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Research article

Toward consumer perception of cellphones sustainability: A social media analytics

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ABSTRACT

Today, sustainability is among the key considerations for company strategy and marketing efforts, especially large and established technology companies with short product life-spans. Companies often provide sustainability agendas that focus on the social, environmental and economic dimensions, also known as the Triple Bottom Line (TBL) of sustainability. Social media provides a trove of evidence on how customers perceive and discuss the sustainability efforts of companies, which companies further utilize to understand and modify their efforts. In this study, we utilize Social Media Analysis to understand the perception of consumers towards sustainability efforts of two major companies in the mobile phone industry. We suggest a dictionary-based framework, including Content analysis, Descriptive Analysis and Sentiment analysis to extract the features that correspond to the three dimensions of TBL. Findings indicate that Environment, Material, Technology and Corporate Social Responsibility (CSR) are among the key topics that customers are interested in. Results of Content analysis and Sentiment analysis indicate that companies differ in terms of perceptions along the TBL dimensions, with company 1 perceived better on environmental dimension, whereas, company 2 is perceived better on social and economic dimensions. We demonstrate how knowledge from user-generated data help understand and improve their supply chain.

1. Introduction

The rapid advancement of cellphone technology has caused the relevant market to replace the old handsets with equal speed (Tanskanen, 2012)Tanskanen, 2013. It is a well-known fact that turnover rates in the mobile market are very high (ITU, 2009; Zadok, 2008). Although typical cellphones have a life-span of about 10 years, most customers change their phones intermittently every 12 to 24 months (Huang et al., 2009). According to the GSMA, by 2005, the number of cellphone subscribers will reach approximately 6 billion, and 80% of communication will be via smartphones (GSMA, 2019). Since most people are looking for innovations in the cellphone market, the use of high- tech materials will continue its upward trend in the production of such products. In many cases, the destructive effects that these materials have on human health and the environment, as well as resource depletion are ignored (Ogunseitan and Schoenung, 2012). As a result, with increasing production volume, the sustainability issues related to cellphones and their supply chains also increase significantly (Bask et al., 2013). On the other hand, despite the definitions of sustainability, perceptions of sustainability differ in various areas (Bell and Morse, 2000). The words used by the manufacturer are different from the words used by a typical consumer. However, the issue may be the same for both of them and customers may be talking about things the manufacturer has never thought of (Hu and Liu, 2004). Thus, Sustainability approaches are different in each industry, meaning that different industries face different challenges (Liew et al., 2014).

According to the theory of stakeholders, companies gradually view sustainability in terms of paying attention to the interests of different stakeholder groups (such as consumers, employees, shareholders, society, government, environment) (Gong et al., 2019). Sustainability estimation is primarily notable for decision-makers of the focal firm in the supply chain, so the responsibility for meeting sustainability metrics will depend on the target organization (Ahi and Searcy, 2014b). Consumers are among the special stakeholders due to their considerable interest in sustainable products as well as their ability to move the system towards a sustainable situation (García-Herrero et al., 2019). Some research shows that consumers are willing to pay higher prices for the products of companies that are more committed to sustainability. Other research has shown that customers are more likely to buy prod-

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ucts from companies that have shown higher social responsibility (Gong et al., 2019). Consumers not only want to know about physical products such as materials used in production and packaging but also want to know more about where raw materials are produced and purchased (Kleindorfer et al., 2005).

Moreover, many consumers are interested in knowing what will happen to the products after the end of their life-span. The effects of the supply chain on the environment and society are increasingly becoming important for consumers (Bask et al., 2012). Besides, to design sustainable purchase models, it is essential to pay attention to customers' perceptions of sustainability (García-Herrero et al., 2019).

With the expanding use of social media in businesses, user-generated data provide valuable information about customers to business owners. Social media data contain valuable data that is useful to both groups of suppliers and customers (Chang et al., 2019; He et al., 2015). He et al. (2018a) believe that the content produced by users on social media is more reliable and trustworthy than the data obtained from the marketing division of the organization. Faster access to this information in comparison with competitors seems to be a competitive advantage for each company (Batrinca and Treleaven, 2015; Hazen et al., 2016). Given that conducting field research or quantitative studies is very expensive and the information obtained in this way will be limited to certain customers, therefore, analyzing the content produced by users on social media is a necessity for any organization. Social media, unlike conventional methods of communication, has unique features. First, social media reflects users' opinions about all aspects of life. Second, the information in this platform is continuously updated through the activities of millions of users, so new content is always available to analysts. Third, metadata about users, such as location, likes, time, and dislikes, can be accessed through social media. (He et al., 2015).

In this study, we look at one of the social media platforms, Twitter. Many organizations and professionals in the supply chain (e.g., news services, IT companies, careers, and manufacturers) use self-standing short textual sentences (tweets) for sharing information, recruitment, and communication with stakeholders. About various topics, such as CSR, risk, manufacturing, supply chain management (SCM), IT and even human rights, some tweets contain significant information about corporate delivery services, sales returns, Environmental standards, risk, and disruption in supply chains (Chae, 2015). In this study, Twitter was chosen because it has the highest growth rate among other social media platforms (Bennett, 2013). Currently, more than 270 active users generate more than 500 million tweets in this medium daily. Customers express their opinions about products, services, and brands through Twitter media (Webster, 2010). Another reason for this choice is that access to Twitter data is open. Therefore, researchers and business owners access this information using the Twitter Application Programming Interface (API). These conditions provide unprecedented information on a large scale to analyze and address challenging issues in various fields (Chae, 2015).

Although the issue of sustainable development is critical for companies and several articles in the thematic literature, have addressed this issue, but the issue of the sustainable supply chain from a consumer perspective has not received much attention. In this case study, we analyze 106,350 twitter data collected from August 2017 to July 2019 about two leading brands in the cellphone industry (in terms of global market share and brand value). Therefore, the purpose of this study is to contribute to the richness of current literature by examining the issue of sustainability in social media. We intend to extend the traditional quantitative studies using social media data analysis methods. These tweets consist of sustainability aspects related to cellphones ranging from packaging and recycling to technology, innovation, circular economy, and even human rights. Researchers determined the role of social media in building positive feelings for environmental conservation (Fan et al., 2006; Sujata et al., 2019). Also, this study emphasizes the current use of Twitter in the field of supply chain and for providing more information about the role of Twitter in supply chain research and practice, provides a framework for analyzing supply chain tweets. Besides, using the Sentiment analysis, we will determine what aspects of the organization's management should improve to ensure the firm's sustainable performance. Twitter Sentiment analysis provides an easy and reliable way for businesses to monitor people's feelings towards their brands, businesses and stakeholders (Saif et al., 2012). This study answers the following questions:

Q1: Which aspects of sustainability do the consumers of cell phones often tweet?

Q2: Do consumers express a positive or negative perception towards these sustainability aspects?

Q3: How do Company 1 and Company 2 compare, along the dimensions of TBL, as measured by the consumer perception scores?

The structure of this study is as follows: Section 2 examines the relevant literature. Then the research methodology will be explained in Section 3. In Section 4, we will discuss and analyze the results. Finally, in Section 5, the theoretical and practical findings of this theory are discussed. Section 6 will also provide conclusions, research limitations, and suggestions for future studies.

2. Literature review

Our literature review is structured in two sub-sections. First, we provide a review of social media in the context of the supply chain, addressing sustainability; Next, we will review the thematic literature on sustainability metrics in the context of TBL.

2.1. Social media data and sustainability

Nowadays, social media is a powerful way for all types of businesses due to its potential to attract customers and prompt them to take the steps. Using social media is a valuable opportunity to connect people around a common subjective. Social media enables knowledge sharing through the internet, idea creation, interaction with people of similar ideas, and dissemination of information through online communities (Sujata et al., 2019). Kassens-Noor (2012) shows the possible benefits and risks that Twitter could add to higher education e-learning groups in the case of sustainable tweets. To understand the importance of effective use of social media and sustainability communication, we refer to Reilly & Hynan (2014) research that shows how international companies in various industries use social media and CSR reports about sustainability. Richardson et al. (2016) demonstrate how social media is used to generate discussion on sustainability with a particular focus on the use of resources and the sustainability concerns in nursing practice. Serna et al. (2017), in their study, examined sustainability problems related to urban mobility based on customer perceptions and experiences using User-Generated-Content(UGC). They showed that travel surveys are performed less often, and there is not enough information to investigate mobility and travel behavior. Thus, the data obtained from social media provides an opportunity to improve conventional travel survey methods and reduce bias in the data and respondent burden.

Tseng et al. (2019) propose a decision-based model intending to explain the characteristics of sustainable supply chain management (SSCM) and their effects on the industry, with an emphasis on the impact of social media. Shan et al. (2020) provide a social media data-driven planning framework for assessing and estimating people's emotional reactions to river pollution. The results of this study showed that the data obtained from social media as input to the Sentiment analysis method was useful and valuable for assessing people's emotional reactions in the form of short text posts on Weibo regarding 55 river sections in Beijing, China. A recent study on green product topics and its various stages on social media such as Twitter showed that people are fully aware of the different stages of green products (Karmugilan and Pachayappan, 2019). Fan et al. (2006); Oakley and Salam (2014)Oakley and Salam, 2014 noted the role of social media in creating optimistic environmental conservation sentiments . Ingold & Balsiger (2013) examined the implementation of sustainability in the Upper Rhone Valley through a cross-sectional and multilevel collaboration of performers in climate adaptation policies. Patterns of their collaboration were examined through the perceptions of these actors regarding sustainability as well as network relationships between them using cluster and social network analysis. Data on perceptions and network relations were analyzed through the cluster and social network analysis. Rivera et al. (2014) attempted to use news media to create useful sustainability indicators. Relying on the document classification algorithm and unification of information retrieval methods, this analysis shows that researching the digitized news media provides managers with valuable information for determining, tracking, and reporting sustainability indicators.

Users of well-known social media like Twitter and Facebook, along with online commerce companies like Amazon, are allowed to communicate their thoughts about different products and services. (Chang et al., 2019). Social media trade websites allow users to participate in the process by integrating UGC into typical business transactions. These sites also enable businesses to accommodate better to customer needs, listen to customers, and adjust their preferences as needed (Farivar et al., 2018). A review of 54 articles in the thematic literature on social media by Rathore et al. (2017) shows that Twitter is the most popular among other platforms due to its variety of functions. Twitter may have a professional (networking, training, and marketing) or organizational (recruitment, stakeholder engagement, market information, and new product development) function. With more than 600 million users and transferring more than 250 million messages per day, Twitter is a valuable tool for the exchange of information by individuals and organizations (Saif et al., 2012) Twitter is valuable not only for researchers to conduct scientific research but also for industry activists to create value for industrial customers (Mishra and Singh, 2016). In the last few years, the number of Twitter users has increased dramatically, and many studies have been conducted to assess the social behavior and opinions of users of this media (Damodar et al., 2015). Pak & Paroubek (2010), demonstrated in how Twitter is used as a repository for evaluating emotions and mining opinion and applied Twitter as the microblogging condition for the reasons provided in the following:

- Various people use micro-blogging platforms to share their viewpoints on different subjects. Hence, it is an authoritative source of opinions.
- There is a massive amount of text posts on Twitter, which increases daily. The gathered corpus can be enormous in an arbitrary manner.
- Due to the diversity of audiences on Twitter, from regular users to celebrities, company representatives, politicians, and even country presidents, gathering text posts of users from various social and interest groups are feasible.
- Users from different nations are the audience of Twitter.

Numerous studies have used Twitter as a source of information to examine customers' opinions about brands (Jansen et al., 2009); This may be because Sentiment analysis over Twitter is a fast and effective way for organizations to discover how people feel about their business and managers (Saif et al., 2012). Sentiment refers to the expression of positive or negative feelings of a person through social media that has an object and an ultimate goal (Jussila et al., 2017). For example, understanding customers' perceptions of the organizational brand and how they feel about it (on social media) allow the organization to take immediate action to improve the customer experience and brand visibility(Stieglitz and Dang-Xuan, 2013)

2.2. Sustainability metrics and TBL

Measuring sustainable development has had several different approaches that often include defining sustainable development indicators and methods of arranging those values, which are also formated to enable comparison (Evans et al., 2015). Consequently, sustainability implementation is a complicated process, including an enormous number of interacting metrics (Ahi and Searcy, 2015). Sustainability metrics are preliminarily sustainability indicators and indices (SIIs) in the sense of sustainable development, which play a vital role in sustainability research and practice. They may better simplify, evaluate, define and convey knowledge from the environmental, economic, and social perspectives (Singh et al., 2012). The metrics are important from a theoretical viewpoint as organizations aim to achieve sustainability or when they determine the degree of sustainability of the current system. Companies contribute to sustainability in many ways, and there are numerous methods that companies measure sustainability(Evans et al., 2015). These metrics might vary from one supply chain to another since different supply chains function in different environments (Ahi and Searcy, 2014a). Companies, even within the same sector, undertake different metrics. These are usually outlined in sustainability reports released annually by many organizations to identify their environmental objectives, strategies and accomplishments. These reports are typically published annually to demonstrate transparency and accountability, involving stakeholders and governments and attracting investors. (Liew et al., 2014).

Moving beyond definitions to actual implementation is a challenge for any organization providing a broader range of considerations required by the TBL concept and the lack of available quantitative metrics for decision-making. Introducing the term TBL, help businesses make the idea of sustainable growth more applicable, maybe more critical, and more comfortable to remember (Dyllick and Muff, 2017). It is needed to implement sustainability, in which advancements follow the TBL dimensions. An investigation carried out by McKinsey shows that the company's sustainability agendas adopt the triple bottom line of sustainability (Bonini, 2012):

- Economic sustainability, which is regarded as one of the TBL dimensions, involves the production stages, financial conditions, market share, and incomes. Furthermore, economically, sustainable improvement in developing economies relies on economic refinement, where it is necessary to meet the needs of the public and protect the environment to accomplish a sustainable supply chain (Kazancoglu et al., 2018).
- Both internal or external parties are included in social sustainability, encouraging autonomy in supply chains, quality of life factors including, wellbeing and security, educational opportunities, and employment rates (Bonini, 2012).
- Environmental sustainability aims to eliminate and diminish the waste, pollution, energy consumption, emissions, consumption of hazardous materials (Akadiri et al., 2012).

Sustainability must be discussed within each category of TBL for development to be defined as sustainable (Evans et al., 2015). In general, defining main sustainability aspects seems relatively easy and straightforward (such as climatic, soil, biological diversity), cycles (such as water, carbon, phosphorus, oxygen, nitrogen),

Table 1
An overview of literature on sustainability aspects based on TBL dimensions. Abbreviations: EN=Environmental; SO=Social; EC= Economic; TBL= Triple Bottom Line.

Publication	TBL Dimensions EN	SO	EC	Sustainability aspects
Liew et al., 2014	a	a	×	h ealth and safety, human rights, reducing GHG, CO2 emission,
Paiano et al., 2013	a	×	×	Resource consumption, Energy consumption, E waste
Hourneaux Jr et al., 2018	a	a	a	EC: on-time delivery, Number of customer complaints, Number of customer satisfaction, materials efficiency variance, rate of materials scrap loss, labor efficiency variance. EN: Materials, Energy, Water, Emissions, Effluents and waste, Environmental aspect of products and services, Environmental compliance, Transporting, General environment issue. SO: Labor/management relations, Occupational health & safety, training & education, non-discrimination, freedom, child labor, forced & compulsory labor, security practices, compliance
Shuaib et al., 2014	a	a	a	6R (reduce, reuse, recycle, recover, redesign, and remanufacture), Cost, Materials, Labor cost, Logistics, Waste and Emissions, Energy use, Safety, health
Mokhtar et al., 2016	a	a	a	SO: Ergonomics, Human Rights, Human Training and development, Occupational Health and Safety, Ethics and integrity, Product utilities, community relationships, Supplier Relationship., Labor wage. EC: Accountability, EBITDA, Energy cost, Operation Income, Net Income, Sales, Raw material cost, R&D cost. EN: Electricity, Biodiversity Conservation, Carbon Footprint, Total energy consumption, chemical substances, Waste Recycling, Waste, Water Use, Environmental management system (EMS)
Swami et al., 2019	a	a	×	E mployment, Occupation Health and Safety, Labor/Management Relations, Training and Education, Diversity and Opportunity, Non-discrimination, Customer Health and Safety Materials, Water, Energy, Waste, Emissions, Biodiversity and Environmental Management Systems (EMS), Environmental Compliance,
Shamraiz and Kuan, 2019	a	a	a	Energy use, Material use, Electricity, Chemical(carbon dioxide), Cost Profit, Labor rights, Working conditions, Labor wellbeing, Labor satisfaction, Society satisfaction
Duque Ciceri et al., 2010	a	a	a	Materials, Energy, Water, Emissions, effluents and waste, Environmental aspect of products and services, Transporting, General environmental issues, On-time delivery, number of customer complaints, survey of customer satisfaction, Labor/management relations, Occupational health and safety, Training and education, Non-discrimination, Child labor, Forced and compulsory labor
Ma and Kremer, 2015	a	×	×	Reusability, Remanufacturing, Primary recycling, Secondary recycling, landfill waste products, reprocessing, refurbishing, obsolete products
Ahi and Searcy, 2015	a	a	a	Raw material which poses wealth, safety and environmental hazards, Safe treatment rate of domestic rubbish, Economic welfare and growth, Health and safety, Work safety and labor health, Worker health and safety, Reduced safety incidents
Narimissa et al., 2019	a	a	a	application of eco-friendly technology, product recycling, waste reduction, product lifecycle management, Cost, Customer satisfaction, Improve the working environment, Staff training
Paiano et al., 2013	a	×	×	Electricity consumption, Resource consumption
Govindan et al., 2012	a	a	a	EC: Costs (product costs, ordering costs. Logistic costs), delivery reliability (on time, lead-time delivery), quality (quality assurance, rejection issue), technology capability (technology level) SO: Health, education, service infrastructure, housing, health and safety incidents, regulatory and public services, supporting educational institutions, security, cultural properties, economic welfare and growth, social pathologies, grants and donations, supporting community projects, Procurement standards, partnership standards, consumers' education. EN: Pollution production, air emission pollutant, waste water, solid wastes and harmful materials releases per day during measurement period Resource consumption in terms of raw material, energy, and water during the measurement period,Eco-design, Design of products for reduced consumption of material/energy, design of products for reuse, recycle, recovery of material, design of products to avoid or reduce use of hazardous materials Environmental management system

and ecological functions of a system. Nevertheless, identifying and measuring many basic features of the resources and processes essential to human needs, and thus to sustainability is difficult. So the first step in evaluating the sustainability of any supply chain is to determine the aspects that affect the supply chain's complexity and power.

Rathore et al., 2011 by analyzing users' perceptions and finding the answer to the main question of whether Indian customers accept remanufactured products or not, as well as the relevance of these products to the market, investigated the feasibility of establishing remanufacturing. Paiano et al. (2013) examined the mobile phone market in Italy, mainly in terms of energy consumption during use. Their study assessed the sustainability of the mobile phone sector in two main aspects: first, concerning the energy consumption of mobile phones and their peripherals, and second, concerning the conflict between potential dematerialization caused by the miniaturization of devices, as well as resource consumption and waste issues in this sector. The results show that the durability and customization of mobile phones have a positive and significant effect on phone preference, and mobile phones with a lifespan of more than five years, which have several options for customization, are more preferred by customers As reported in Table 1, some articles in the literature discussed sustainability aspects. Research shows that the dimensions of sustainability in supply chains are different. Different features of sustainable consumption reveal the difference between what existing sustainability measurement methodologies offer, and whether they satisfy the customers' expectations or not (García-Herrero et al., 2019). However, there is few of academic literature on how the sustainable aspects of a product or service are derived from user-generated data in social media platforms; even, few studies have been conducted on the affective dimensions of the supply chain from the customer perspective. Given the benefits of social media Content analysis for SSCM, further studies in this area seem necessary. Our purpose is to analyze the product sustainability aspects from the viewpoint of the supply chain by analyzing social media and reviewing consumer tweets related to mobile phones and thus contribute to the enrichment of the thematic literature in this field.

3. Methodology

The social media data is less structured (e.g., texts, informal expressions) and more enriched (e.g., user profiles, followers, hashtags, URLs) compared to the traditional data (e.g., sales data, transaction data). Thus, it is essential to apply different research methods and measurements to extract information from exceptionally enriched and unstructured social media data (Zeng et al., 2010). Social media analytics is a method of collecting and analyzing user-generated data, which aims to provide the data needed for organizational decision-making and other business-related activities (Brandenburg et al., 2014; Chang et al., 2019). Taking into account Social Media Analysis consequences, there are two significant viewpoints that both have an impact on the research agenda (Stieglitz et al., 2014)Stieglitz et al., 2014. First, Social Networking is a field of research with its research questions which are not considered to be addressed generically; e.g. What approach should be used, and how can such approaches be matched with different social media interactions requirements; or what can be the best choice among various tools. Second, Social media analytics considers being a methodological approach which might be usefully applied in various domains such as communication, teaching and marketing. Referring to the view of (Rathore et al., 2017), on the selection of special analytic methods for specific industries, we used a combination of compatible methods to explore consumer perceptions. Chae (2015) proposed a mechanism to analyze the 22,399 #SupplyChain tweets in the domains of SCM. This framework consists of three procedures from various intellectual foundations, which are entitled as Descriptive analysis, Content analysis, and Network Analysis. His-subjective was to understand better the role of Twitter in implementing supply chain management and future research(Mishra and Singh, 2016; Papadopoulos et al., 2016; Samuel et al., 2020) . Mishra and Singh (2016), obtained useful information about the unstructured beef supply chain from Twitter to discover the reasons for the waste in the beef supply chain, using the methods of Sentiment analysis, Descriptive analysis, and Content analysis. They used document summarization to analyze the content of messages on Twitter. He et al., 2018b, conducted a study to analyze people's online discussion about different types of laptop brands. After collecting the initial data using Twitter search APIs, they used statistical analysis, text mining, and Sentiment analysis methods to analyze the data taken from this social media as well as showing the relevant patterns and information and understanding the customers' perceptions. Zhong et al., 2018 suggested a framework including data collection, data pre-processing, feature extraction, and Sentiment analysis. They aimed to analyze the purchase behavior of people in different cultures by examining the value of consumer reviews in different countries. Fig. 1 illustrated the description of our proposed framework. Referring to the reviewed literature on knowledge extraction from user-generated data, in the present study, we used the proposed framework by Chae (2015). According to the Morstatter & Carley (2013) study,

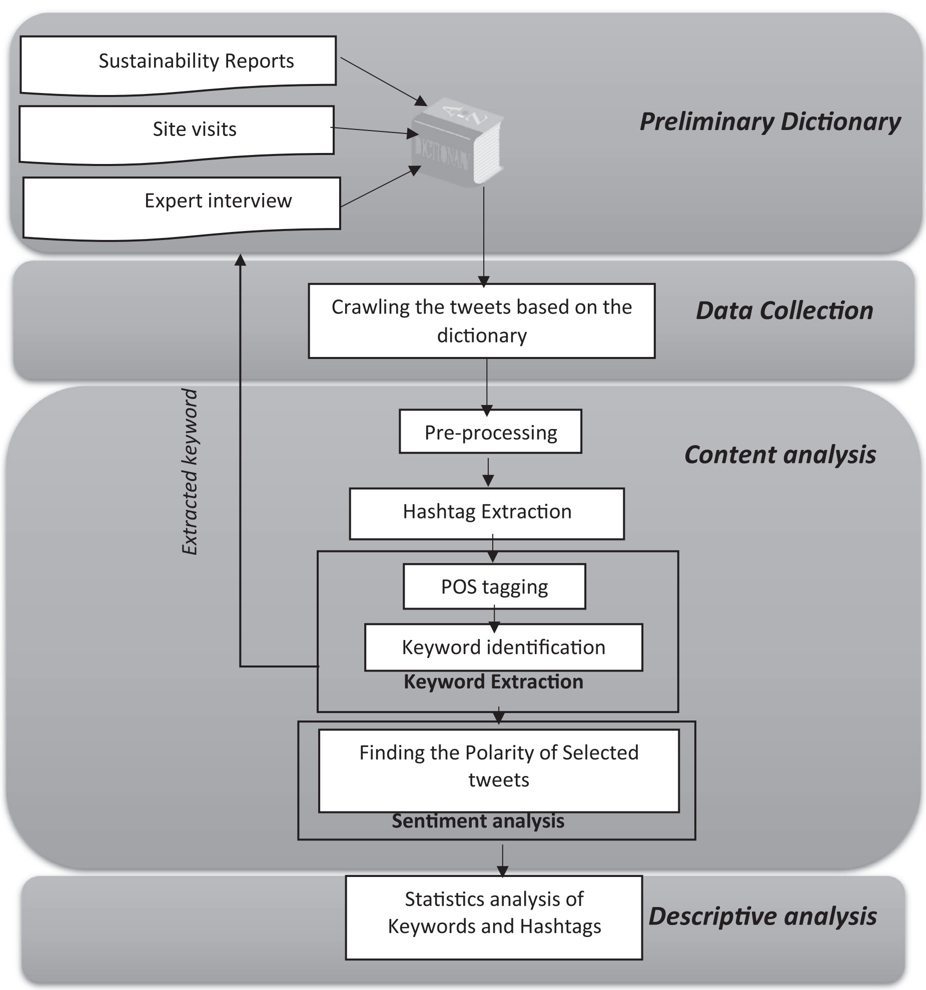

Fig. 1. Research methodology.

Table 2
Highlighting issue occurring at companies' 2019 sustainability report and case study companies website corresponding to TBL.

TBL dimensions	Issues
Environment	Product Stewardship, Climate Strategy, Recycle, Energy Management, Waste and Hazardous Materials Management, Water and Wastewater Management, Emission reduction, Component reduction, Renewable energy, Supplier clean energy, Product energy efficiency, Product Design, Facilities, energy efficiency, Materials, Zero Waste, environmental friendly Chemistry, Innovation, Low carbon design, Climate change, Emission Reduction, Consumption Reduction, Development, Distribution, Repair, Use, Manufacturing, EOL (Products End of Life), Transportation, Carbon footprint
Social	Labor Practices and Human Rights, Human Resource Development and Welfare, Customer Support, Labor Practices in Supply Chain, Community Development and Business Citizenship Activities, Health and Safety in Supply Chain, Diversity, Operational Health and Safety Accessibility, Responsible materials, Privacy, Data Security, Freedom of Expression, Global Stakeholder Engagement, Transparency in Chemical Management, Workplace chemical management.
Economic	(Delivery, Technology, Quality, Human resources) cost optimization, Circular Economy, Responsible Technology Use, Transparency in Accountability and Reporting, Transparency in Governance, Product Safety and Quality Management, Responsibility in Marketing economy, Customer Relationship Management, Management and Compliance

the concept of sustainability is an unpopular category (i.e., less than six tweets/minute on the subject). To increase the number of keywords for tweet searching, we added a step that integrated into our methodology to send the extracted keywords back to the preliminary dictionary. The main idea of this linkage is the summarization approach for the feature-based opinions of customers about the products that are sold online (Hu, and Liu, ;2004)Hu and Liu, 2004. In this approach, first, the "hot" features that many people have commented on are identified, and then with the help of them the infrequent items are determined. In this article, we consider the most frequent hashtags equivalent to "hot features" in their article and our subjective is to find infrequent sustainability keywords.

Table 3
The keywords and hashtags associated with sustainability issues, used for extracting tweets.

#sustainability	#smartphone	#environment	#social
#recycling	#refurbishing	#reuse	#renewable
#green	#climate	change	#material
#efficiency	#packaging	#Circular	#economy
#Labor	#humanrights	welfare	#health
#CSR	#responsible	harmful	#plastic
#technology	#delivery	cost	#quality
#resource	#remanufacturing	#landfill	#recovery
#solar	#consumer	#satisfaction	#pollution
#SupplyChain	clean	#Electronic	work
#consumption	safety	#waste	#EOL
#Carbon	#transparency	#ecofriendly	#logistic
#education	#chemical	#energy	#economic

3.1. Preliminary dictionary

Dictionary is considered to be a necessity for extracting tweets associated with sustainability. Medhat et al. (2014) used a dictionary-oriented method. That is, they first specify the opinion seed word and then look for its synonyms and antonyms. Their corpus-based approach starts with an initial list of opinion words. It then searches for opinion words in a great concept to help identify opinion words with contextual orientations; This could be possible by utilizing statistical or semantic methods (Medhat and Korashy, 2014). (García et al., 2012) implemented a dictionary-oriented approach that demonstrated the polarity of the sentences of the survey through a dictionary of more than 6000 UGC words. Schmunk et al. (2014) went further by categorizing not just the feelings but also the properties of the product to which the feeling relates. Different organizations conduct different measures, even within the same industrial field. Many organizations emphasized the sentiments in sustainability reports and have voluntarily published them to describe their sustainable issues, attempts, and attainments (Liew et al., 2014). It was required to discover the sustainability aspects to make the desired dictionary. Firstly, in this study, the sustainability reports were reviewed on the two companies' website to recognize their sustainability issues. We have also recognized issues by visiting their websites as sources of suggestions for cellphone purchases (See Table 2.). Moreover, this research has allowed preliminary dictionary access for some SCM experts to evaluate the Keywords relevant to sustainability. The selection of our paper experts was based on their thorough knowledge about the mobile supply chain. Table 3 includes keywords and hashtags obtained using the three above methods. All three of these methods from multiple sources increase the likelihood of biased data collection Olteanu et al., 2019.

3.2. Data collection

In this study, APIs are necessary to gather publicly available data from Twitter. It is essential to have some information, including API key, API secret, access token, and access token secret (available in https://apps.Twitter.com/) to reach a Twitter-streaming API (Lomborg and Bechmann, 2014). This plainness of data gathering through APIs, unlike other networks, allows a better investigation of Twitter data. Different tools and computing libraries are also available to evaluate Twitter results, which also encourages the exploration of useful ideas without too much computational complexity (Rathore et al., 2017).

The main drawback of the Twitter API is the lack of guidelines on what data users receive and how much; This causes one to doubt whether the data being sampled is a true reflection of actual Twitter behavior. We are suggested to consider variables such as data collection topics (keywords and hashtags), time, language, geolocation, as they affect Twitter APIs' performance (Lossio-ventura et al., 2019). Morstatter & Carley (2013) analyzed whether data collected from the sampled Streaming API from Twitter is an appropriate reflection of Twitter operation as a whole. They collected data from the open and limited, Streaming API and the unlimited and costly, Firehose with the same parameters. The statistical variations between the two datasets have shown that the top hashtags are perfect for a big n but are also inaccurate when n is small. They compare the frequency distribution of terms from the two similarly related topics and note that when the scope of the Streaming API is largest, we are most similar. The outcome was that as we get more data from the Streaming API, the contextual analysis is the most reliable.

On the other hand, the period was one of the essential factors that give validity to our Twitter research results. Dataset decay and lose value over time is a concern in Twitter data validity and social data decays over time because users may delete their posts and profiles; This considered as another bias in data collection(Olteanu et al., 2019). In our study, we chose the time frame of two years to collect more keywords to address our data collection validity. The paper proposed a model of data extraction and analysis implemented using Anaconda Python, which is an open-source implementation of the Python and R programming languages for applications related to data mining and machine learning. It is installable on Windows, Linux, and macOS (Branz and Brockmann, 2018). Next, Twitter API streamed the tweets into a data set using a parsing method. Finally, the parsing method output for example, tweet texts and Date were stored in the Comma Separated Values (CSV) file (Mishra and Singh, 2016). Some of the tweets contained hashtag of both companies. Redundancy may affect the validity our dataset at this level (Olteanu et al., 2019). It may negatively impact the result. To address this bias, we split them into two separate tweets while parsing them into a file .

3.3. Content analysis

It is needed to apply Content analysis, alluding to a full arrangement of natural language processing (NLP) as well as text mining methods (Chau and Xu, 2012) to extract information from fundamentally unstructured Web 2.0 data. Given that a tweet's text is informal and includes a shortlist of words, URLs, hashtags, and other data, text cleaning and processing the collected data must be done very carefully (Chae, 2015). Content analysis is an appropriate method for e-research, though it is often associated with the analysis of text documents. This methodology generates research that is valid, rigorous, reliable, and replicable (Small, 2011). Content analysis is regarded as a manual or partial manual approach through human interpretations (Seuring & Gold, 2012)(Seuring and Gold, 2012). The first step of Content analysis, i.e., word analysis, includes document summarization, term frequency, analysis of term frequency, and clustering . Term frequency has been used a lot to retrieve the information.

3.3.1. Hashtag extraction

Hashtags are known as a major part of tweets, and they perform the subject role (Chae, 2015). Many of the tweets contain a broad variety of user-defined hashtags (Davidov, 2010). Hashtags are used before a keyword to assign the tweets to a specific class or tag according to the construction of tweets (Mishra and Singh, 2016). At this level, we extracted all the hashtags from the data collection using Python and then saved them into a CSV file.

3.3.2. Keyword extraction

Before beginning a complete analysis, it is usually needed to pre-process the raw tweets. There are some standard pre-processing steps include tokenization, stop word elimination, stemming, parts of speech (POS) tagging, feature extraction, and representation (Ravi and Ravi, 2015). Tokenization step may be applied to parse a sentence into words, phrases, symbols, or other understandable tokens through removing the punctuation marks. Given that stop words (e.g., "a", "an" and "the") are not considered as a useful analysis component, they are eliminated during the pre-processing step (Ravi and Ravi, 2015).

Association Rule Mining is considered as a domain of data mining, which concentrates on pruning applicant keys. Moreover, it finds the connections existing between hashtags Chae, 2015. The most frequently used Association Rule Mining is the Apriori algorithm. In this study, hashtag extraction output is a set of hashtags per tweet. Each set of hashtags gathered from the above is stored in a dataset. All different phases in the dataset are possible by running association rule miner, a Content-Based Analysis (CBA), which is based on the Apriori algorithm (Liu et al., 1998). Any frequent itemset resulting from this is a possible feature. This study has identified an itemset as "frequent" if it emerges more than 1%, which is the minimum support of the review sentences. In this step, the Apriori algorithm identifies all the frequent set of hashtags from a collection of transactions that meet minimum support specified by the user. It means that we discover the most frequently used keywords from a frequent set of hashtags with Association rule mining (Hu and Liu, 2004).

3.3.3. Sentiment analysis

Tweets embody both information and ideas (Shen et al., 2013). Sentiment analysis, a developed text mining technique, is viewed as a key for extracting these ideas Chae, 2015. Sentiment analysis is a computational field of study that analyzes individuals' ideas, attitudes, and emotions towards an entity. The entity is a representative of individuals, occasions, or subjects (Medhat and Korashy, 2014). Methods of Sentiment analysis, Opinion mining, and Subjectivity analysis are mutually connected areas that use different approaches like Natural Language Processing (NLP), information retrieval, as well as structured and unstructured data mining (Montoyo et al., 2012; Ravi and Ravi, 2015). Most of the data collected globally remain unstructured, such as the text of the tweets. Several attempts have been made to acquire their definition to deal with the data, which tends to result in automated Sentiment analysis, an enlarged analysis area of the NLP (Ravi and Ravi, 2015). Sentiment analysis includes four different approaches: subjectivity classification, word sentiment classification, text sentiment classification, and opinion extraction. Analysis of the sentiment is divided into specific subtasks (Batrinca and Treleaven, 2015):

1- Sentiment context— To gain an opinion, it is essential to know the 'context' of the document, which vary significantly from expert review portals to general websites where views address a variety of subjects.
2- Sentiment level— Text analysis may be performed at the level of the text, the sentence, or the attribute.
3- Sentiment subjectivity—Deciding whether the text in question reflects a viewpoint or is a fact (i.e. without offering a positive/negative perception).
4- Sentiment orientation/polarity—Deciding whether a view is positive, neutral, or negative in a text.
5- Sentiment strength—Understanding the 'strength' of an idea in a text: weak, moderate, or intense.

To our paper goal, we studied the sentiment polarity using SentiStrength. SentiStrength (http://sentistrength.wlv.ac.uk/) is a Sentiment analysis program to discern the strength of sentiments communicated in online reviews (Chae, 2015; Wang and Wang, 2014). Islam & Zibran (2018) argued that there are three methods (i.e., SentiStrength, NLTK (Natural Language Toolkit) and Stanford NLP) to automatically extract feelings from textual data in the information engineering domain while the use of SentiStrength is considered dominant. The other popular Sentiment analysis tools or services are Lexalytics, SentiWordNet, Social Mention, Trackur, Sysomos, Viralheat. Sentiment analysis results rely intensely on the performance of the tool (He et al., 2018). We used SentiStrength because its Sentiment analysis algorithm is programmed for informal texts such as tweets to detect sentiments of a particular tweet in the data set (Chae, 2015) and has a higher level of preciseness than typical machine learning algorithms for positive feeling strength and the same one for negative feeling strength (Thelwall et al., 2010). It seems more appropriate for tweets than the most comparable algorithm, as the text has fewer features and is checked for accuracy less extensively (Thelwall et al., 2011). The SentiStrength foundation is built from a dictionary of 2310 words of thought and expression extracted from the Linguistic Inquiry and Word Count (LIWC) system (Kappas, 2017).

3.4. Descriptive analysis

To extract the desired tweet from Twitter, which is associated with the sustainability of cell phones, we need descriptive figures, to show us the most mentioned hashtags in the whole dataset. Hashtag frequency analysis indicates the way that each one is popular (Chae, 2015). Tweets total number, hashtags total number, and the categorization of keywords into different categories, are provided by Descriptive analysis (Mishra and Singh, 2016). The suggested framework by Ghaly et al. (2016) helped classifying tweets to be extended in tweets published in other languages. There are three Social media tagging types (folksonomy, social tagging systems, and tagging user behavior patterns). Social hashtag prediction belongs to the second group to enhance the efficiency and accuracy of the system. The studies in this area is classified into three categories: 1- determining the subject from text content 2- predicting new keywords in the same topic based on the hashtags in the text that we need in this paper. 3- addressing the resources using hashtags(Ghaly et al., 2016; Li and Wu, 2010; Murfi and Obermayer, 2009).

4. Result

4.1. Twitter data

To collect tweets with sustainability-related topics from Twitter, we initially conducted our preliminary dictionary keywords, such as "supply chain"," SCM" "cellphone", "sustainability", "environment", "social", and so on next to company name hashtags. A dataset of 106,350 text posts was gathered from Twitter from August 2017 to July 2019. Table 4 shows the data set used in this study. Reviews talking about irrelevant features to sustainability are excluded (Hao and Dai, 2016). Moreover, Fig. 2 provides the dispersion of tweets and their sentiment score. The Number of tweets and their sentiment score in this period, represented by tweets "Frequency" and "Polarity".

Table 4
Twitter data set used in this case study.

Companies	Number of tweets containing the company name
Company 1	**44,250**
Company 2	**62,100**

4.2. Content analysis

4.2.1. Data pre-processing

Some sort of problematic data will affect the results of the study. Since the quality of the results obtained by data mining is dependent on the quality of the data, addressing the problem of noise data is necessary (García et al., 2016). The following steps are taken to clean the information presented in this research (Pak and Paroubek, 2010):

1 Filtering – URL links (e.g., http://example.com), Twitter user names (e.g., @Philip – with the symbol @ indicating a user name), Twitter uncommon words (such as "RT"), and emoticons are eliminated.
2 Tokenization – the text is fragmented by splitting it into spaces and punctuation marks, and a bag of words is shaped. However, we ensure that short forms like "don't," "I'll, "she'd" are known as one word.
3 Stop words elimination – the articles ("a", "an" and "the") are eliminated from the bag of words.

4.2.2. Hashtag finding

The number of 4668 hashtags were found among all the cleaning reviews. Each specific sustainability-related hashtag must be added to our dictionary for further extraction of tweets. Tweets

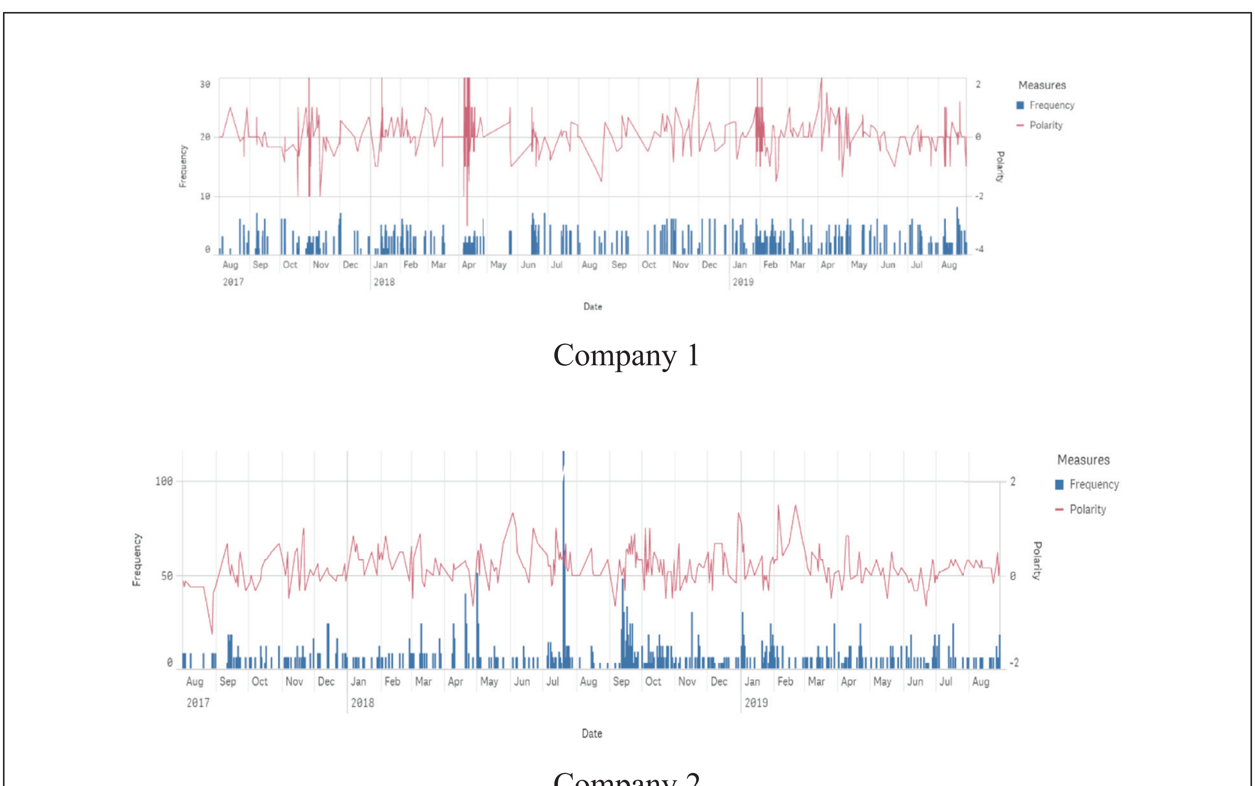

Fig. 2. The frequency and polarity of the research dataset tweets during 2017- 2019.

Table 5
keywords extracted from Content analysis.

Context	Keywords
Environmental	Packaging, PlasticPackaging, plasticfree, PlasticSolution, Energy, Renewable Energy, Clean, Energy, Solar, Electricity, waterconseravtion, Nature, Reduce, Reduce Waste, Reduce Emission, Reusability, Secondhand, Recycling, Repair, toxic, chemical, Materials, Tin, Aluminum, Paper, Cobalt, ethicalColalt, gold, steel, circuits, electronic, Battery, charger, Circulareconomy, Cracked Screen, Modular, battery, problems, case, charger, Solar, bioethanol, bamboo, solar panels, SolarPower, robot, pollution, zero waste, emission, delivery, Fashion, PlannedObsolence, Trend, Environment, Planet, Earth, Ecofriendly, Climatechange, Climate, carbon footprint, CO_2, Update, eRecycle
Economic	Technology, Application, gadget, Responsibility, cost, Training cost, quality, sustainableTech, Economy, greenEconomy, Energy cost, marketing Cost, packaging cost,labor cost,material cost, defective/returned products lost, warranty cost, EBook, RightToRepair, compliance, Unpacked, ResponsibleBusiness
Social	Children, Child labor, initiation, ethics, future, globalgoals, SDG, Education, work, workplace, workplace death, job satisfaction, ethical, postconsumer, benefit corporation, society, Employee, Job, Safety, Health, Privacy, cancer, welfare, freedom, Futurism, Social, Social Impact, Corporate Social Responsibility (CSR), Fashion, PlannedObsolence, Trend, accessibility

extracted using theses hashtags consist of some keywords, which are determined in the “keyword identification” step (Zhong et al., 2018).

4.2.3. Part-Of-Speech tagging (POS)

The POS tagging, which is important for natural language processing, is implemented to identify different pieces of a expression in a text. The Python NLTK library is applied to accomplish word segmentation and to split the text into sentences and generate the part-of-speech tag for each word (whether the word is a noun, a verb or an adjective). Regarding dispersion and extreme noise in textual data, an extreme degree of feature extraction is always needed that is one of the main pre-processing steps (Ravi and Ravi, 2015). Here is an example of this level:

(’Environmental’, ’JJ’), (’sustainability’, ’NN’), (’is’, ’VBZ’), (’a’, ’DT’), (’must’, ’MD’), (’for’, ’IN’), (’all’, ’DT’), (’and’, ’CC’), (’we’, ’PRP’), (’hope’, ’VBP’), (’competitors’, ’NNS’), (’follow’, ’VBP’), (’suit’, ’NN’), (’soon’, ’RB’), (’.’, ’.’)

4.2.4. Frequent features identification

According to the statistical results of hashtag frequency, it can be seen that mobile sustainability aspects incorporate nouns or noun phrases in review sentences. At this level, the significant keywords are identified in the reviews database to determine the frequency of the words (Zhong et al., 2018). Therefore, the Apriori algorithm was implemented in python on the transaction set of noun/noun phrases. Each subsequent frequent itemset is an inherent characteristic. Association rule mining discovers all the rules existing in the database that fulfill minimum support and minimum confidence constraint (Liu et al., 1998). So, an item set is characterized as frequent, if it is observed in more than 1% (minimum support) of the review sentences. However, some high-frequency nouns such as “phone” and company names are not directly associated with the sustainability aspects of these products and were disregarded.

4.2.5. Keywords identification

Various keywords are gathered from the frequent item set to distinguish the new keywords for including in the preliminary dictionary. Moreover, an online dictionary, WordNet was applied to discover the synonyms of the recognized keywords to incorporate them into the dictionary. For example, the synset of features such as “recycling” contains “reuse” and “reprocess” (Abirami and Gayathri, 2016). Table 5 represents the results of the keyword extraction method divided into TBL dimensions with the assistance of experts and pertinent literature, which were assumed as the cell phone sustainability aspects in this research. For future use, they can be expanded as needed.

4.3. Descriptive analysis

After analyzing all 106,350 original tweets, some retweets and replies were observed. In 6496 (6.1%) cases, retweets have appeared, while 3.5% of cases are comprised of replies. Here, the focus is on the most debated subjects by users. In this regard, 5610 different hashtags (similar to sustainability aspects) were identified through hashtags extraction. Figs. 3 and 4 demonstrate the top mentioned ones, which are more frequent than others.

As shown in Fig. 3, #Environment, #CSR, and #green are the most commonly used hashtags in Company 1 tweets and #Technology, #green, and # App is top mentioned in Company 2 tweets. Sometimes more than one hashtag appears in a tweet. In our research, over 59,000 tweets (55% of the tweets) contained more than two hashtags. Table 6 shows an example of keywords and hashtags tweeted by consumers using #CSR about Company 1. During this analysis, it was found that the most commonly used keywords or hashtags in Company 1 tweets following #CSR are “Human rights," “Child Labour,” Forced Labour,” and “Ethics”. The research focused on CSR and sustainability indicates that organizations must enhance their corporate culture so that they comprehensively respond to social and economic challenges (Schönborn et al., 2019).

CSR, Environmental and Innovation frameworks are valuable and play a vital role in developing an analytical structure within the compensation concept to assess practical organizational sustainability (Nikolaou et al., 2019). Thus, Studying the link between the cellphone’s sustainability and the top-mentioned tweet features like CSR is our future research recommendation.

4.4. Sentiment analysis

Although the number of sustainability hashtags will clarify the fields of consumer perception and degree of awareness, it can not represent the positive or negative emotional inclination of the customers. At this level, with the help of SentiStrength, we had two pieces of information on the raw Twitter data: the number of tweets for a date and their polarity varies from −5 to 5. Zero means neutral (no sentiment neither positive nor negative) and 5 means very strong negative/positive sentiment (Thelwall et al., 2010). The average of total polarity was determined by adding all

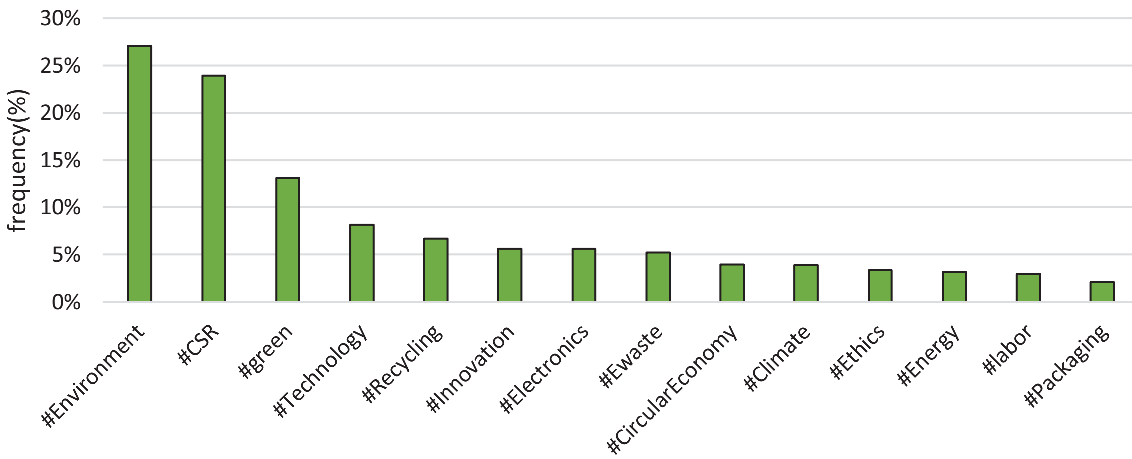

Fig. 3. Frequency of top mentioned hashtags of Company 1.

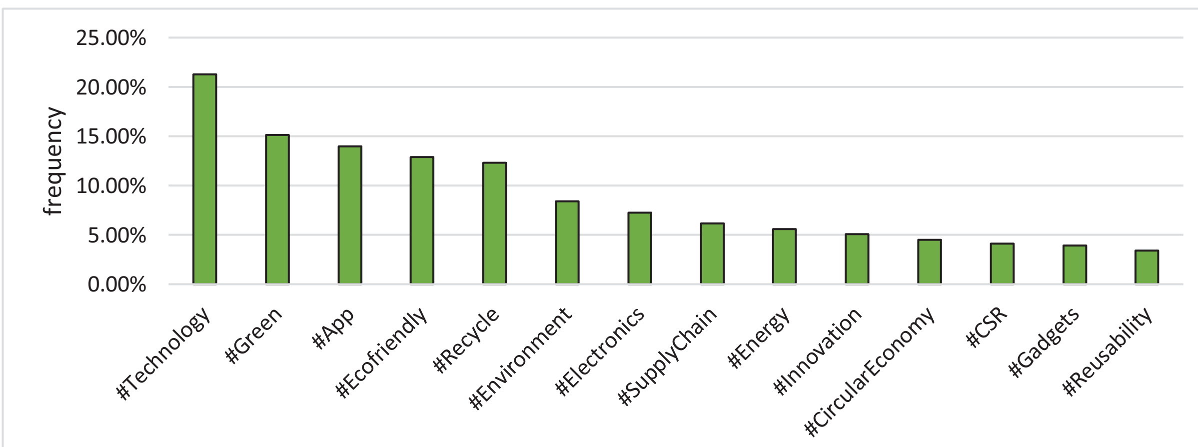

Fig.4. Frequency of top mentioned hashtags of Company 2.

Table 6
Examples of keywords and hashtags coming with #CSR in the tweets.

No.	Keywords & Hashtags
1.	*labor, suppliers, #China, #SouthKorea, #HumanRights, #CSR*
2.	*#BizHumanRights, company 1, #CSR, #SupplyChain, #ChildLabour, #TransnationalLaw, #CriminalLawhttps*
3.	*#CSR, responsiblebusiness, ethicalbusiness*
4.	*#Company 1, #ChildLabor, #HumanRights*
5.	*#Companies, #Blind, #Child, #Labor, #slavery, #corporations, #childlabor, #resources, #cobalt, # company 2, #company 1*

the total amount of polarity of the tweets in a date and thereupon averaging the overall amount ranges from (−3,0) for negative polarity and (0,3) for positive ones in this study. Fig. 5 shows the average of the polarity of entire tweets from Aug 2017 to Jul 2019, categorized regarding the company name. It seems that most tweets are neutral, as a large portion of tweets is scored 0. In general, the total polarity of Company 1 is 6%, which is the positive-neutral and total polarity of Company 2 is 21% positive.

Fig. 5 empowers us to discover a previously unknown knowledge. Also, some sudden spikes were observed on specific dates. It was pointed out that some very negative tweets of Company 1 appeared from Dec 2018 to Feb 2019. So, many of the tweets were read during this period, and some Google searches were also done. As a consequence, it appeared that the spikes resulted from Company 1 are ethical practices with "labor exploitation" and "child labor" in their factories. Table 7 shows the result of the Sentiment analysis, indicating the proportion of all the tweets classified by their polarity: positive, neutral, and negative.

Despite the total volume of the tweets and Sentiment analysis, the people's feelings about the top mentioned features could also be captured. Table 8 represents the extracted keywords with the average of positive, negative sentiment score of the tweets, containing them. In positive tweets of Company 2, the keyword "Secondhand" has score 3, which means that the average sentiment of all the tweets containing the keyword "Secondhand" is positive with the highest score, 3. This issue indicates that people had the most positive feeling when they tweeted about the "Secondhand" feature of cellphones of Company 2. On the other hand, "Human rights", "Ethics" and "CSR" are the most negative issues of company 1. Chae (2015), divided the tweets into five clusters using themes such as CSR, Risk, Logistics, Manufacturing, and IT. Tweets are posted to comment on a particular matter which can be categorized under a specific domain or topic. Ghaly et al. (2016) agreed

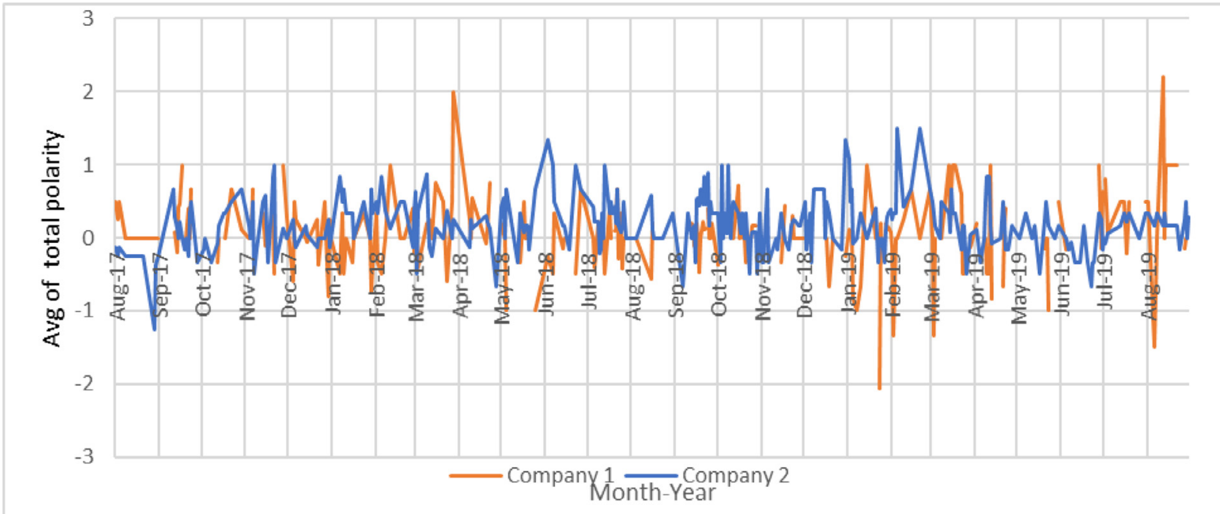

Fig. 5. The polarity of tweets during the months.

Table 7
The result of the Sentiment analysis of each company Twitter data.

TBL	company	No. of Tweets	Positive polarity	Neutral polarity	Negative polarity	Overall Sentiment
Environmental	1	52%	35%	47.8%	17.2%	Positive
	2	52.3%	22.2%	62%	15.8%	Neutral-Positive
Social	1	41.5%	13.9%	69.3%	16.8%	Neutral-Negative
	2	32%	26.7%	53.3%	10%	Positive
Economic	1	6.5%	3.1%	71.9%	25%	Negative-Neutral
	2	51.7%	49.3%	38.9%	11.8%	Positive

Table 8
The average of total sentiment score for each extracted keyword.

Company 1 extracted keywords				*Company 2 extracted keywords*			
Positive sentiment	*Score*	*Negative sentiment*	*Score*	*Positive sentiment*	*Score*	*Negative sentiment*	*Score*
Ecofriendly	2	repair	−2	*Secondhand*	3	{Carbonemissions, Carbonfootprint, Charger, Cobalt, Electronics Energyconservation, eWaste, Green}	−1
Innovation, fashion	1.5	zerowaste	−1.4	Technology	2.75	GreenEnergy	−0.5
{ProductDesign, Nature PlannedObsolence, Profit, Resources, Reusability, SDGs, SupplyChain}	1	{Children, Charger, cobalt, Culture, Education, energyefficiency Ewaste, Forcedlabour Futures, gadget Labor, lowcarbon Trends}	−1	{litter, Repurposing}	2	Children, Ethics	−0.1
Jobs	0.75	Environment	−0.66	{Innovation, Nature Phone case, PlannedObsolence}	1.5	{Environment, Fashion}	−0.14
{ClimateChange Green, Packaging Plastics, Technology}	0.66	humanrights	−0.6	recycling	1.15		
{Cleanenergy, Education, Recycling}	0.5	Ethics	−0.5	{Battery, Humanrights, Modular, Pollution Postconsumer, Reducewaste, Refurbished,Reusablity, Social,Solar, Toxic, water, zerowaste}	1		
		CSR	−0.25	{Renewableenergy, educatio	0.6		
				Jobs	0.3		
				{Circulareconomy, Ecofriendly, Labor}	0.2		

Table 9
Categorization the result into TBL dimension according to the existing literature.

Environmental	Environment	Environment-related issues (environmental resources and general environmental issues such as water, biodiversity conservation pollution (Mokhtar et al., 2016) (Hourneaux Jr et al., 2018); Water resources, pollution()(Park and Kremer, 2017);
	Material	Materials use for electronic product manufacturing and electronic, waste management processes such as Nickle, Cobalt, Litter (Singh et al., 2019);
	Energy	Renewable energy sources to reduce reliance on fossil fuels (Haji Esmaeili et al., 2020), total energy consumption (Mokhtar et al., 2016);
	Waste	Resource consumption / e-waste/ waste recycling, waste, water use (Mokhtar et al., 2016);
	Carbon footprint	Chemical substances (Mokhtar et al., 2016), CO_2 and GHG emission (Liew et al., 2014);
	Chemicals	Toxic chemicals and materials (Ogunseitan and Schoenung, 2012), chemical substances (Mokhtar et al., 2016), carbon dioxide (Shamraiz and Kuan, 2019);
	Design	Eco-design, design of products for reduced consumption of material/energy, design of products for reuse, recycle, recovery of material, Design of Products to avoid or reduce use of hazardous materials environmental management system (Govindan et al., 2012)
	6R	End of Life recovery processes i.e., repair, reuse, remanufacture and refurbish (Raihanian et al., 2016)), (reducing GHG, recycling consumer products (Liew et al., 2014)), (part replacement, disassembling or cleaning the product (Ma and Kremer, 2015); Raihanian et al., 2016; Shuaib et al., 2014);Improving sustainability through effective reuse of product returns e minimizing (French, 2008);
Social	Children	Health & safety, training & education, non-discrimination of children (Hourneaux Jr et al., 2018), child labor (Nikolaou et al., 2019)
	Ethics	Ethics and integrity (Mokhtar et al., 2016), Ethical labor (Bask et al., 2013)
	Fashion	Fashion marketing trends in social media and sustainability in fashion management (Kim and Kim, 2020)
	Human rights	Human health, human toxicity (Ma and Kremer, 2015; Nikolaou et al., 2019) investment and procurement practices, non- discrimination, freedom of association and collective bargaining, child Labour, forced compulsory Labour, security practices, and indigenous rights (Santiteerakul et al., 2018)
	Jobs	Issues relating to work improvements, workers' well-being, support for changes and new sustainability-related work requirements (Mokhtar et al., 2016)
	CSR	(Reilly and Hynan, 2014a);(Grover et al., 2019)
	labor	Child labor (Nikolaou et al., 2019),Labour/employment issues: standard issues such as health and safety, education, training, industrial relations, wages, benefits, conditions of work/employment accountability, image/reputation and harassment (Santiteerakul et al., 2018)
	Culture	Corporate social sustainability culture (Schönborn et al., 2019)
	Education	Consumer educational program e.g. to solve problems of vehicle safety and air pollution, being involved with driver's education program and public transportation policy (Santiteerakul et al., 2018)
Economic	Circular economy	To keep products, components, and materials at their highest utility and value throughout the entire lifecycle, seeking to decouple the creation of value from the consumption of finite resources (Azevedo and Nunes, 2017);
	Innovation	Using compliance to induce the company and its partners to experiment with sustainable technologies, materials, and processes/ Creating monetization models that relate to services rather than products (Nidumolu et al., 2009)
	Planned obsolescence	Limited functional life design such as death dating was standard practice for many appliances, Design for limited repair, Design aesthetics that lead to reduced satisfaction. esthetic characteristics can influence premature disposal e.g. design of "faultless forms and surfaces" on products like small appliances which leave a pristine and polished appearance which, with everyday quickly becomes damaged, engendering user dissatisfaction and premature disposal(Wilhelm, 2012), high cost of repair and planned obsolescence program (Raihanian et al., 2016)
	Technology	Technology capability, Technology level (Govindan et al., 2012);
	Profit	(Golmohammadi et al., 2018; Starr and Gupta, 2017));
	Trend	Toxicity trends in e-waste(Singh et al., 2019), sustainability trends in the process (Liew et al., 2014);
	Gadget	Mobile gadget(Saif et al., 2012), electronic gadget(Luzio and Lemke, 2013);

that each tweet could be evaluated to come under more than one area, but it would have a dominant domain.

As a consequence, we reduced the final number of extracted keywords to several major categories. To ensure the validity of our categorization, we attempt to make these metrics generic based on TBL dimensions and reviewed literature so that they are adjusted for a specific product or application as needed. We also did an extensive discussion with experts from several industrial organizations. Table 9 is the result of our categorization of the sustainability issues that consumers have the highest concern about based on the existing literature in the TBL dimension.

Figs. 6, 7 and 8 depict the tweet's sentiment score based on the categories above. This presentation helps us compare TBL dimensions of both companies more efficiently and accurately.

In terms of environmental dimension, Company 1 is favored more than Company 2 when consumers debate sustainability aspects like Environment, Material, Green, Chemicals, and Carbon footprint. However, regarding other features like 6R (reusability, recycling, reduction, redesign, refurbished, repurposed), Waste categories, and Design of cellphones, Company 2 is more positive.

Most of the negative sustainability keywords of Company 1 associated with social dissatisfaction are: "Forced Labour," "Labour," and "Human rights," which are followed by hashtag #CSR in many tweets.

In terms of the economic parameters, Company 2 outperforms Company 1 except for "Profit" that is categorized in this field. It means that people feel more positive when they talk about the economic features of cellphones of Company 2 versus cellphones of Company 1.

According to the comparison, some useful insights are found:

- While Company 2 leads the tweets, including "Design", "6R" and "waste" category keywords; Company 1 surpasses in environmental sustainability-related categories such as "Material," "Chemicals", "Carbon footprint" and "Green" related issues.
- The most negatively discussed features in Company 1, including "child Labour," which may be related to human rights aspects of its policies, are due to some negative tweets of children working at Company 1 supplier.
- Company 2 is a more positively discussed brand on Twitter in terms of Economic issues such as "Planned obsolescence," "Technology," and "Gadget." We will demonstrate that social media users perceived Company 1 more positively regarding their opposition against Planned obsolescence. It means that those who prefer better longevity will demand a slightly longer

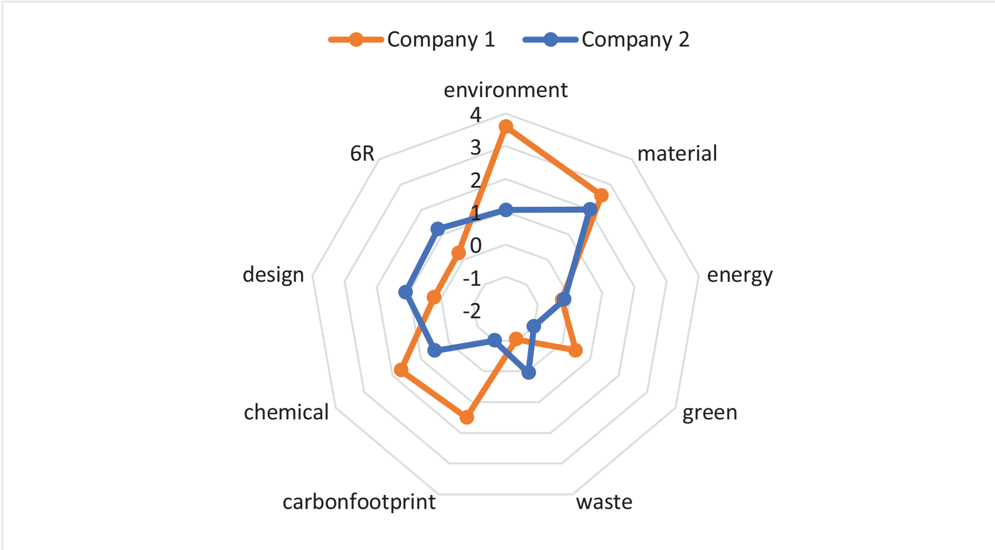

Fig. 6. The Comparison result of the Environmental dimension.

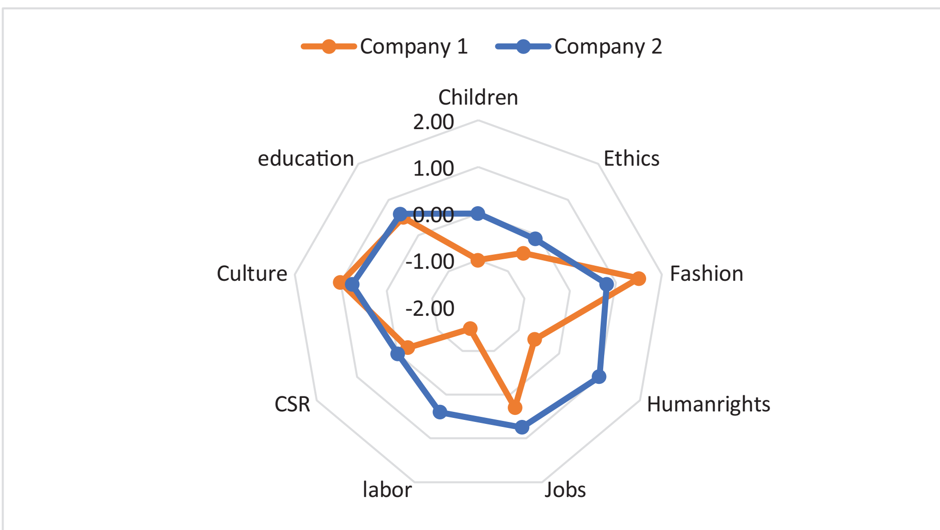

Fig. 7. The comparison result of the Social dimension.

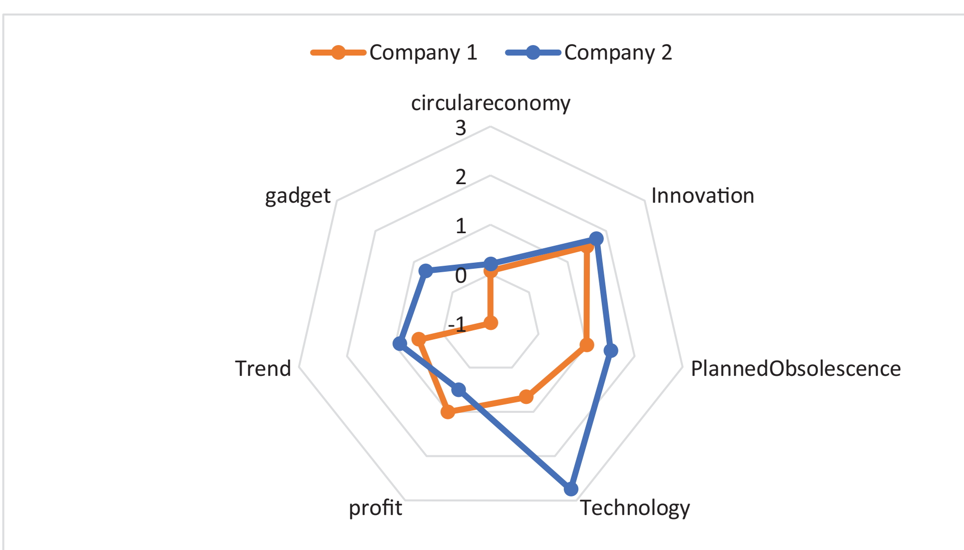

Fig. 8. The comparison result of the Economic dimension.

life span for appliances. Consumers are likely to be sceptical of manufacturers, but most agree that products subject to rapid innovation will be replaced relatively often (Cooper, 2004).

5. Discussion

5.1. Theoretical implication

This study identified cell phone sustainability aspects perceived by consumers from a social media analytic perspective as a faster and less expensive alternative to traditional survey and polling methods (Branz and Brockmann, 2018). While some of these factors have been previously investigated in other research areas which we addressed in Table 1, a few studies have been conducted on the sustainable supply chain from the consumer point of view and theoretically validated them in a UGC like Twitter. Our case study fills a gap in the literature focusing on consumers' tweets to find cellphone sustainability issues. Findings indicate their most frequently mentioned hashtags ranging from packaging and recycling to Technology, Innovation, Circular economy, CSR, and even Human rights.

Our Sentiment analysis provides metrics of consumers' perception in a sort of two pieces of information according to the raw Twitter data: the number of tweets for a date (frequency) and the average of total sentiment score of a tweet (polarity). We also identified the sentiment score of top mention keywords. There is some literature aimed to determine the weights of the supply chain sustainability issue. (Mokhtar et al., 2016) studied this that "Human right", have the most and "Safety occupational", have the least serious concern between the other social and economic sustainability issues. In this way, our study extends the previous works developing of sentiment score of cellphone sustainability aspects in their supply chain.

5.2. Practical implication

The findings are important in that they enable managers or stakeholders with interest to improve a sustainable supply chain concerning sustainability aspects and, consequently, to have a better understanding of consumers' perception of sustainability. Organizations use research methods such as surveys or focus groups on recognizing customer perceptions and opinions. However, these conventional methods cannot be applied to large samples because data gathering would be costly and time-consuming (Lipizzi et al., 2015). Although consumers reflect their views and attitudes via reviews (Lee et al., 2008), further studies are required to bridge the gap between gathering insights, which resulted from social media like Twitter and applying them in business decision making. We hope that both the case study and the proposed framework will add value to researchers and practitioners and motivate the creation of a new Social media analysis tool to determine the perception of consumers in any TBL context. Companies who want to assess their supply chain sustainability in social media can use our methodology and approach to understand the opinions of consumers not only about their sustainability concerns but also about the sustainability of their competitors, using Social media analytics.

Furthermore, companies can overcome shortcomings in their service and products by changing their strategy more quickly than they might use more traditional methods of collecting public opinion. It can be a valuable organizational advantage that can be utilized by companies to gain a competitive advantage, including strengthening marketing strategies, developing the brand, and generating loyalty. It may also help developers in the supply chain identify areas where quality needs to be increased.

From the viewpoint of better customer engagement, we recommend that companies improve customer involvement by using this paper's sustainability aspects to create different social media topics. The customers can then get deeply involved in these topics. We also suggest that Twitter may be the source for learning customer issues and that some supply chain professionals are already using Twitter for these activities. Finally, the frequency and feelings of tweets allow a researcher or business to monitor the timeline and spike line to identify strange and unexpected events relevant to the change in feelings. In future studies, the spikes can be produced in a real-time alert system. For example, it helps the customer service team to consider the dissatisfaction of customers when thereredun have been some negative comments on social media (He et al., 2018a). Study on the relationship between such temporary variations in the outcome and consumer perception is also recommended in future research. We believe that Twitter through the API provide opportunities for SCM researchers (and industry practitioners) to access not only open public data, but also "big data," which is significant in terms of scale, size and speed. Our finding suggests that the features related to environmental sustainability need more attention in company 1. Given the increasing demand for energy, climate change, and environmental problems about using fossil fuels, the demand for an alternative renewable source of energy is increasingly crucial (Esmaeili et al., 2020). It also indicates that Company 1 is recommended to enhance its sustainable development in social and economic aspects. Studying what consumers say in terms of these positive, negative issues is suggested for future research.

6. Conclusion and future research

This paper provides a case study of two popular cellphone brands in the mobile industry to show how Social media analytics help companies obtain knowledge from user-generated data. It first presented a dictionary-based framework of Twitter data to find the most common aspects consumers perceive about "Sustainability". The results show the most commonly used keywords and hashtags ranging from packaging and recycling to Technology, Innovation, Circular economy, CSR, and even Human rights. Next, Content analysis and Sentiment analysis are utilized to ensure whether consumers perceive these aspects negatively or positively. In total, 25 aspects of TBL dimension have been used to compare the two companies, which are as follows:

Environmental__Environment, Material, Energy, Green, Waste, Carbon footprint, Chemicals, Design, 6R;

Social__Children, Ethics, Fashion, Humanrights, Jobs, Labour, CSR, Culture, Education;

Economic__Circular economy, Innovation, PlannedObsolence, Technology, profit, Trend and gadget;

One of the contributions of this paper is to develop a picture of how companies benefit from social media data analytics. The methodology consists of three steps which provide a better understanding of Content analysis and Sentiment analysis of Twitter data—conducting a study on the two companies allowed us to access 106,350 tweets about the sustainability aspects within two years. Analyzing tweets and assessing the results of the surveys help us understand how people perceive the sustainability of their cell phones that address sustainability concerns to some extent.

Our approach enriches current survey data and expands traditional research analytics approaches to derive sustainability aspects from Twitter data through social media. Our proposed framework improves the availability of keywords for collecting Twitter data. Alternatively, we used Descriptive analysis and Content analysis to gather more keywords relevant to sustainability aspects from a small collection of words which is a preliminary dictionary. Our dictionary can be a perfect dataset in future research using other text mining methods, as well as other social media platforms like Facebook and Instagram.

Sentiment analysis approach allows our study to determine the weights of the supply chain sustainability issue to extend the previous works developing sentiment weights of cellphones sustainability aspects in their supply chain.

Our research had several limitations. First, we focused only on Twitter and did not examine other social media sites like Facebook. Social media posts from a diverse range of social media platforms will be used in future research. Second, we collected only English-written tweets and excluded tweets in other languages. A tweets context, consist of several attributes such as tweet text, hyperlinks, hashtags, user identifier, and location (Watson et al., 2018). Future research should expand the scope of our research into other tweet features other than "text" and "date" studied here, such as tweet "language" to extract tweets in different languages and regions. Finally, in our Sentiment analysis, we just examined the positivity and negativity sentiment score of the tweets. Since the distinction between opinion, sentiment, and emotion is somehow unclear, opinion is described as a universal definition that reflects an attitude towards an entity. The sentiment represents feeling or emotion, while emotion represents an attitude(Medhat et al., 2014). In future studies, it is recommended to review consumer attitudes toward the sustainability of cellphones from tweets data collection . The other suggestion is to study on the other supply chain themes such as green logistics, reverse logistics, closed-loop supply chain, life cycle assessment, green supplier/vendor/logistics, provider evaluation, and eco-design to enlarge our dictionary with more sustainability-related issues.

Further reading

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.spc.2020.08.012.

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