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Sustainability in the Electrical and Electronic Equipment Industry: Leveraging Twitter Data Analytics for Effective End-of-Life Product Management

Sara Shafahi[1] **Akbar Alemtabriz**[2] **Alireza Motameni**[3]

[1] PhD student in Information Technology Management, Faculty of Management and Accounting, Shahid Beheshti University, Corresponding Author, Email: Shafahisarah01@gmail.com.
[2] Professor of Management, Department of Industrial and Information Technology Management, Faculty of Management and Accounting, Shahid Beheshti University, Email: a-tabriz@sbu.ac.ir.
[3] Associate Professor of Management, Production and Operations Management Track, Faculty of Management and Accounting, Shahid Beheshti University, Email: a_motameni@sbu.ac.ir.

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Abstract:
In today's rapidly advancing electronics industry, the widespread use of electrical and electronic equipment has made sustainable management of end-of-life (EOL) equipment a pressing need. A global system is required to facilitate informed decision-making regarding e-waste. Manufacturers must therefore devise strategies for effectively managing products during the EOL phase. This article introduces a novel framework for managing e-waste during the EOL phase to identify the most appropriate EOL options to minimize e-waste. The proposed framework harnesses the power of Twitter as a data source, utilizing data mining techniques to extract consumer opinions on e-waste. The article also outlines the development of a Fuzzy Analytic Hierarchy Process method and a multi-objective mathematical framework, enabling efficient decision-making in EOL processes based on e-waste information obtained from Twitter data. The study's findings have the potential to assist equipment manufacturers in identifying flaws in electrical and electronic equipment by analyzing customer opinions shared on social media platforms. Furthermore, by analyzing consumer sentiment towards e-waste, manufacturers can gain a deeper understanding of customer perspectives and develop appropriate strategic plans for selecting suitable EOL processes for returned products. This study underscores the significance of social media data in addressing e-waste management challenges, showcasing the profound impact of customer opinions.

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1. Introduction

In today's world, the proper disposal of Waste Electrical and Electronic Equipment (WEEE) has become increasingly important due to the rapid population growth and the widespread use of electronic devices. WEEE encompasses all electrical and electronic equipment damaged or destroyed and holds no value for the user (Awasthi et al., 2018). The concept of reverse logistics (RL) has gained acceptance and widespread application in manufacturing industries across the globe based on environmental laws, sustainable development practices, and the recovery of valuable material resources for the secondary market. Typically, supply chain management refers to the Forward Supply Chain (FSC) and is not responsible for end-of-life (EOL) product management (Soleimani et al, 2017). Research has demonstrated that solving the issue of electronic waste requires multidisciplinary expertise from environmental, social, political, and moral sciences. Comprehending the factors that enhance management performance is essential for sustainable management (Galante & Campos, 2012; Huisman, 2012). Technical expertise alone is insufficient, as experience has shown that e-waste management failure is likely in the absence of cooperation among stakeholders representing a combination of social, ethical, political, and technical perspectives (Nelson et al., 2021). waste management companies adopt strategic policies to improve their efforts by fostering relationships among various stakeholders (Frempong et al., 2020). Achieving sustainability necessitates reassessing existing production, consumption, and waste management systems while bolstering the resilience of energy generation and production industries (Mele et al., 2011). The standardized recycling of renewable resources can contribute significantly to sustainable development and the optimization of the urban environment (Qu et al., 2013). However, measuring sustainability goals is challenging since sustainability indicators encompass economic, social, and environmental aspects, and quantifying them is complex (Bubicz et al., 2019). Consumers must be encouraged to adopt eco-friendly practices to achieve sustainable development and preserve the environment for future generations. By purchasing greener products, using and maintaining products properly, and disposing of waste appropriately, consumers can help minimize environmental impact (Jafari, Heydari, and Keramati, 2017). Proper WEEE management has become increasingly important due to the rapid growth of the electronics industry and increasing consumer demand for new electronic products (Agrawal et al, 2018). E-waste is a significant issue among the various EOL products examined in RL research. However, previous publications still need to adequately address the distinctions between RL systems for WEEE and other EOL products. In addition, electronic waste often contains hazardous materials such as lead, mercury, and cadmium, which require careful handling and disposal to prevent environmental contamination and harm to human health (Schluep, 2014). Moreover, the components of electronic products have different levels of recyclability and recovery value, which require specialized technologies and techniques for proper dismantling and processing (Baldé et al., 2017). These unique characteristics of e-waste highlight the need for specialized RL systems that consider the specificities of this waste stream.

The volume of e-waste produced is much higher compared to other end-of-life products. While only 8-9 million tons of end-of-life vehicles (ELV) are produced each year, the generation of WEEE is rapidly increasing and is expected to reach 74.7 Mt by 2030, up from 53.6 Mt in 2019 (Forti et al., 2020). Efforts in implementation, effective legislation, and consumer education are crucial in addressing the issue of electronic waste (e-waste) disposal and recycling (Tansel, 2017). An optimized reverse logistics (RL) network is necessary for the success of the e-waste recycling process. The growing global consumption trend of WEEE highlights the importance of WEEE recycling (Guo et al., 2021). With rapid advancements in technology and changing consumer lifestyles, the global consumption of electronic products and reduced useful life have significantly increased e-waste generation (Kosai et al., 2020).

Furthermore, the handling and transportation of WEEE require specialized expertise and equipment due to the presence of hazardous substances, which pose risks to human health and the environment. Effective management of WEEE requires coordination between various stakeholders, including manufacturers, governments, recyclers, and consumers. Governments must provide regulations and policies that encourage the proper handling of WEEE. In contrast, manufacturers and recyclers must invest in better infrastructure and technology to collect and recycle e-waste (Tansel, 2017). In addition, raising awareness among consumers about the importance of proper disposal and recycling of electronic products can play a crucial role in reducing the negative impact of WEEE on the environment and human health (Golev & Glen, 2017). Recycling is collecting and separating recyclable waste materials to use as raw materials for creating new products. While it is one of the most effective ways to combat waste, it can only solve some solid waste management problems in urban areas. Still, it can prevent significant materials from being sent to landfills. (Farjami et al., 2020). China and other developing nations have been increasingly focused on creating sustainable policies to manage WEEE recycling effectively (Govindan et al., 2017). In China, government intervention in the e-waste recycling market comprises regulations and subsidies. Researchers have suggested that government subsidies should be used to increase the involvement of authorized recyclers in the WEEE recycling market, which would help reduce environmental pollution and improve recycling rates (Fu et al., 2020). As WEEE poses a significant threat to the environment and human health, it is imperative to take measures for its proper treatment. Encouraging consumers to participate in this process actively is beneficial. Hence, this study aims to identify the factors influencing consumer participation in the appropriate treatment of WEEE. The increasing prevalence of social media in recent years has turned it into a valuable source of information. Social media has become essential for people's daily lives, providing a wealth of data. It lets users stay up-to-date with the latest news, regulations, and opportunities (Mintz et al., 2019). Given that the novelty of regulations can affect behaviors and their implementation, social media can encourage waste recycling and enhance stakeholder participation by effectively communicating with the public (Knickmeyer, 2020). The rise of the Internet of Things (IoT) has led to the innovative use of social media platforms for household waste management. For instance, Facebook and Instagram have been used for food waste management, while We-Chat and Weibo have been utilized for e-waste collection (Zuo et al., 2020). Despite the creative application of subscription accounts on social media platforms for waste management, there needs to be more literature on measuring social media advertising in this area (Jiang et al., 2021).

In this study, we aimed to identify the factors affecting the proper treatment of WEEE using social media data. To ensure the validity of our findings, we employed a combined approach of social media data analysis and the Fuzzy Analytic Hierarchy Process method. Among the various social media platforms, Twitter is one of the most widely used, with an average of 340 million active users and 500 million tweets per day in the first quarter of 2020 (Sun, 2022). It is also one of the fastest-growing social media platforms (Chae, 2015). Therefore, we selected Twitter as our data collection platform for this study. Therefore, this study holds significant importance for electrical and electronic equipment manufacturers seeking to adopt effective waste management practices on a global scale. The results of this study can assist manufacturers in making informed decisions regarding EOL products. The innovative ideas and contributions of this work address several critical issues, including:

- Introducing a novel method for identifying electrical and electronic equipment defects through customer feedback on Twitter data.
- Enhancing the understanding of consumer feedback through data mining in electronic waste management. This proposed research helps electrical and electronic equipment companies establish a clear decision-making framework for waste management and develop plans using social media data to minimize waste, maximize consumer satisfaction, and generate profits.
- Providing a planning framework for selecting optimal EOL management options based on sustainability dimensions, including minimizing costs and negative environmental effects, using the Fuzzy Analytic Hierarchy Process method and a multi-objective mathematical framework to reduce waste and enhance waste management system efficiency.

- Identifying and prioritizing the factors that significantly impact consumer participation in finding the most appropriate methods for the treatment of WEEE. Prioritizing these factors assists communities in minimizing the environmental damage caused by WEEE. For this purpose, a mixed method involving quantitative and qualitative approaches was employed.

This research is structured as follows: Section 2 reviews the relevant literature. Section 3 explains the research methodology. Section 4 discusses and analyzes the results. Section 5 discusses the theoretical and practical implications of the study. Finally, Section 6 provides conclusions, highlights research limitations, and suggests areas for future research.

2. Research literature

A literature review is essential to scholarly research as it allows for a comprehensive exploration and organization of a specific research area (Brocke et al., 2009). To combat the negative effects of waste, governments worldwide have established regulations governing waste management. While national governments create these laws, local municipalities usually handle waste collection, transport, disposal, and infrastructure maintenance. In many developing nations, municipalities often lack the resources and expertise needed for efficient waste management. This results in issues like poor governance, enforcement, service delays, and illegal waste disposal, causing littering and environmental pollution (Roos et al, 2023). By reviewing relevant literature, key concepts in the field can be identified, and it can provide a roadmap for developing new theories. WEEE encompasses four categories: light sources, large household appliances, refrigerators, and various electronic devices (Andersson et al., 2019). Due to its rapid increase, recycling and reuse of WEEE are essential to safeguard the environment and human health (Garrido-Hidalgo et al., 2020). Zhu et al. (2017) investigated consumers' decision-making regarding online and offline recycling channels and their consumption behavior regarding environmental protection. Their study revealed that the age of consumers plays a significant role in choosing recycling channels. The offline recycling network of WEEE consists of six components: consumers, retail stores, separation, and testing centers, remanufacturing centers, secondary markets, and processing centers. Meanwhile, the online platform recycling channels for WEEE comprise consumers, online platforms, separation and testing centers, re-production centers, secondary markets, and processing centers (Guo et al., 2021).

€a-Mella and et al in their 2015 study, examined consumers' awareness and perceptions towards mobile phone recycling and re-use. They found that although consumers were aware of the importance and existence of waste recovery systems, this awareness did not necessarily translate into recycling behavior. The authors concluded that more information and awareness campaigns were needed in Finland to encourage consumers to recycle their mobile phones, particularly retailers' take-back programs (€a-Mella et al., 2015). The Hong Kong government has considered four regulatory policies to reduce the illegal disposal of WEEE. These policies include the Base policy; Advance recycling fee (ARF) 1 policy; ARF 2 policy; Take back policy. Yang's study examines how regulatory policy changes affect product pricing, sales, and profits for retailers, illegal disposal rates of WEEE, and government investment in WEEE collection centers. The study found that the "take-back" policy is the most effective approach for regulating WEEE disposal in Hong Kong. It increases retailer sales, reduces illegal WEEE disposal rates, and attracts government investment. This policy should be prioritized over other policies such as "Advance Recycling Fee (ARF) 1 and 2" and the "Basic Policy" (Yang, 2014).

In 2018, Dias and her colleagues focused on the number and locations of e-waste recyclers in Brazil and planned the optimal recycling route for their collection (Dias et al., 2018). In a 2011 study in Sweden, Bernstad et al. explored the impact of access to waste collection centers on household willingness to separate hazardous waste and WEEE. These centers were often located on the outskirts of cities and required a car to use. The study found that the ease of access to waste collection centers significantly impacted households' willingness to separate hazardous waste and WEEE (Bernstad et al., 2011). In 2020, Knickmeyer conducted a study to support waste management practitioners and policymakers from various backgrounds in understanding and motivating household waste separation behavior. The study focused on identifying the main social factors that affect household recycling behavior and the primary drivers of motivation for urban residents to change their behavior.

The importance of social factors for the effective implementation of MSWMS (municipal solid waste management systems) is emphasized in the research. It highlights the need for targeted communication and educational programs involving the community and presenting waste sorting as a social norm (Knickmeyer, 2020). Shevchenko et al. also explored incentives to increase consumer collection rates for end-of-life electrical and electronic equipment (EoL EEE), proposing an alternative to existing consumer incentives. Their study revealed that the electronic reward card system (EBCS) as an economic incentive for the good collection of end-of-life electrical and electronic equipment has several advantages over existing incentives. This system compensates consumers for transaction costs related to the collection and satisfies the perception of EoL EEE having residual value (Shevchenko et al. 2019). However, current research on WEEE recycling has mostly focused on individual factors, such as route planning or channel selection, without considering the entire recycling network or presenting a sustainable model for WEEE recycling. The literature review highlights that various interconnected factors influence waste management systems' regulation, which determines people's recycling behavior (Corsini, Gusmerotti, and Frey, 2020). However, there needs to be more focus on the human aspect of recycling programs (Varotto & Spagnolli, 2017). Recently, research has been increasingly exploring consumers' attitudes and perceptions toward recycling services. Bhattacharjya et al. researched to evaluate the effectiveness of retailers' customer service interactions on Twitter in addressing logistics-related queries. The study aimed to identify successful and unsuccessful social media customer service strategies employed by e-retailers. The findings revealed several significant results, including the tendency of e-retailers and logistics providers to direct customers to alternative channels to address their issues, ignoring customers' implicit preference for using Twitter for query resolution. Moreover, there needs to be more collaboration between e-retailers and logistics providers on Twitter to assist customers in resolving queries resulting in ineffective customer service (Bhattacharjya, Tripathi, and Ellison, 2016).

The study involved three main phases. Firstly, a thorough analysis was conducted to identify the various factors impacting consumers' participation in WEEE recycling. Next, Twitter data was collected and analyzed using descriptive and content analysis techniques. Finally, the researchers used the Fuzzy Analytic Hierarchy Process method and a multi-objective mathematical optimization problem to analyze and interpret the findings.

3. Research methodology

Consumers play a crucial role in determining the end-of-life of electrical and electronic equipment (EEE) through purchasing decisions, repair or replacement choices, and disposal practices. Hence, analyzing consumer behavior toward WEEE management is vital for effective waste management (Hennies & Stamminger, 2016; Islam et al., 2016; Sabbaghi et al., 2016). Identifying factors that influence consumers to participate in appropriate treatment programs for WEEE is crucial in selecting the optimal EOL strategy. The primary objective of this study is to propose a model that utilizes Twitter data to provide waste management recommendations for the electronic and electrical industries. The model considers repair, reuse, recycling, and disposal as EOL strategies to enhance waste management systems and policies for companies focusing on waste management. The Fuzzy Analytic Hierarchy Process method and a multi-objective mathematical approach are used to select the appropriate option based on the cost of each decision and its environmental impact. Due to the unique structure of social media data compared to traditional data, it is necessary to utilize different research techniques and methods to extract useful information from Twitter data. Gathering customer feedback from social media can provide valuable data useful for business activities and organizational decision-making. In light of the potential benefits of social media analysis, it is important to develop methods for extracting valuable information from the Twitter database. This paper proposes combining data mining methods for analyzing social media data. The research methodology consists of the following steps:

1. Collecting relevant tweets
2. Conducting a content analysis of the tweets to extract factors influencing consumers' participation in WEEE treatment schemes
3. Using the Fuzzy Analytic Hierarchy Process technique and a multi-objective mathematical method to determine the optimal EOL options for better WEEE management

The content of each stage of the research procedure is as follows:

3.1. Data collection

Twitter has 330 million active users globally who generate 500 million tweets daily, offering information for evaluating user interests and exploring current trends. Analyzing social media data requires addressing three primary concerns: data capturing, storage, and analysis. Given the immense volume of Twitter data, hashtags and keywords capture data in the desired domains. Python programming language libraries, utilizing Application Programming Interface (API), enable access to public tweets. The search API captures tweets from the past based on various criteria, such as keywords, hashtags, senders, and location. The data obtained from Twitter API are in JavaScript Object Notation (.JSON). Our study collected online reviews in English as big data without geographic limitations. Furthermore, we applied criteria for Twitter account selection, examining tweets from accounts with at least an average of 100 tweets, retweets, or replies annually (a minimum of one tweet a week from the account's inception).

3.2. Content analysis

To extract information from the unstructured data of social media, content analysis is required, which involves utilizing natural language processing (NLP) and text mining techniques. The content analysis aims to infer information from the text of the communication message by identifying its distinct characteristics. However, due to the informal text in tweets, which typically contains a limited number of words, URLs, hashtags, and other data, the obtained data must be carefully cleaned and processed (Chae, 2015). Therefore, the text needs to be coded or segmented into manageable code segments to gain insights from unstructured data using content analysis.

3.2.1. Pre-processing

Pre-processing is an essential step in analyzing Twitter data. It involves removing unnecessary elements (such as emojis and stop words) and extracting relevant information (such as URLs, hashtags, and retweet counts) to obtain valuable insights. By cleaning and organizing the data, pre-processing prepares it for further analysis. The first step is filtering out non-English tweets, cleaning the text by removing numbers and punctuation, and converting it to lowercase. The text is then tokenized into individual words, and stop words are removed and steamed. Parts of speech (POS) tagging, feature extraction, and representation are performed before storing the output in a CSV file (Radi & Shokouhyar, 2021).

3.2.2. Word and Hashtag analysis

In social media data analysis, word analysis is a crucial step that employs various techniques, including document summarization, term frequency analysis, and word clustering (Mishra & Singh, 2018). Term frequency analysis is commonly utilized to identify word clusters and detect text data, aiding in identifying key phrases and topics discussed in tweets. Hashtags are crucial in Twitter postings as they categorize tweets, and hashtag analysis can uncover frequent hashtags and association rule mining (Chae, 2015). This study extracted tweets that contained hashtags like #weee and #ewaste from the Twitter data.

3.2.3 Sentiment analysis

Sentiment analysis is a crucial text mining technique used to automate the classification of opinions, emotions, and tendencies in tweet content. It involves various approaches, such as natural language processing (NLP), data mining, and information retrieval. This technique enables the identification of positive and negative opinions and the measurement of sentiments towards different entities such as individuals, organizations, events, places, products, and topics. Sentiment analysis is a valuable tool for microblogging companies to understand customers' opinions about their products, services, brand, and reputation. Machine learning techniques and human sentiment analysis are used to accurately obtain practical conclusions about human behavior and understanding of human writings (Symeonidis et al., 2018). Social media platforms, including Twitter, offer customers a platform to express their opinions and dissatisfaction with stores, which they may need to do through other means. Dissatisfied customers often mention the company name in their complaints, which attracts the attention of other users and creates an ideal environment to assess company performance. Consequently, major product issues can be identified through customer tweets. Sentiment analysis techniques can be used to understand the features of a product that cause customer dissatisfaction and to identify product defects. This study aims to create a feedback system by analyzing sentiments of electronic equipment, providing valuable information about consumer opinions on electrical waste issues. Therefore, sentiment analysis was conducted to investigate the sentiments of tweets concerning electronic waste. This study aimed to analyze tweets related to WEEE, specifically focusing on negative sentiments commonly associated with consumer complaints and concerns about e-waste. A supervised machine learning model called SVM was used to achieve this, which employs classification algorithms for binary classification problems. The SVM model was trained on labeled datasets for each category, allowing for the classification of new text as either positive or negative sentiment. The next section will present an optimization framework to determine the best decision based on this sentiment analysis.

3.3. Descriptive analysis

3.3.1. Problem statement

In the realm of Twitter data, a vast amount of information exists on tweets and user profiles. The descriptive analysis seeks to provide a quantitative summary of the data, including measures such as tweet counts, tweet types, and hashtag frequencies. This approach distills the data's key features (Mishra & Sukla, 2018). This study has analyzed hashtags, user ages, and locations to gain a deeper understanding of the issue.

3.3.2. Research Hypotheses

The proposed framework and aim of this research give rise to the following hypotheses:

- Prioritization of the factors affecting consumers' participation in suitable WEEE treatment programs is required to select the best solution. This framework applies to waste management companies that make decisions regarding the EOL phase to reduce electronic waste.
- The proposed framework considers four optimal and suitable EOL strategies for electrical and electronic equipment which minimize cost and environmental impact: reuse, remanufacturing, recycling, and disposal.
- Researchers consider six factors as influential in selecting suitable and optimal EOL strategies for electrical and electronic equipment:

1. Accessibility and ease (to waste recycling centers).
2. Raising consciousness and Awareness (of appropriate treatments for recycling electrical equipment).
3. Lack of confidence (of governments for properly implementing recycling programs).
4. Financial incentives (to participate in suitable treatment programs for electrical equipment recycling).
5. Charitable donations (donation of second-hand electrical equipment to deprived areas and individuals).
6. Concerns around data disclosure (concerns about disclosing information contained in electronic devices such as laptops and phones).

This research identifies which factor has a greater impact on which EOL component. Therefore, decision-making on optimal EOL options becomes easier using this framework.

3-4. Optimization Model

In the modern world, the amount of e-waste or WEEE increased significantly. When products reach their end-of-life phase, manufacturers have four possible options for product recovery: reuse, remanufacturing, recycling, and disposal. Each decision has specific costs and environmental impacts, making it crucial to analyze the EOL of a product to enhance its recovery and reduce its environmental impact. A multi-objective optimization model has been proposed in this study, aimed at minimizing the total cost and environmental impact during the EOL phase (Nowakowski et al., 2017). Additionally, the study utilizes the FAHP method to identify the best EOL options for promoting WEEE recycling. The study results will be used to develop monitoring measures for selecting appropriate EOL options to reduce WEEE. This section demonstrates how the proposed model can determine the optimal EOL options during the end-of-life phase. The proposed approach for EOL decision-making comprises two stages. The first stage involves analyzing Twitter data to identify the factors influencing consumer participation in WEEE treatment programs. The second stage employs the FAHP method for EOL design to manage WEEE, using the insights gleaned from the Twitter analysis. The data collected in this study were used to select the most suitable EOL options, including reuse, remanufacturing, recycling, and disposal, to reduce waste and optimize decision-making processes in the EOL phase. SimaPro software was used as a case study to investigate the environmental impacts of laptops. SimaPro is a life cycle assessment (LCA) software that assesses the environmental impacts of electrical and electronic equipment.

This study employed the NSGA-II algorithm to address the proposed problem. The I-NSGA algorithm, a multi-objective optimization algorithm based on genetic algorithms, was utilized to obtain the corresponding Pareto set and solve optimization problems with multiple objectives. The product under consideration consisted of 20 parts, each having four possible EOL decisions. This resulted in a vast search space of 420 potential solutions that needed to be evaluated.

3-5. The Fuzzy Analytic Hierarchy Process method

To review the descriptive framework based on the defined evaluation criteria in WEEE management, the researchers utilized the Fuzzy Analytic Hierarchy Process technique to seek opinions from experts and practitioners (A de Jesus et al., 2019; Shoukohyar & Seddigh, 2020). This provided an opportunity to gather perspectives and revise the framework. The survey process was conducted in three phases with 39 prominent experts, including those who have contributed substantially to waste management through academic literature and conferences or have more than five years of practical experience in the field. However, since the Fuzzy Analytic Hierarchy Process can be time-consuming and may lead to a loss of motivation among participants, it was important to gain their interest and consent before starting the process (Hardy, 2004). Therefore, personalized emails were sent to potential candidates introducing the study's objectives, the Fuzzy Analytic Hierarchy Process procedure, the framework, and clear and explicit descriptions of the process. Therefore, the authors sent personalized emails to the potential candidates to introduce the objectives, the Fuzzy Analytic Hierarchy

Process procedure, and the framework. It is worth noting that the Fuzzy Analytic Hierarchy Process study demands the participants' time to study and evaluate the study critically. Additionally, it is a new concept to many researchers and practitioners, so a clear introduction and an explicit description of the process were provided to the potential participants.

Among the 39 candidates invited, 20 (51%) accepted the invitation to participate in the study and review the descriptive framework, demonstrating their commitment to the process. The 20 participants included 15 (75%) distinguished academics at the professorial, programming directorship, and departmental head levels and 5 (25%) practitioners at the managerial and consultancy levels. One of the participants was both a practitioner and an academic. Throughout the study, each participant possessed 5 to 25 years of experience in WEEE management or related fields through university education or professional practice. Of the participants, 7 were female, and 13 were male, and they hailed from the United States, Canada, Germany, China, Turkey, Malaysia, Iran, Australia, France, and India.

4. Results and Discussion

4.1. Case study

The EOL phase of products allows manufacturers to recover and repurpose materials through four potential alternatives: reuse, remanufacturing, recycling, and disposal. Each option has its own associated costs and environmental impacts. The current study proposes a multi-objective optimization model to minimize the total cost and environmental impact during the EOL phase. With the growing concern over the accumulation of electronic waste or WEEE in modern times, it has become crucial to evaluate a product's End-of-Life stage to improve its recovery and environmental impact (Nowakowski et al., 2017). To this end, the present study adopted the Fuzzy Analytic Hierarchy Process technique to identify the most effective EOL options for promoting WEEE recycling. The aim was to use the findings to formulate regulatory policies for selecting suitable EOL alternatives that can reduce WEEE. This section demonstrates how the proposed model can determine the most suitable EOL options in the end-of-life phase. The EOL decision-making process involves two steps. The first step involves identifying the factors influencing consumers' participation in WEEE treatment schemes. This is achieved by analyzing data from Twitter. The second step involves using the Fuzzy Analytic Hierarchy Process method to develop an EOL plan for WEEE management based on the data obtained from Twitter.

4.2. Twitter data

In order to identify the factors that affect consumers' participation in WEEE treatment schemes, we utilized Twitter as a data source. Our approach involved analyzing Twitter data to gain insights based on consumer feedback. To collect tweets related to mobile phone defects, we used Python programming language libraries and API to conduct keyword and hashtag searches, including terms such as "WEEE" and "e-waste." We collected a dataset of 2,905,579 text posts from Twitter related to WEEE treatment between May 2018 and April 2022. We only considered tweets written in English and did not impose any geographical constraints. We selected specific keywords to capture tweets relevant to our study's goal of identifying the factors influencing consumers' participation in WEEE treatment schemes. To identify suitable keywords, we interviewed various stakeholders involved in WEEE management, including suppliers, distributors, retailers, and consumers. In addition, we spoke with several consumers to understand the keywords they commonly use to express their opinions on the topic. These extensive interviews gave us insights into the factors influencing consumers' participation in WEEE treatment programs. Our research team analyzed the data collected from these interviews and identified various keywords used on Twitter for WEEE products. We prepared a comprehensive list of these keywords, as displayed in Table 1, to better explore issues related to WEEE that consumers raised on Twitter. Subsequently, we filtered the total tweets using this list of keywords.

Table 1 keywords and hashtags used for extracting consumer tweets.

Keywords and hashtags	The number of hashtags	Keywords and hashtags	The number of hashtags
#ewaste	421170	#WEEE	100394
#recycling	582325	#electronic recycling	3365
#sustainability	122023	#electronicsrecycling	1000
#circulareconomy	572265	#EPEAT	986
#techwaste	16253	#Sustainableelectronics	33654
#reducereuserecycle	1123	#Upcyclingelectronics	1542
#upcycling	223256	#Hazardouswaste	9215
. circularelectronics	2155	#ewaste day	4865
#epr	1333	#DigitalClutter	2563
#responsibleelectronics	1756	#greentechnology	1765
#ewasterecycling	26523	#Electronicwastedisposal	2356
#electronicwaste	4423	#Eco-friendlyelectronics	1986
#recycleelectronics	2365	#sustainabletech	1247
#eWasteManagement	6562	#Mobile recycling	44ñ56
gITrecycling	20i 6a5	#ewaste junk	986
#GreenIT	9326	#Cellphone recycling	m98p5
#goGreen	4ng84h	#ewaste disposal	658
#CircularElectronicsDay	e321	#EarthDay	365411

4.3. Content analysis

4.3.1. Data pre-processing

For obtaining meaningful insights from Twitter data, pre-processing is necessary as the raw data can be disorganized and complex, which could impact the accuracy of the study findings. In this research, the following steps were taken to clean the information:

1. Filtering: Elimination of Twitter user names (indicated by the symbol "@"), URL links, emotions, and Twitter-specific words (e.g., "RT").
2. Tokenization: The text is fragmented by splitting into spaces and punctuation marks, creating a bag of words. However, we ensure that shortened forms such as "don't," "I'll," and "she'd" are considered single words.
3. Stop Words Elimination: Articles such as "a," "an," and "the" are removed from the bag of words.

The following operations were performed on the tweets as part of pre-processing: lowercasing, removing user mentions, removing URLs, removing punctuation marks, removing stop words, removing redundant words, stemming, and tokenization**.**

4.3.2. Word and Hashtag analysis

The prevalent words related to challenges, issues, and obstacles regarding treating e-waste were identified as environmental knowledge, e-waste, mobile recycling, and electronic waste. The tweets were classified into six popular themes based on the dataset - Ease of access and Convenience, Awareness, Absence of trust, Economic incentives, Donation, and Data concern. Further, word analysis was conducted, and the detailed findings are presented in Appendix 1. We observed numerous hashtags in the gathered tweets, with a total count of 55681. The most commonly used hashtags were #electronicwaste, #e-waste, and #WEEE. Through analysis, we found that the most frequently used hashtags were #Awareness, #Economicincentives, and #Absenceoftrust, which were utilized in most tweets.

4.4. Descriptive analysis

Upon analyzing the original tweets, we also observed some retweets and replies. Therefore, in this phase, we focused on gaining basic insights from the data and identifying the most discussed topics by users. According to results, #WEEE, #recycling, and #e-waste were the most frequently used hashtags. These hashtags were primarily used in advertisements and announcements to increase consumers' awareness and participation in e-waste treatment activities. This indicates that there is a need for more efforts to draw consumers' attention to these issues. It is important to acknowledge that not all individuals are comfortable sharing their personal information, such as age and location, on public platforms like Twitter. However, among the most active Twitter users in WEEE and e-waste discussions, most fell in the 30-40 age range. Furthermore, Europe showed the highest level of engagement in these discussions, whereas Asia, South America, and Africa had lower levels of participation. This emphasizes the importance for experts in electronic and electrical equipment recycling in these continents to take additional actions to raise awareness among consumers, given the size of their populations.

4.5. Sentiment Analysis

Previous research has established that social media is crucial in generating positive emotions toward environmental protection (Sujata et al., 2019). This study employs sentiment analysis to determine which electrical and electronic equipment producer management aspects require improvement to ensure sustainable company performance. For conducting the sentiment analysis, tweets extracted using SVM were used, SVM is the most famous classifier method (Farjami et al., 2020). This method boasts high accuracy and the ability to identify complex patterns in data via machine learning. The SVM data mining method provides two parts of information on raw Twitter data: the number of tweets for a given date and their polarity expressed as a variable ranging from -1 to 1. The value of zero indicates neutrality, while 1 denotes the most positive emotions, and -1 the most negative emotions. SVM categorizes polarity into distinct categories using a specific set of requirements. Firstly, the data features must be chosen, labeling the training dataset with its real classes. Lastly, the optimal combination of model settings and constraints must be calculated. Unigrams and bigrams denote single-word and two-word symbols recognized from microblogs, with a length constraint on microblog posts. Sentiment analysis of the 29,055,579 collected tweets revealed that 13,453,665 were negative, 9,138,843 were positive, and 6,463,668 were neutral. Negative tweets about environmental effects often contained words associated with chemicals, carbon footprint, and electronic waste. Conversely, negative tweets regarding economic effects contained words associated with financial losses and the obsolescence of planned programs. Figure 1 shows the overall average sentiment polarity of all tweets from May 2019 to April 2022, indicating that most tweets were negative, with a score of 1 polarity.

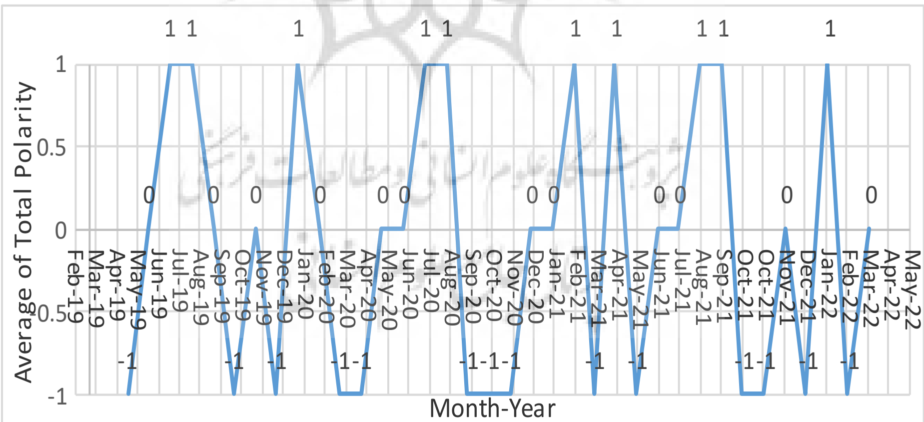

Fig. 1: Sentiment polarity of tweets over months

Table 2 presents the outcome of the sentiment analysis, which reveals the percentage of tweets classified as positive, neutral, and negative. Although sentiment analysis provided insights into people's emotions regarding the topic, it is also essential to comprehend their perceptions of the top features mentioned.

Table 2: Result of sentiment analysis of Twitter data.

Dimensions	Frequency of tweets	Positive polarity	Neutral polarity	Negative polarity	General feelings
environmental	%99	%26.5	%30.5	%33	**negative**
Economic	%11	%41.5	%31.3	%27.2	**positive-neutral**

Ghaly et al. (2016) proposed that each tweet can fall under more than one category but will have a predominant domain. Thus, we streamlined the final list of extracted keywords into several key categories. To ensure the credibility of our classification, we generalized the criteria based on the environmental and economic impact dimensions, two critical components of sustainability. We consulted relevant literature for specific products or programs. We also extensively discussed with industry experts from multiple electrical and electronic equipment manufacturing organizations. Table 3 displays the classification results of sustainability issues that consumers are most concerned about, based on available literature in the environmental and economic dimensions.

Table 3: The classification results of sustainability issues

Environmental dimension	Related phrases	Economic dimension	Related phrases
	Environment		Investment
	Sustainability		Profit
	Chemicals		Budget
	Pollution		Revenue
	carbonfootprint		Financial waste
	Eco-friendly		Circular economy
	Green		Planned
	Hazardous		obsolescence
	Material		Innovation
	E-waste		
	End-of-life (recycling- reuse- remanufacture- disposal)		

Figures 2 provides a more accurate and efficient comparison of electronic waste's environmental and economic dimensions. Consumers have negative emotions regarding materials, chemicals, pollution, carbon footprint, and hazardous and electronic waste.
Regarding economic indicators, stakeholders interested in investment, profitability, income, innovation, circular economy, and planned obsolescence tend to express positive emotions on social media. Users who prioritize product lifespan demand longer-lasting household appliances. Although consumers may be skeptical about manufacturers, many believe that products subject to rapid innovation are more likely to be replaced. Analyzing negative tweets can assist companies in comprehending customer complaints and issues with electronic and electrical products. This analysis can help identify the main reasons for product returns and provide recommendations to minimize product returns and waste, enhance customer satisfaction, and increase competitiveness.

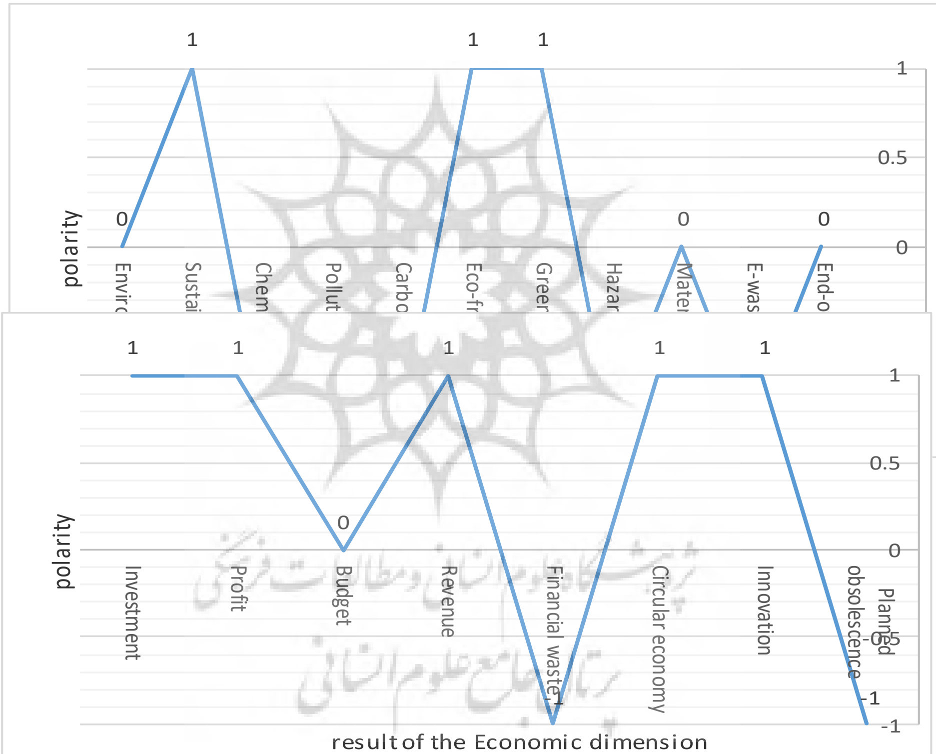

Fig 2. Result of the Environmental dimension and Economic dimension

4.6. Optimization Model

When products reach their EOL phase, manufacturers may consider four possible options for product recovery: reuse, remanufacturing, recycling, and disposal. Each decision has its costs and environmental impacts. Given the ultimate goal of this study, which is to reduce waste and optimize decision-making processes at the EOL stage, the collected data has been used to select the best EOL options: reuse, remanufacturing, recycling, and disposal. As mentioned, SimaPro is a life cycle assessment (LCA) software that can measure electronic equipment's environmental impacts. Given the breadth of the field of electronic equipment, in this study, we have selected laptops as a case study to examine their environmental impacts using SimaPro software. On average, a laptop consists of 50 components. In this study, we selected Apple laptops as the case study. One of the official representatives of Apple products' sales and after-sales services provides the cost parameters related to the economic objective function. On average, the EOL costs of some of the most important components in an Apple laptop, including the display, keyboard, hard drive, internal guard, motherboard, graphics card, and battery, were collected for two years and used as the average in the model based on US dollars. The following will examine the laptop display component as a case study. Generally, the components that make up a laptop include the LCD or OLED module, communication cables between the display panel and the motherboard, metal or plastic body for mounting the display, and protective glass on the display panel. In the appendix 2, the economic value of each EOL option for each of the display components has been examined.

This software calculates the environmental impacts of various EOL phases of each part of the laptops using the 99 indicator-Eco methods. In this regard, in the EOL stage of the product, the manufacturer selects the EOL options for each part of the product based on which function has the least environmental impact, considering the product conditions. SimaPro works based on Life Cycle Assessment (LCA) methodology and has various applications in similar research fields. LCA is a process for evaluating the environmental impacts of a product throughout its entire life cycle. LCA can be used as a decision-support tool to provide information about the environmental impacts of products. Therefore, SimaPro can be useful because it converts environmental impacts to a normalized scale and makes comparisons easier (Giudice & Fargione, 2007; Mangun & Thurston, 2002). This software can calculate the negative environmental impacts of different product parts, from the extraction and preparation of raw materials through various production processes or use phases to the end of life. SimaPro v9.0 "PhD" was used in this study to determine the number of environmental impacts. The type of material, the weight of each part of the product, and the processes required to perform each EOL option are considered input data for estimating environmental impacts using SimaPro. In the upper stages, environmental impacts are calculated in milli-points (MPT) using SimaPro software. One mil-point is 1/1000 of a point (a point (Pt) represents the annual environmental burden (i.e., all production/consumption activities in the economy) in the United States, divided by the share of one American). Mille Point results are more applicable for expressing the environmental impacts of most products. Appendix 3 summarizes the environmental impact assessment results for each EOL option of laptop display components.

4-6-1. Optimization results

This study used the NSGA-II algorithm to solve the proposed problem. The I-NSGA algorithm is a multi-objective genetic optimization algorithm used to solve optimization problems with multiple objectives. MATLAB R2019a was used on a 64-bit personal computer to implement the NSGA-II algorithm. The best method to adjust NSGA-II algorithm parameters such as crossover rate, mutation rate, population size, and other algorithm parameters is through observation and experience in the relevant field. After several initial parameter tests, crossover rate, mutation rate, and population size were identified as 0.9, 0.1, and 200, respectively, for optimizing the environmental impacts of laptops. The product is divided into 20 main parts in the design model studied. After running the optimization model for simulating the design, the initial response is considered the best. All obtained responses are optimal, and there is no superiority among them. One of the optimal responses can be selected depending on the importance that decision-makers attach to it. Appendix 4 displays the results of 20 samples showing different optimal solutions for Parto. In this table, each part's best End-of-Life options have been separately calculated based on various criteria such as costs and environmental impacts. The economic and environmental objective function should be minimized. This model aims to increase economic value and reduce negative environmental impacts. Initially, a single-objective function was used to calculate optimal results for each objective function (j*f) to solve the problem. Then, based on the obtained results, the Weighted Performance Deviation (WPD) of the objective function was calculated according to Equation 1.

$$WPD_i = \sum_{i=1}^{2} w_j \frac{|f_i^j - f_j^*|}{f_j^*}$$

In this formula, w_j represents the weight of each objective function in the i model execution. In this study, based on decision-makers' opinions, the values of 1 and 2 were assigned to j (economic value and environmental impacts). f_i^j represents the value of the objective function for solving i, and f_j^* indicates the optimal value of the jth objective function for this single-objective problem. Since the units of the objective function components in this example are different (mPt for economic impacts and US dollars for economic value), the optimal value of the objective function is divided to normalize and standardize the distance based on existing differences and uniform direction.

$w_{eco} = w_{env} = \overline{0.5}$

Based on the data obtained from the optimal solutions for Parto, a set of values for minimizing environmental impacts and maximizing economic value objectives have been calculated and presented in Figure 3. The designed model provides a suitable tool for simultaneous decision-making about the environmental impacts of the product and its associated costs. Based on the results obtained from the designed model, manufacturers of electrical and electronic equipment (in this case, laptops) can make the best decision regarding the optimal EOL options and compare the costs and environmental impacts of the EOL period with each other. In addition, 20 results obtained from Pareto solutions have been shown in Figures 4 for more detailed analysis.

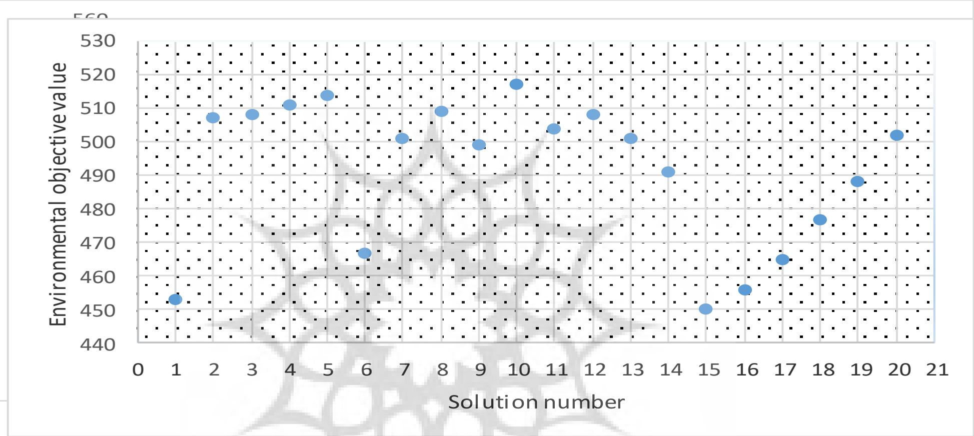

Fig. 3: results obtained from Pareto solutions

The manufacturer can choose the optimal solution for each objective function based on the importance of each function by using the definition of WPD according to their preferences. The lower the percentage of WPD, the more agreement exists among decision-makers. Based on Figure 4, the solution with the least deviation from the optimal solution can be selected. For example, solution 5 has the lowest deviation from the optimal single-objective solutions based on the weight of the objective functions. Therefore, it can be chosen as the most desirable optimal Pareto solution for the laptop display components. Based on the developed framework, decision-makers can evaluate the environmental and economic impacts based on different decisions during the EOL phase.

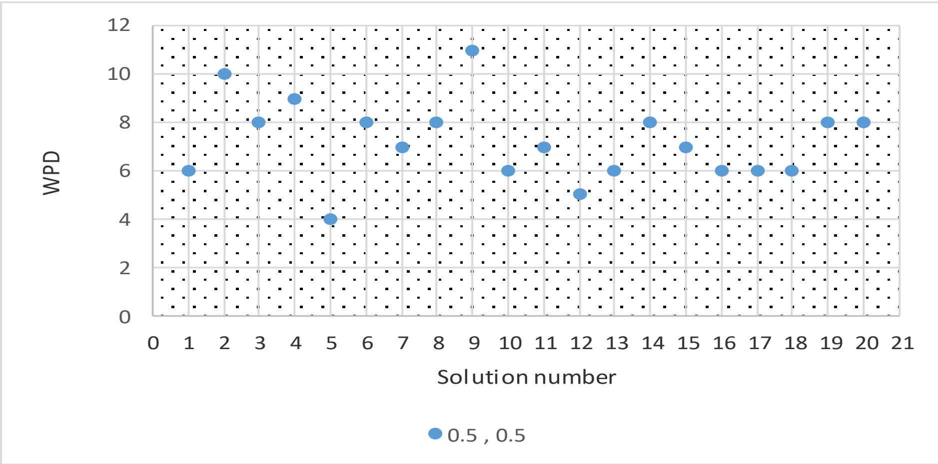

Fig. 4: Calculated WPD for all Pareto optimal solutions.

4.7. The Fuzzy Analytic Hierarchy Process method

In this phase, the findings from Twitter data are presented to panels of experts in the field of WEEE recycling using the Fuzzy Analytic Hierarchy Process method in order to determine the appropriate EOL options for WEEE in the end-of-life phase based on influential factors on consumer behavior toward the proper treatment of WEEE. The approach provided the opportunity to gather the experts' perspectives and to revise the descriptive framework. After collecting the experts' questionnaires, the indices' geometric mean was calculated pairwise. The pairwise comparison questionnaire was analyzed using the AHP method with the EXPERT CHOICE 11 software. The pairwise comparison questionnaire for the AHP method is provided in Appendix 5. The final weights obtained for the criteria are shown in the table below:

Table 4: The final weights obtained for the criteria

data concern	donation	economic motivation	absence of trust	awareness	accessibility and convenience	
0.283	0.236	0.264	0.270	0.234	0.355	**Remanufacture**
0.218	0.381	0.202	0.217	0.370	0.258	**Reuse**
0.313	0.111	0.167	0.192	0.201	0.221	**Recycle**
0.186	0.252	0.367	0.320	0.194	165.	**Disposal**

Therefore, according to the results obtained:

- The best option for EOL recovery is based on accessibility and convenience factors.
- The best option for EOL reuse is based on awareness factors.
- The best option for EOL disposal is based on the absence of trust factors.
- Based on economic motivation factors, EOL disposal is the best option.
- The best option for EOL reuse is based on donation factors.
- The best option for EOL recycling is based on data concern factors.

5. Conclusion

In today's digital world, electrical and electronic equipment has become essential to daily life. However, due to their increased usage, limited lifespan, and potential environmental hazards, proper waste management and recycling of such equipment have become critical. Research has shown that waste electrical and electronic equipment (WEEE) can significantly affect the environment and human health. Governments must support WEEE recovery efforts and urge manufacturers to recycle properly to prevent adverse effects on environmental degradation. It is also crucial to analyze the factors that influence consumer participation in recycling schemes and determine appropriate end-of-life options, as consumers are significant contributors to both the use and production of WEEE.

This article aims to assist readers in understanding consumer participation in the management of waste electrical and electronic equipment (WEEE). The study aims to identify and rank the variables that significantly impact customer engagement in determining the most effective WEEE recycling techniques. To develop the proposed model, the researchers analyzed Twitter data to extract tweets related to electrical and electronic equipment recycling using data mining. They used the Delphi technique to determine appropriate end-of-life options for WEEE, considering four strategies: reusing, remanufacturing, recycling, and disposal. Implementing these strategies can improve the management of electrical and electronic waste and reduce the damage of WEEE to the environment and human health. The research findings contribute to finding the appropriate treatment for WEEE at the EOL stage and formulating long-term strategies for better e-waste management by companies producing electrical and electronic equipment. Overall, this study can promote better management of WEEE and enhance the adoption of effective e-waste recycling techniques, leading to a more sustainable future.

Future research

After conducting a comprehensive evaluation, several research gaps were identified. The following future study directions are proposed: Despite the recent growth in research on WEEE, more efforts are needed to develop a recycling network for each electrical and electronic equipment. Therefore, further research is needed to investigate the recycling of each specific type of equipment. Moreover, in future studies, alternative approaches such as software modeling, market theory, or other exploratory techniques can be used to examine customer engagement in recycling waste electrical and electronic equipment. This study only used English-language tweets, so future research should consider tweets in other languages to broaden the scope of analysis. Furthermore, this research was limited to using Twitter as a social network. Utilizing other social media platforms, such as Facebook, Instagram, or others, is recommended to gain a more comprehensive understanding of consumer behavior in WEEE management. These future studies can help address the research gaps and improve the overall effectiveness of WEEE recycling efforts.

Compliance with Ethical Standards

This article does not contain any studies with human participants or animals performed by any of the authors.

Reference

1. Islam, M. T., & Huda, N. (2018). Reverse logistics and closed-loop supply chain of Waste Electrical and Electronic Equipment (WEEE)/E-waste: A comprehensive literature review. *Resources, Conservation and Recycling*, *137*, 48-75.
2. Brocke, J. V., Simons, A., Niehaves, B., Niehaves, B., Reimer, K., Plattfaut, R., & Cleven, A. (2009). Reconstructing the giant: On the importance of rigour in documenting the literature search process.
3. Mele, F. D., Kostin, A. M., Guillen-Gosalbez, G., & Jiménez, L. (2011). Multiobjective model for more sustainable fuel supply chains. A case study of the sugar cane industry in Argentina. *Industrial & Engineering Chemistry Research*, *50*(9), 4939-4958.
4. Soleimani, H., Govindan, K., Saghafi, H., & Jafari, H. (2017). Fuzzy multi-objective sustainable and green closed-loop supply chain network design. *Computers & industrial engineering*, *109*, 191-203.
5. Agrawal, S., Singh, R. K., & Murtaza, Q. (2018). Reverse supply chain issues in Indian electronics industry: a case study. *Journal of Remanufacturing*, *8*(3), 115-129.
6. Forti, V., Baldé, C. P., Kuehr, R., & Bel, G. (2020). The global e-waste monitor 2020. *Quantities, flows, and the circular economy potential*, 1-119.
7. Tansel, B. (2017). From electronic consumer products to e-wastes: Global outlook, waste quantities, recycling challenges. *Environment international*, *98*, 35-45.
8. Singh, A., Shukla, N., & Mishra, N. (2018). Social media data analytics to improve supply chain management in food industries. *Transportation Research Part E: Logistics and Transportation Review*, *114*, 398-415.
9. Baldé, C. P., Forti, V., Gray, V., Kuehr, R., & Stegmann, P. (2017). The global e-waste monitor 2017: Quantities, flows and resources. United Nations University, International Telecommunication Union, and International Solid Waste Association.
10. Sun, Y. (2022). Social Media and Influence Detection: A Literature Review on Twitter.
11. Chae, B. K. (2015). Insights from hashtag# supplychain and Twitter Analytics: Considering Twitter and Twitter data for supply chain practice and research. International Journal of Production Economics, 165, 247-259.
12. Jafari, A., Heydari, J., & Keramati, A. (2017). Factors affecting incentive dependency of residents to participate in e-waste recycling: a case study on adoption of e-waste reverse supply chain in Iran. *Environment, Development and Sustainability*, *19*(1), 325-338.
13. Ylä-Mella, J., Keiski, R. L., & Pongrácz, E. (2015). Electronic waste recovery in Finland: Consumers' perceptions towards recycling and re-use of mobile phones. *Waste management*, *45*, 374-384.
14. Dias, A. L. G., Freitas, J. A., Micai, B., Azevedo, R. A., Greco, L. F., & Santos, J. E. P. (2018). Effects of supplementing yeast culture to diets differing in starch content on performance and feeding behavior of dairy cows. Journal of Dairy Science, 101(1), 186-200.

15. Roos, C., Alberts, R. C., Retief, F. P., Cilliers, D. P., & Bond, A. J. (2023). Proposing principles towards responsible waste management in South African protected areas. Koedoe, 65(1), 10.
16. Mangun, D., & Thurston, D. L. (2002). Incorporating component reuse, remanufacture, and recycle into product portfolio design. IEEE transactions on engineering management, 49(4), 479-490.
17. Sujata, M., Khor, K. S., Ramayah, T., & Teoh, A. P. (2019). The role of social media on recycling behaviour. Sustainable Production and Consumption, 20, 365-374.
18. Guo, J., Tang, B., Huo, Q., Liang, C., & Gen, M. (2021). Fuzzy programming of dual recycling channels of sustainable multi-objective waste electrical and electronic equipment (WEEE) based on triple bottom line (TBL) theory. *Arabian Journal for Science and Engineering*, *46*(10), 10231-10244.
19. Bernstad, A., la Cour Jansen, J., & Aspegren, H. (2011). Property-close source separation of hazardous waste and waste electrical and electronic equipment–A Swedish case study. *Waste Management*, *31*(3), 536-543.
20. Andersson, M., Söderman, M. L., & Sandén, B. A. (2019). Challenges of recycling multiple scarce metals: The case of Swedish ELV and WEEE recycling. Resources Policy, 63, 101403.
21. Sabbaghi, M., Behdad, S., & Zhuang, J. (2016). Managing consumer behavior toward on-time return of the waste electrical and electronic equipment: A game theoretic approach. International Journal of Production Economics, 182, 545-563.
22. Knickmeyer, D. (2020). Social factors influencing household waste separation: A literature review on good practices to improve the recycling performance of urban areas. *Journal of cleaner production*, *245*, 118605.
23. Shevchenko, T., Laitala, K., & Danko, Y. (2019). Understanding consumer E-waste recycling behavior: introducing a new economic incentive to increase the collection rates. *Sustainability*, *11*(9), 2656.
24. Zhu, X., Wang, J., & Tang, J. (2017). Recycling pricing and coordination of WEEE dual-channel closed-loop supply chain considering consumers' bargaining. *International Journal of Environmental Research and Public Health*, *14*(12), 1578.
25. Garrido-Hidalgo, C., Ramirez, F. J., Olivares, T., & Roda-Sanchez, L. (2020). The adoption of internet of things in a circular supply chain framework for the recovery of WEEE: The case of lithium-ion electric vehicle battery packs. Waste Management, 103, 32-44.
26. Hardy, C. (2004). Scaling up and bearing down in discourse analysis: Questions regarding textual agencies and their context. Organization, 11(3), 415-425.
27. Bubicz, M. E., Barbosa-Póvoa, A. P. F. D., & Carvalho, A. (2019). Incorporating social aspects in sustainable supply chains: Trends and future directions. Journal of Cleaner Production, 237, 117500.

28. Corsini, F., Gusmerotti, N. M., & Frey, M. (2020). Consumer's circular behaviors in relation to the purchase, extension of life, and end of life management of electrical and electronic products: A review. *Sustainability*, *12*(24), 10443.
29. Nelson, N., Dongjie, N., Mwamlima, P., & Mwitalemi, S. Assessment of Stakeholder's Collaboration in the Management of Waste Electrical and Electronic Equipments in Dar es Salaam, Tanzania. Management, 10, 13.
30. Varotto, A., & Spagnolli, A. (2017). Psychological strategies to promote household recycling. A systematic review with meta-analysis of validated field interventions. *Journal of Environmental Psychology*, *51*, 168-188.
31. Bhattacharjya, J., Ellison, A., & Tripathi, S. (2016). An exploration of logistics-related customer service provision on Twitter: The case of e-retailers. *International Journal of Physical Distribution & Logistics Management*, *46*(6/7), 659-680.
32. Kosai, S., Kishita, Y., & Yamasue, E. (2020). Estimation of the metal flow of WEEE in Vietnam considering lifespan transition. *Resources, Conservation and Recycling*, *154*, 104621.
33. Farjami, J., Dehyouri, S., & Mohamadi, M. (2020). Evaluation of waste recycling of fruits based on Support Vector Machine (SVM). Cogent Environmental Science, 6(1), 1712146.
34. Golev, A., & Corder, G. D. (2017). Quantifying metal values in e-waste in Australia: The value chain perspective. Minerals Engineering, 107, 81-87.
35. Govindan, K., Darbari, J. D., Agarwal, V., & Jha, P. C. (2017). Fuzzy multi-objective approach for optimal selection of suppliers and transportation decisions in an eco-efficient closed loop supply chain network. *Journal of Cleaner Production*, *165*, 1598-1619.
36. Awasthi, A. K., Cucchiella, F., D'Adamo, I., Li, J., Rosa, P., Terzi, S., & Zeng, X. (2018). Modelling the correlations of e-waste quantity with economic increase. Science of the Total Environment, 613, 46-53.
37. Huisman, J. (2012). Eco-efficiency evaluation of WEEE take-back systems. In Waste electrical and electronic equipment (WEEE) handbook (pp. 93-119). Woodhead Publishing.
38. Galante, A. M. S., & Campos, L. L. (2012). Mapping radiation fields in containers for industrial γ-irradiation using polycarbonate dosimeters. Applied Radiation and Isotopes, 70(7), 1264-1266.
39. Symeonidis, S., Effrosynidis, D., & Arampatzis, A. (2018). A comparative evaluation of pre-processing techniques and their interactions for twitter sentiment analysis. Expert Systems with Applications, 110, 298-310.
40. Frempong, J., Chai, J., Ampaw, E. M., Amofah, D. O., & Ansong, K. W. (2020). The relationship among customer operant resources, online value co-creation and electronic-word-of-mouth in solid waste management marketing. Journal of Cleaner Production, 248, 119228.
41. Radi, S. A., & Shokouhyar, S. (2021). Toward consumer perception of cellphones sustainability: A social media analytics. Sustainable Production and Consumption, 25, 217-233.

42. Giudice, F., & Fargione, G. (2007). Disassembly planning of mechanical systems for service and recovery: a genetic algorithms based approach. Journal of Intelligent Manufacturing, 18(3), 313.
43. Fu, J., Zhong, J., Chen, D., & Liu, Q. (2020). Urban environmental governance, government intervention, and optimal strategies: A perspective on electronic waste management in China. Resources, Conservation and Recycling, 154, 104547.
44. Zuo, L., Wang, C., & Sun, Q. (2020). Sustaining WEEE collection business in China: The case of online to offline (O2O) development strategies. *Waste Management*, *101*, 222-230.
45. Mintz, K. K., Henn, L., Park, J., & Kurman, J. (2019). What predicts household waste management behaviors? Culture and type of behavior as moderators. Resources, Conservation and Recycling, 145, 11-18.
46. Yang, B. (2014). Modeling the effects of Hong Kong WEEE management policies on retailers, customers and the Government. INFOR: Information Systems and Operational Research, 52(2), 59-72.
47. Jiang, P., Van Fan, Y., & Klemeš, J. J. (2021). Data analytics of social media publicity to enhance household waste management. Resources, Conservation and Recycling, 164, 105146.
48. De Jesus, A., Antunes, P., Santos, R., & Mendonça, S. (2019). Eco-innovation pathways to a circular economy: Envisioning priorities through a Delphi approach. Journal of Cleaner Production, 228, 1494-1513.
49. Ghaly, R. S., Elabd, E., & Mostafa, M. A. (2016, July). Tweets classification, hashtags suggestion and tweets linking in social semantic web. In 2016 SAI Computing Conference (SAI) (pp. 1140-1146). IEEE.
50. Shoukohyar, S., & Seddigh, M. R. (2020). Uncovering the dark and bright sides of implementing collaborative forecasting throughout sustainable supply chains: An exploratory approach. *Technological Forecasting and Social Change*, *158*, 120059.
51. Schluep, M. (2014). Waste Electrical and Electronic Equipment Management. In Handbook of Recycling (pp. 397-403). Elsevier.
52. Hennies, L., & Stamminger, R. (2016). An empirical survey on the obsolescence of appliances in German households. Resources, conservation and recycling, 112, 73-82.
53. Nowakowski, P. (2017). A proposal to improve e-waste collection efficiency in urban mining: Container loading and vehicle routing problems–A case study of Poland. Waste Management, 60, 494-504.

Appendix 1 Detailed word analyses

Ease of access and Convenience	Awareness	Absence of trust	Economic incentives	Donation	Privacy and Data Concerns
limited number and remoteness of electronic recycling centers	Increasing Awareness of the value of e-wastes	Doubts consumer's to the governments regarding proper disposal of waste	Lack of fair value recycling schemes	Refurbishing recycled products	Data bearing components
electronic recycling centers	Increasing Environmental Knowledge	Consumers' negative attitudes e-waste recycling schemes regarding proper disposal of waste	proper economic incentives	Reusing recycled products	Data stays safe
	Proper recycling and disposal of dangerous electronic	Lack suitable formal collection systems	free recycling	Redistribute	Safely and securely dispose
	Recycling program	harm to human health	Cashback	Electronic recycling	Secure data destruction services
		harm to environment		New lease of life	Wipe the data
				Keeps out of landfills	
				Repurposing	

Appendix 2: Cost parameters for laptop display components (in US dollars)

EOL options				Screen parts
reuse	remanufacture	Recycle	disposal	
$00	$00	$00	$000	**LCD**
$1	$00	$8	$55	**Communication cable**
$55	$55	$..	$00	**Screen frame**
$4	$55	$00	$00	**protective glass**

Appendix 3: Environmental impacts of EOL options for key laptop components (mPt)

EOL options						
reuse	**remanufacture**	**Recycle**	**disposal**	**weight (gram)**	**Constituent elements**	**Screen parts**
12.23 mPt	17.97 mPt	23.24 mPt	57.33 mPt	400	Liquid crystal, glass, iron and aluminum metals, ABS plastic, PC plastic, PMMA plastic, PVC plastic	**LCD**
6.42 mPt	9.52 mPt	12.15 mPt	30.06 mPt	20	Polymers, metals such as copper or silver	**Communication cable**
11.72 mPt	17.85mPt	22.31 mPt	55.14 mPt	1500	Plastic, aluminum, steel, carbon fiber	**Screen frame**
9.39 mPt	13.83 mPt	17.65 mPt	43.67 mPt	50	silicon, aluminum oxide, copper oxide	**protective glass**

Appendix 4: Optimal solutions for Parto example

	EOL options					
Simulation number	Reuse	Remanufacture	recycle	Disposal	Environmental effects (mPt)	Economic effects ($)
1	4	9	2	4	333	777
2	3	6	.	9	777	333
3	3	6	1	00	888	000
4	7	3	5	5	111	999
5	8	5	1	6	444	555
6	6	7	3	4	777	333
7	2	1	9	8	111	333
8	6	2	5	7	999	222
9	3	3	4	00	999	000
00	1	4	3	22	777	111
11	3	2	8	7	444	555
22	2	2	7	9	888	222
33	1	1	7	11	111	999
44	5	2	3	00	111	222
55	7	9	1	3	000	333
66	4	5	2	9	666	999
77	1	4	4	11	555	222
88	4	3	3	00	777	333
99	7	1	6	6	888	531
00	2	5	2	11	222	333

Appendix 5: Answers of the experts to the questionnaire

Indicators (j	**Priorities**																	**Indicators (i)**
Based on Accessibility to recycling facilities factors:																		
reusing	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	remanufacturing
recycling	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	remanufacturing
disposal	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	remanufacturing
recycling	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	reusing
disposal	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	reusing
disposal	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	recycling
Based on Raising consciousness and awareness factors																		
reusing	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	remanufacturing
recycling	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	remanufacturing
disposal	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	remanufacturing
recycling	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	reusing
disposal	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	reusing
disposal	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	recycling
Based on Lack of confidence to the system factors:																		
reusing	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	remanufacturing
recycling	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	remanufacturing
disposal	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	remanufacturing
recycling	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	reusing
disposal	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	reusing
disposal	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	recycling
Based on Financial incentives factors:																		
reusing	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	remanufacturing
recycling	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	remanufacturing

disposal	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	remanufacturing
recycling	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	reusing
disposal	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	reusing
disposal	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	recycling
Based on Charitable donations factors:																		
reusing	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	remanufacturing
recycling	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	remanufacturing
disposal	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	remanufacturing
recycling	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	reusing
disposal	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	reusing
disposal	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	recycling
Based on Concerns around data disclosure factors:																		
reusing	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	remanufacturing
recycling	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	remanufacturing
disposal	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	remanufacturing
recycling	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	reusing
disposal	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	reusing
disposal	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	recycling

پایداری در صنعت تجهیزات الکترونیکی و الکترونیکی: تجزیه و تحلیل داده‌های توییتر برای مدیریت مؤثر محصولات در پایان عمر

چکیده:

در صنعت الکترونیک که به سرعت در حال پیشرفت است، استفاده گسترده از تجهیزات الکتریکی و الکترونیکی، مدیریت پایدار تجهیزات در پایان عمر (EOL) را به یک نیاز مبرم تبدیل کرده است. برای تسهیل تصمیم‌گیری آگاهانه در مورد زباله‌های الکترونیکی، به یک سیستم جهانی نیاز است. بنابراین، تولیدکنندگان باید استراتژی‌هایی برای مدیریت مؤثر محصولات در مرحله EOL طراحی کنند. این مقاله چارچوبی نوآورانه برای مدیریت زباله‌های الکترونیکی در مرحله پایان عمر معرفی می‌کند تا مناسب‌ترین گزینه‌های EOL را برای به حداقل رساندن زباله‌های الکترونیکی شناسایی کند. چارچوب پیشنهادی از قدرت توییتر به عنوان منبع داده بهره می‌برد و از تکنیک‌های داده‌کاوی برای استخراج نظرات مصرف‌کنندگان در مورد زباله‌های الکترونیکی استفاده می‌کند. این مقاله همچنین روش فرآیند تحلیل سلسله مراتبی فازی و یک چارچوب ریاضی چندهدفه را تشریح می‌کند که امکان تصمیم‌گیری کارآمد در فرآیندهای EOL را بر اساس اطلاعات زباله‌های الکترونیکی به دست آمده از داده‌های توییتر فراهم می‌کند. نتایج این مطالعه می‌تواند به تولیدکنندگان تجهیزات کمک کند تا با تحلیل نظرات مشتریان به اشتراک گذاشته شده در پلتفرم‌های رسانه‌های اجتماعی، ایرادات تجهیزات الکتریکی و الکترونیکی را شناسایی کنند. علاوه بر این، با تحلیل احساسات مصرف‌کنندگان نسبت به زباله‌های الکترونیکی، تولیدکنندگان می‌توانند درک عمیق‌تری از دیدگاه‌های مشتریان به دست آورند و برنامه‌های استراتژیک مناسب برای انتخاب فرآیندهای EOL مناسب برای محصولات برگشتی توسعه دهند. این مطالعه بر اهمیت داده‌های رسانه‌های اجتماعی در رسیدگی به چالش‌های مدیریت زباله‌های الکترونیکی تأکید می‌کند و تأثیر عمیق نظرات مشتریان را نشان می‌دهد.

کلمات کلیدی: پایان عمر (EOL)، اطلاعات زباله‌های الکترونیکی، رسانه‌های اجتماعی، تجهیزات برقی و الکترونیکی.