0.000	0.075
F18	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

	D	*R*	*D* + *R*	Rank	*D–R*	Cause/effect
F1	0.561	0.360	0.922	7	0.201	Cause
F2	0.937	0.302	1.239	5	0.634	Cause
F3	0.947	0.381	1.328	4	0.566	Cause
F4	0.230	0.404	0.635	12	−0.174	Effect
F5	1.311	0.082	1.393	3	1.228	Cause
F6	0.901	0.614	1.516	1	0.287	Cause
F7	0.200	0.118	0.318	15	0.082	Cause
F8	0.272	0.837	1.109	6	−0.565	Effect
F9	0.227	0.000	0.227	17	0.227	Cause
F10	0.719	0.158	0.878	8	0.561	Cause
F11	0.213	0.081	0.294	16	0.132	Cause
F12	0.000	0.694	0.694	11	−0.694	Effect
F13	0.153	1.321	1.474	2	−1.167	Effect
F14	0.000	0.390	0.390	14	−0.390	Effect
F15	0.015	0.195	0.210	18	−0.180	Effect
F16	0.000	0.789	0.789	10	−0.789	Effect
F17	0.722	0.089	0.811	9	0.633	Cause
F18	0.000	0.593	0.593	13	−0.593	Effect

Table 10. Direct–indirect impact matrix

primarily by others. This classification of cause and effect features is depicted in Table 10. A total of 10 features, namely capacity (F1 = 0.201), screen (F2 = 0.634), design (F3 = 0.566), chip (F5 = 1.228), camera (F6 = 0.287), cellular (F7 = 0.082), headphones (F9 = 0.227), sensors (F10 = 0.561), connector (F11 = 0.132) and iOS (F17 = 0.633) are categorized as cause features. From Table 10 and Figure 3, it is visible that F5 (chip) has the highest driving power (1.228) and acting as the causal feature to influence all the other features except F9 (headphones), F11(connector) and F15 (Siri); therefore, it is the most significant feature that affects customer buying behavior; hence, mobile phone manufacturers realize that this is to be addressed first. In addition, eight features have negative (*D*-*R*) values. These features consist of resistance (F4 = −0.174), battery (F8 = −0.565), featured iPhone accessories (F12 = −0.694), price (F13 = −1.167), security (F14 = −0.39), Siri (F15 = −0.18), warranty (F16 = −0.789) and Apple Trade-in (F18 = −0.593) are the features that are classified as "effect barriers". These features (F4, F8, F12, F13, F14, F15, F16 and F18) are influenced by the cause feature. In the effect group, F4 (resistance) and F15 (Siri) were nearer to the center. This indicates that the identified causal features less influenced them.

Prominence (*D* + *R*) represents the importance of each feature in the overall analysis structure. The prominence of the 18 features rank from the largest to the smallest as follows: F6 (camera), F13 (price), F5 (chip), F3 (design), F2 (screen), F8 (battery), F1 (capacity), F10 (sensors), F17 (iOS), F16 (warranty), F12 (featured iPhone accessories), F4 (resistance), F18 (Apple Trade-in), F14 (security), F7 (cellular), F11 (connector), F9 (headphones) and F15 (Siri). In the view of the (*D* + *R*) value, 10 features from the cause group can be attained in order: camera (F6) > chip (F5) > design (F3) > screen (F2) > capacity (F1) > sensors (F10) > iOS (F17) > cellular (F7) > connector (F11) > headphones (F9).

In the net cause–effect diagram (Figure 3), the cause features are shown on the positive side of *Y*-axis, while "effect features" are on the negative *Y*-axis. In Figure 3, the horizontal axis includes (*D* + *R*) values showing the prominence of the features, while the vertical axis contains (*D*-*R*) values showing the degree of influence (Seker and Zavadskas, 2017).

6. Practical implications

Based on the proposed study, several key findings and implications for decision-makers, policy planners and managers were generated:

Table 11.
Inner dependency matrix

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18
F1								0.099				0.084	0.122			0.090		0.098
F2			0.117	0.117		0.125		0.106				0.039	0.144			0.116		0.129
F3		0.052		0.111		0.111		0.104		0.039	0.060	0.126	0.150			0.029		0.112
F4			0.026							0.025			0.102			0.038		
F5	0.105	0.118	0.027	0.025	0.028	0.118	0.097	0.133		0.074		0.038	0.165	0.106		0.135	0.085	0.040
F6	0.075		0.042	0.099				0.106				0.161	0.140	0.048		0.109		0.095
F7								0.084							0.094			
F8			0.024									0.086	0.099			0.037		
F9													0.109			0.084		
F10		0.112	0.087	0.027		0.087		0.027				0.024	0.131	0.112		0.047		0.028
F11								0.047				0.086				0.072		
F12																		
F13	0.028					0.050												
F14																		
F15																		
F16																		
F17	0.102					0.067		0.100				0.026	0.135	0.098	0.082			0.075
F18																		

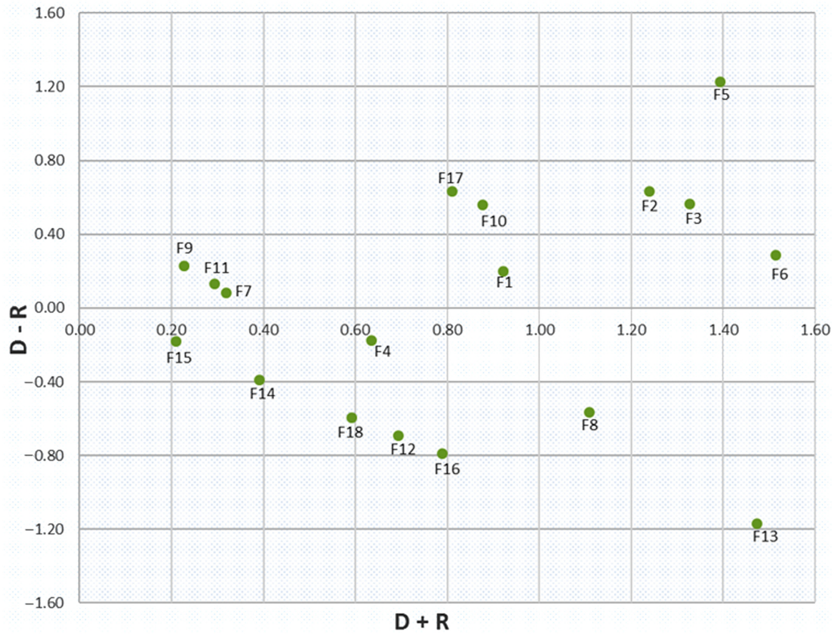

Figure 3.
Net cause–effect diagram

6.1
The results showed that the features of the chip, screen and iOS have the highest positive values (*D-R*) and have the greatest impact on other features. Because causal features act as drivers that can significantly influence the overall system, Apple's policymakers and managers need to pay more attention to and control these features in the RL decision process. Therefore, reviewing customer feedback on these three features can provide valuable information to the company's RL managers, which we refer to below.

6.1.1 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 compared to other models within the same brand or another brand. 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 CS 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 6s and iPhone 7 chips.

6.1.2 Screen. The major dissatisfaction with users was in two areas. First, comparing it with other competitors of any other brands and mobile phone models; and second, 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. Besides, 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 6s and iPhone 8 models.

6.1.3 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 two weeks, and the same was true for versions 10, 11 and 12. Users of the iPhone 5 and iPhone 5s also tend to use the newer capabilities of the newer iPhones' iOS such as dark/light appearance.

6.2

In this study, it was found that the three features of price, warranty, and featured iPhone accessories are the most affected of the other features. Therefore, Apple's policymakers and managers can take action to address customer dissatisfaction with these three features by resolving issues with other features. In other words, these features themselves do not have an indirect effect on other features but are affected by other features. So these three features are also important in the RL decision process, and reviewing customer feedback on them can help Apple's decision-makers that describe these features below.

6.2.1 Price. 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 previous models' price is reduced, and users are not satisfied with the iPhone X and later prices due to comparing 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.

6.2.2 Warranty. Customers have heavily criticized Apple's Warranty program. Most users expect Apple to repair/replace in the form of a warranty plan when the battery is depleted and the screen is crushed. They claimed that this should happen in the 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 suggest to each other the use of mobile phone protective equipment such as a case and LCD protector 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 USA.

6.2.3 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.

6.3

Conceptual analysis of tweets showed that the highest number of tweets related to the features identified in 18 mobile phone models examined in this study include iPhone 5 (headphones), iPhone 5c (design), iPhone 5s (resistance), iPhone SE (price), iPhone 6 (headphones), iPhone 6

Plus (sensors), iPhone 6s (camera), iPhone 6s Plus (resistance), iPhone 7 (price), iPhone 7 Plus (security), iPhone 8 (design), iPhone 8 Plus (price), iPhone X (price), iPhone XR (capacity), iPhone XS (capacity), iPhone XS Max (Siri), iPhone 11 (battery), iPhone 11 Pro (camera) and iPhone 11 Pro Max (screen). So Apple's policymakers and managers find out which feature is more important to customers in each mobile phone model. The results of the analysis of strengths and weaknesses of Apple mobile phones and their features can be effective in increasing profitability and improving the decision-making process in Apple's RL.

6.4

The results of this study guide the policymakers, managers, and SC designers to review their strategies for the implementation of RL processes. They must pay close attention to their decisions, continuously capture customer feedback related to the product or service they have purchased, and take necessary corrective through the SC to achieve CS. In other words, knowing the level of CS or customer dissatisfaction with the product or service provided causes policymakers and managers of the RSC in the decision-making process, take necessary actions and planning during RL such as inventory control, supply of parts for the after-sales service center, collection and distribution, etc., which in turn leads to increased company performance and increased CS. In RSC, each decision made by an RSC member affects all other members, and therefore, the RSC actors should coordinate their decisions. For instance, the quality of remanufactured products influences the purchasing behavior of customers. Therefore, improving the quality of remanufactured products by the remanufacturer increases the remanufactured products' demand. Under such a case, not only the CS increases but also all RSC members obtain more market share. In the traditional business environments, retailers, collectors and remanufacturers individually optimize their decisions in pricing, collection and quality management process. However, cooperation and coordination among RSC members could influence the performance of the whole system. Moreover, in many real cases, there are two RSCs, which compete on different factors such as the quality level of the remanufactured products. Under such a case, horizontal cooperation, which can occur among members at the same level, will affect all RSC activities. For example, when two remanufacturers cooperatively make decisions, the quality level of the used products, transfer price and the wholesale price could be changed. It results in changing the collection price and the retail price. According to the discussions above, the decisions on different levels are closely interdependent on each other, and consequently, a proper strategy should be planned to effectively coordinate such decisions, thereby improving the economic profits of the whole RSC and providing a win-win situation for all members.

In this study, the results obtained from SM and the DEMATEL method show the priority of decision-making on mobile features for managers and decision-makers, for example, when the results show that the chipset is more important than other features. All members of the RSC must work in concert to improve the quality of this feature, which means horizontal and vertical cooperation throughout the RSC. Therefore, investigation of the revealing 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 to increase the market share of a business firm, have an advantage over their rivals and develop a consumer-centric supply chain. This mechanism will assist in appropriate partner selection within the supply chain to improve sustainability.

6.5

The paper, specifically by using SM data, develops a model to explore mobile phone features that affect customer buying behavior, and yet, it presents a generalized approach in order to be utilized in other manufacturing industries.

In addition to the above, in order to further enhance the insight of Apple's policymakers and managers, we provide an overview of users' opinions on some essential iPhone features, along with the proposed RL decisions:

Capacity: Therefore, users are reluctant to use 64 GB capacity and less. Additionally, newer Apple operating systems, such as iOS 13, come with higher capabilities and require more space than older models to install on the device. Therefore, the user's effective space 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 returning to the supplier or reclaim materials.

Design: All models of the iPhone 5 series, iPhone SE, iPhone 6s and iPhone 6 have been criticized for their small screen sizes. Some users have also mentioned the high weight of the iPhone 6s. Meanwhile, the large screen of iPhone 6 Plus and iPhone 6s 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 consider this in designing future products.

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 of 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 onward, the home button is removed. Therefore, iPhone's vulnerability has increased significantly due to 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.

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 cameras' internal components such as charged coupled device (CCD), lens, etc. 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, 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 iPhone 8 model's criticism 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.

Battery: This feature has the most dissatisfaction within all iPhone models. CS 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 as well as 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, 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's official report, the iPhones are designed to run 500 cycles of charge (Apple, 2021). Due to consumer dissatisfaction, it seems it is time for Apple to change its battery production policies.

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.

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. From the RL point of view, this connector is common to all iPhone mobile phone models and can be used in all different phone models.

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 four or six-digit codes. However, fingerprints were used for authentication for the iPhone 5s 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 3D 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).

Siri: The use of 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 CS include phone and text actions, schedule events and reminders, handle device settings and more.

Apple Trade-in: 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. Users are fully satisfied with the Apple Trade-in program and have suggested that Apple develop more trade-in plans for older iPhones.

7. Conclusions and future research directions

In competitive markets, consumers are very selective. In order to be sustainable in this competitive scenario, manufacturers must examine customers' purchasing behavior and the factors affecting its effectiveness. They need to see how these factors relate 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 SM operating systems. Manufacturers use SM in order to promote their services and to connect with their customers. This study tries to incorporate SM data by using the DEMATEL method to establish a customer-centric RL. The involvement of information from SM data will give consumers a sense of empowerment (Mishra *et al.*, 2017). In order to achieve this goal, cell phone features influencing customers' purchasing behavior are 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 cellphone features affecting consumers' purchasing behavior and their mutual relationship can give decision-makers crucial information.

In this study, first, several product review' websites were examined to identify the features that affect the consumers' decision to purchase 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, DEMATEL method, is used to classify 18 features into cause and effect features, and their interrelationships are explored. During the study, it was observed that F5 (chip) has the highest driving power (1.228) and was the most significant feature that affects customers' purchasing behavior; 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 in order 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 behavior to form customer-oriented RL. Based on the findings, recommendations were given for making consumer centric RL. Future investigations can be carried out in order to develop a theoretical mechanism for consumer-centric RL by assimilating some more aspects.

The developed theoretical model is limited to the identification of mobile phone features influencing consumers' purchasing behavior. 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 interrelationship may be diverse according to 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 DEMATEL technique, other techniques may also be engaged with a larger sample size. The model proposed in this paper can be further statistically validated by using systems dynamic modeling and structural equation modeling. Although the study involves DEMATEL approach, the results can also be compared with other approaches such as analytical network process and analytical hierarchical process or fuzzy analytic network process. Moreover, the identified feature could be further ranked by utilizing interpretive ranking process to develop consumer-centric mobile phone RL. In the future, an improved list of keywords can be used to further analyze 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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