

TEXT MINING FOR DECISION MAKING OF REFURBISHED SMARTPHONE BASED ON AMAZON REVIEWS

Abhishek Tripathi, Motilal Nehru National Institute of Technology
Tripti Singh, Motilal Nehru National Institute of Technology
Yatish Joshi, Motilal Nehru National Institute of Technology

ABSTRACT

With the focus on the circular economy, the online purchase of remanufactured products, especially refurbished smart phones, has surged drastically over the years. With varying benefits and challenges of refurbished products, it is important to understand the consumer concerns and refurbished product preference criteria. The present paper attempts to review customer opinions to identify the salient traits of their purchasing patterns of refurbished smart phones through online E-Commerce sites. The methods employ extracting customer reviews from the Amazon website and then processing them using the computer aided programming method such as cluster analysis. It attempts to identify the factors influencing consumer purchase behavior, identify various product flaws, and split the consumer groups based on their sentiments. The findings reveal six consumer groups based on their preference for features, quality, and overall value, less cost, camera, and good battery life. Among them, budget-friendly and quality seekers account for the most significant proportion who intends to buy refurbished electronic products. The finding can assist in resolving customer issues and serve as a basis for making suitable decisions for marketing refurbished products.

Keywords: Amazon, Online Reviews, Text Mining, Product Defects.

INTRODUCTION

A circularity (CE) is a resurgence system in which emission and energy use are minimized by narrowing material and energy loops. CE focuses on the valuable application of material, the endurance of the product and its parts, and smarter product use and manufacture. Smarter product use and manufacture include reusing, refurbishing, remanufacturing, and repurposing (Potting et al., 2018). Refurbishing is putting a Li et al. (2011) product back in excellent operating order such that performance may be reduced, but that suitable functional and aesthetic conditions are obtained (Rathore et al., 2011). Over the years, there has been an increase in the production and sales of refurbished smartphones. Electronic commerce platforms have emerged as a significant channel for the sale of refurbished smartphones. According to Statista (2019), The average life span of a Smartphone worldwide in 2020 is estimated at 2.8 years Abrahams et al. (2013). The End-of-life scenario leads to electronic waste and the loss of scarce materials. Academic studies related to the longevity of smartphones have primarily focused on refurbished products. However, a prominent factor in expanding the market size of the refurbished product includes the various factors and criteria that affect consumer preference and purchase decisions. Consumer segmentation based on consumer opinions and preferences can support marketing strategies Li et al. (2020).

Customer reviews and opinions may highlight the required corrective measures for the company. Conventionally, the source of reviews includes consumer feedback, complaint, and after-sales service center feedback Guo et al. (2018). The other methods of gauging customer opinions include a questionnaire survey to carry out structured quantitative research; these methods are usually exorbitant and cumbersome (Zhou et al., 2016). With the development of new technology, consumer content has begun to rise. The number of comments on online forums has grown exponentially, which can guide a company to align their strategies based on the associated feedback. The user reviews on E-commerce platforms are an essential source of information for enterprises to analyze consumer buying patterns Guo et al. (2017a). The unstructured data comprehensively reflect user intent for a specific product (Zhan et al., 2009). In the era of big data, the natural learning process has become an efficacious tool for deciphering consumer behavior Chen & Xu (2017). The consumer has left a lot of comment/review data on various aspects of products on different e-commerce platforms. The data is unstructured yet valuable in terms of enterprise feedback and help expand the market. However, the literature lacks this alternative approach to studying consumer preference toward refurbished products (...). The present article attempted to utilize user-generated data in the form of user comments/reviews on E-Commerce platforms and used it to uncover the consumer decision-making criteria Martínez-Torres (2015).

The online reviews published on Amazon (a leading E-Commerce platform) were used as a dataset for this study. The paper uses advanced computer aided programming method to analyze consumer intention and preferences Coussement et al. (2015).

The paper is arranged in the following section; Section 2 involves a Literature review, Section 3 presents the research design, and section 4 represents analysis and results. The implication and the conclusion are present in sections 5 and 6.

LITERATURE REVIEW

Online Review

Online reviews are the information evaluated about the product attributes encrypted by a consumer on an online shopping platform through a third-party website (Mudambi and Schuff, 2010). Online reviews are now considered an important aspect (Park et al., 2014) as they express the natural feeling of the consumer on the goods after purchase. The online review offers a more comprehensive understanding of the product.

Prior research has emphasized considering online consumer reviews as essential in consumer buying decision-making. Researchers from several fields have emphasized the importance of identifying the various factors that influence why people post online reviews. Chen et al. (2011), the various characteristics of online review publishers Forman et al. (2008), The reviews' characteristics (Park et al., 2011), information attributes Liu et al. (2013) and how they impact customer attitude and intention The main concern when businesses create refurbished products is evaluating the efficacy and accuracy of internet evaluations and finding the crucial product characteristics and flaws that need to be evaluated and fixed Liu et al. (2013). The current study will begin from the standpoint of product upgrading and use topic modelling, machine learning, and other techniques to objectively and scientifically detect the product error from unstructured data and determine the elements that influence consumer purchasing.

Text Mining

Feldman first presented the idea of text mining in 1995. Text mining is a computer tool for linguistic and mathematical research. A big chunk of unstructured data is refined through information retrieval and machine learning into insightful knowledge. Forman et al. (2008) Topic modeling and sentiment analysis are two different categories of text mining.

Topic Modeling

Through the use of several themes, such as the lattice Dirichlet allocation (LDA) model, latent semantic analysis, and probabilistic latent semantic analysis (PLSA) model, topic modelling is used to extract the hidden topic from the huge body of text. The Lattice Dirichlet Allocation (LDA) model is utilized for topic model analysis within the analysis model. According to Martineaz-Torres (2015), Guo et al. (2017b), and Korfiatis et al. (2019), the LDA model has been utilized in a variety of online businesses to discover consumer preferences by hotel visitors and online reviews to assess the quality of the airline service.

Sentiment Analysis

Medhat et al. (2014) reviewed the articles and proclaimed that sentiment analysis is based on two segments: commodity reviews and online public opinions. The sentiment analysis divides the reviews into positive and negative sentiments, helping the enterprise or the seller to understand the consumer level of attachment with the product. It uses the machine learning tool to label sentiment data and trains the classifier to predict the attribute class of the unlabeled data. Machine learning is used for text sentiment analysis to identify the positive, negative and neutral sentiment and analyze the advantages and disadvantages of various methods Pang et al. (2002); Tripathi et al., 2016).

In the recent decade, there has been a preliminary analysis based on sentiment tendency and service evaluation based on consumer-based reviews. Scholars used text mining for in-depth analysis, such as product defects revealed through online reviews.

Consumer Segmentation Research

In order to better understand the characteristics of user behavior in the market and to assist sellers in creating effective marketing strategies for consumers to make purchases, consumer segmentation is a crucial component of user relationship management Raju et al. (2006). Online consumer shopping has significantly risen during the last few years.

Segmentation Bases

According to Wedel & Kamakura (2000), segmentation bases are a group of factors used to categorise consumers into various homogenous groups. They also categories the product using generic or product-specific criteria. The general class offers the fundamental data about clients, including details about their lives and demographics. Using general variables has various drawbacks, according to and Drozdenko & Drake (2002), including the inability to forecast future consumer behaviour from basic consumer data. Brand, category, psychographics, and customer purchasing power are among the characteristics that are product-specific in the second class.

Segmenting Method

A marketer-relevant quantitative study based on a survey approach is typically used for consumer segmentation, allowing businesses to target their products and consumers appropriately. According to a distinct depiction of various industries, Jang et al. (2002) segment customers using the hierarchical clustering and k-means methods. According on user behaviour, the study segments consumers using a self-organizing map fuzzy technique (Fu et al., 2017). the use of cluster analysis to a survey of quickly moving consumer items (Lin et al., 2019;Li et al., 2020) The consumer is segmented using the same research based on an evaluation of online consumer reviews.

There is a dearth of research based on text analysis of internet reviews, despite the fact that numerous studies on customer segmentation have been conducted. Additionally, current research mostly focuses on customer group segmentation, and product advocates' results are quite less, which constitutes the expansion of the companies. The paper applies the text mining method to segment consumer groups in accordance with the specification using the information from the online reviews.

RESEARCH DESIGN AND DATA ANALYSIS METHODS

Research Design

The paper used a general framework for refurbished products to evaluate consumer preference and identify the product defect and consumer segmentation. It includes the following steps: (1) Data collection: This step involves the preprocessing and filtering the dataset extracted from the amazon website, eliminating noise data, and deleting invalid reviews. The processing of the dataset involves word segmentation, vector space model, and preprocessing of the dataset. (2) Data analysis: The paper uses topic modeling and text classification to identify the product defect and classify the consumer based on interest. (3) Then, we analyze the result with future work and prospects in the last section Figure 1 is a flowchart of the paper research design.

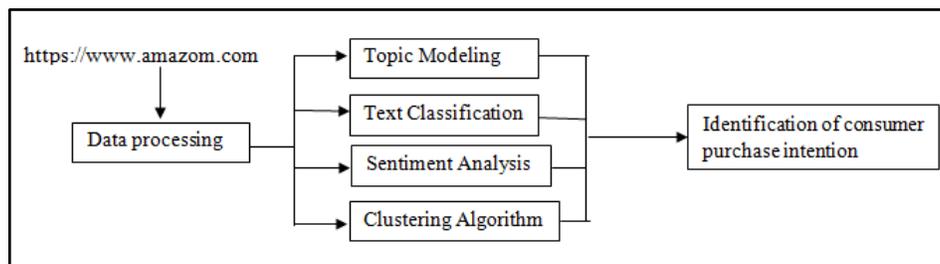


FIGURE 1
RESEARCH DESIGN FLOWCHART

DATA ANALYSIS METHOD

LDA Model

The paper uses the LDA model to analyze the topics of the online reviews of the refurbished product to identify the product preferences and the product's defects. The method used unsupervised learning, which is used to determine the hidden topic from the unstructured text. In the probability model, LDA finds the word probability of the occurrence using the Dirichlet distribution and limits the document topics Ranjan & Sood (2017).

In LDA model,

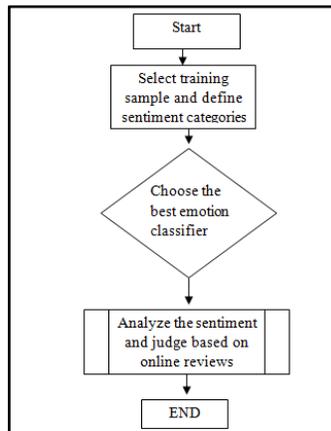
$$Dir(\theta|\alpha) = \frac{\prod(\sum_{k=1}^k ak)}{\prod_{k=1}^k ak} \prod_{k=1}^k \theta_{dk}^{ak-1}$$

Where θ_{dk} represents the distribution of document d in the topic k . An indirect inferences algorithm is needed to estimate the parameters of the LDA model, among which Gibbs sampling, EM algorithm, variational inference algorithm, and expectation proportional algorithm are used, but the Gibbs algorithm is used for the present study because of its effective nature and less computational complexity (Heinrich, 2005). The model can effectively extract hidden topics and, based on that, find large-scale text topics.

Sentiment Analysis

This paper uses the sentiment analysis approach based on machine learning to determine the consumer's sentiment and purchase intention. Sentiment analysis differentiates and classifies the positive, negative, and neutral sentiments. The sentiment analysis helps enterprises ensure the consumer's preference, which can't be done individually for unstructured text.

The flow diagram of the sentiment analysis is depicted in Figure 2



**FIGURE 2
FLOWDIAGRAM OF SENTIMENT CLASSIFIER**

This involves four steps, including selecting the training dataset and sentiment categories, which could be positive and negative, assigned as 1,0. Selection of the features, choosing the best classifier and analyzing the sentiment tendencies based on the different classifiers Monika & Jose (2017).

Text Classification

The content of the reviews involves one or more features that the consumer is concerned about and represents characteristics of consumer demand. Each online review has more than one demand. The paper deploys the approach of text classification for one or more dimensions of

consumer demand representations. Text classification is a supervised learning algorithm that uses a training set to train the high evaluation quality of the model. It includes the construction of the text classifier and representation dimension. Secondly, they must select the best classification algorithm to identify the accuracy and the roc value.

K-Mean Clustering

This is a technique to segment consumer groups based on k-point space, and the cluster is iterated until the best clustering result is obtained.

RESEARCH RESULT AND DISCUSSION

Data Collection

With the rapid development and industrialization, people's use of electronic products has increased rapidly for the ease of their life and lifestyle. Therefore the paper focuses on the reuse of the electronic product from the amazon website. The website will provide first-hand information from the consumer on various aspects of the refurbished product. The paper uses an Amazon scraper to scrape amazon reviews which contact basic user information, the product rating, and the review text Roth & Ockenfels (2002). There are 15,000 reviews extracted and filtered from the amazon website. The random selection of about 5000 reviews with a higher rating and around 1000 reviews with a lower rating can be named as product preferred group and product not preferred category Jin et al. (2016).

Analysis of the Influencing Factors of Consumer Purchase Behavior

The analysis is done through the LDA approach in r-studio, where the data is filtered and stop words are removed. The parameter used to set the model is alpha=0.1. The topic word is identified from the high probabilities at that time and divided into five topics. After analysis of the LDA topic model, the topic is aligned with five themes and subject names, as shown in Table 1. The table is divided into five categories: budget, phone features, quality supplied to the user, camera, and battery lifetime. The above topics are the consideration to decide to buy a refurbished phone. Therefore the paper argues that budget, phone features, quality supplied to the user, camera, and battery lifetime are the main factors affecting consumers to buy refurbished electronic products.

Table 1
TOPIC INFORMATION ABOUT CONSUMER'S REVIEW TEXTS ABOUT THE INFLUENCING FACTORS FOR REFURBISHED E-PRODUCT

	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
Topic Words	Good	Mobile	Camera	good	Phone
	Phone	Wifi	Quality	Phone	Product
	product	price	money	camera	camera
	working	better	value	quality	battery
	issue	5g	phone	life	heavy
	Nokia	budget	mobile	fingerprint	overall
	time	buy	nice	reader	weight
	Samsung	one	amazon	finger	bit
	charger	m12	excellent	print	price
	wifi	best	Samsung	usage	Budget
Topic Names	Phone features	Budget	Product quality	Camera usage	battery lifetime
Proportion	32%	14%	20%	19%	15%

Further from table 1, among all the influencing factors of consumer refurbished mobile phone; the phone features are the highest, reaching 32%, indicating that phone features are the most significant factor affecting consumer purchase behavior. Secondly is product quality which accounts for 20% and suggests that consumers are concerned about the quality of the product. Product quality is the second appealing factor that affects consumer behavior. The consumer prefers a camera that accounts for 19% and chooses good camera quality. The budget and battery lifetime share an equal proportion which highlights that people's concern for refurbished products on these issues is negligible; it portrays that people shift to new goods in the same budget rather than considering the option of renewed ones Lin & Chien (2010).

Identification of the Product Defects

The sentiment of the online review on the amazon website reflects whether a consumer intends to buy the refurbished product and thus distinguish and discover the positive and negative reviews of the customer. Sentiment analysis in r is performed to characterize various sentiments of the preprocessed reviews. In general, there are 6000 total reviews; among them, 5000 (83%) reviews are positive about the refurbished product, and 1000 (16%) reviews are negative about the refurbished product.

Further, we randomly selected the 100 online comments and ensured the consistency of the judgment through simultaneous annotation and mutual verification. Therefore, to identify the product defect, the LDA approach is used from r language to model the negative reviews of the refurbished product. Table 2 defines the topic names of each online review.

Table 2			
TOPIC INFORMATION ABOUT CONSUMER'S REVIEW TEXTS ABOUT THE NEGATIVE INFLUENCING FACTORS FOR REFURBISHED E-PRODUCT			
	Topic 1	Topic 2	Topic 3
Topic Words	phone	product	camera
	working	amazon	quality
	wifi	phone	bad
	network	return	buy
	properly	received	good
	call	want	phone
	issue	bad	product
	mobile	one	bad
	apps	replacement	mobile
	touch	screen	oppo
Topic Names	Network issues	Return policies	Camera quality
Proportion	32%	31%	37%

As seen in table 2, online reviews of negative reviews are divided into three broad aspects: network issues, return policies, and camera quality. The proportion of the three factors remains the same. The issues that emerged out to be wear and tear of the touch screen, the network antenna issues, and the budget could be the issues for the switchers Zheng et al. (2020).

Consumer Segmentation

To determine the demand for the refurbished product, the paper first used the LDA topic

model to obtain the online review information by the positive aspect of the review. The paper demonstrated five topics, and the number of the topic words was ten. Table 3. depict the topic names and the topic word. It is seen from the table that the topic includes budget, phone features, quality supplied to the user, camera, and battery lifetime. It is consistent with the factors of the refurbished purchase behavior Tripathy et al. (2016).

Table 3
TOPIC INFORMATION ABOUT CONSUMER'S REVIEW TEXTS ABOUT THE INFLUENCING FACTORS FOR REFURBISHED E-PRODUCT

	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
Topic Words	phone	phone	good	good	good
	mobile	Samsung	product	battery	phone
	good	price	money	camera	camera
	working	better	value	quality	battery
	issue	go	phone	life	heavy
	Nokia	budget	mobile	fingerprint	overall
	time	buy	nice	reader	weight
	Samsung	one	amazon	finger	bit
	charger	m12	excellent	print	price
	wifi	best	Samsung	usage	Budget
Topic Names	Phone features	Budget	Product quality	Camera usage	battery lifetime

The strategy encourages the use of text mining to identify the characteristic of an online review based on consumer representations, as was previously described. The study randomly chooses 1000 data for training and 200 text data sets from 5,000 online comment text data in order to pick and train data. The classification algorithm is trained using the training set, and the accuracy of the classification method is tested using the test data. In order to evaluate the efficiency of the classification algorithm with the best performance, the label for each data text was chosen depending on the ranking. The accuracy rate and rocvalue are the foundation of the classification algorithm Table 4.

Table 4
EVALUATION TABLE FOR DIFFERENT CLASSIFIERS

	Evaluation Index	Phone features	budget	Camera usage	Battery lifetime	Product quality
NB	Accuracy	0.7896	0.8044	0.7933	0.7638	0.7688
	ROC AREA	0.7864	0.8003	0.7903	0.7601	0.771
Logisitc	Accuracy	0.8413	0.8487	0.797	0.7933	0.8118
	ROC AREA	0.8421	0.8498	0.7986	0.7954	0.8126
Decision Tree	Accuracy	0.7269	0.749	0.738	0.7011	0.7601
	ROC AREA	0.7282	0.7495	0.7398	0.704	0.7607
KNN	Accuracy	0.6273	0.6236	0.594	0.6014	0.5719
	ROC AREA	0.6382	0.6349	0.606	0.6016	0.5783
SVM	Accuracy	0.8413	0.8302	0.8003	0.7749	0.8044
	ROC AREA	0.8427	0.7767	0.8034	0.7767	0.80511

Therefore the paper determines a logistic classifier to be used in three dimensions: budget, battery lifetime, quality, and (Support Vector Machine) SVM for the two dimensions, which have the camera and phone features. The accuracy and the (Receiver Operating Characteristics) ROC are shown in Table 4. Overall, the classifier performs well in the entire dimension, with an

accuracy greater than 0.7.

Using the above-mentioned classifier to perform attribute discrimination, there is a one-to-one correspondence between the discrimination and the user name. On the basis that the consumer belongs to a different group representation dimension is counted to form the distribution vectors. Based on the distribution vectors, k-mean clustering is used to segment consumers in the k consumer groups. The k=6 consumer group. Table 5 represents the consumer group based on various dimensionalities.

Dimension	Cluster0	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5
Phone Feature	2.750	0.1052	0.2560	0.7176	1.8861	0.143
Budget	0.2222	0.1105	0.03605	0.0850	0.3414	0.0282
Camera Usage	1.0833	0.3280	0.7932	0.4897	0.7967	0.0950
Battery Lifetime	1.1388	0.4122	0.5276	0.4217	0.8048	0.1097
Product Quality	0.1388	0.1403	0.0937	0.0884	0.0894	0.1937

According to the characteristics of the different groups, the six types of consumer groups are analyzed as follows:

The first type of consumer group (cluster0) accounts for 0.71% of the total number of positive reviews; the consumer group pays more attention to the attribute of the phone, which involves its appearance. The features of the refurbished electronic product account for a prominent indicator to enhance the effectiveness to purchase intention among the consumer Nasiri & Shokouhyar (2021). Therefore there should be a special mix-match of technology to promote the refurbished product.

The second type of consumer group (Cluster 1) accounts for 11% of the total positive reviews;it highlights the importance of battery lifetime and ignores the quality and the budget. Consumer financial motivation is less compared to battery lifetime Sharifi & Shokouhyar (2021).

The third type of consumer group (cluster 2) accounts for 16%,showing interest in the camera quality; they constitute the techno-friendly user and are netizens. The consumer is highly motivated to buy a product that has good camera quality and is technical friendly Sharifi & Shokouhyar (2021).

The fourth and fifth types of consumer groups (cluster 3) and (cluster4) account for 5% and 2%, which also have features of the phone as the important aspect and completely ignore the budget and the quality aspect.

The sixth type of consumer group(cluster 5) accounts for 63% of the significant proportion and recognizes the quality and the features as essential aspects. Therefore when a consumer evaluates the product, they check the physical appearance of the phone, camera quality with battery life; if they feel satisfied, they completely ignore the budget and the quality, which signifies that people are techno-friendly irrespective of the quality.

Implications

The current study has a methodological contribution as it presents a novel method to analyze consumer preference using E-Commerce websites' consumer reviews. The current study contributes to the sustainable consumption and circular economy literature and highlights the crucial criteria for purchasing refurbished smartphones. The study observes the positive transition in consumer sentiments about refurbished products and highlights the vital consideration criteria in refurbished smartphones, including battery strength and camera. Further various consumers are

price sensitive. The findings will help managers improve the product's design and efficiency.

Further, the study analyses consumers' sentiment and accordingly classify customers in various clusters highlighting the different aspect of refurbished smartphones preferred by the various customers. Managers can utilize the study findings to map consumer thinking and create appropriate initiatives to boost the circular economy. The research aims to raise customer knowledge and readiness to promote refurbished smartphones. The significance of the sentiment analysis could help motivate consumers to adopt sustainable practices. It also involves positive feedback and customer relationship to enhance the use of sustainable products. Companies can take benefit from the trend by focusing on refurbished goods.

CONCLUSION

The article is based on the users of refurbished smartphones. The key elements influencing customer intentions to purchase reconditioned goods are found using the LDA model. Based on the consumer's negative feedback, further product flaws are found. Customers were separated into five key categories based on their preferred purchasing criteria, including product features, affordability, camera usage, battery longevity, and product quality. The study offers a fresh research perspectives and aids managers in formulating plans in line with the qualities of the product. The research contains certain shortcomings that might be addressed in follow-up studies. Initially, only Amazon.com was used to collect the internet data; however, future studies may take additional E-Commerce platforms into account to strengthen their exploratory and descriptive study. Future study may be successful.

DECLARATION

Conflict of Interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

REFERENCES

- Abrahams, A.S., Jiao, J., Fan, W., Wang, G.A., & Zhang, Z. (2013). What's buzzing in the blizzard of buzz? Automotive component isolation in social media postings. *Decision Support Systems*, 55(4), 871-882.
- Chen, R., & Xu, W. (2017). The determinants of online customer ratings: a combined domain ontology and topic text analytics approach. *Electronic Commerce Research*, 17(1), 31-50.
- Chen, Y., Fay, S., & Wang, Q. (2011). The role of marketing in social media: How online consumer reviews evolve. *Journal of interactive marketing*, 25(2), 85-94.
- Coussement, K., Benoit, D.F., & Antioco, M. (2015). A Bayesian approach for incorporating expert opinions into decision support systems: A case study of online consumer-satisfaction detection. *Decision Support Systems*, 79, 24-32.
- Drozdenko, R.G., & Drake, P.D. (2002). *Optimal database marketing: Strategy, development, and data mining*. Sage.
- Forman, H., Kerr, J., Norman, G.J., Saelens, B.E., Durant, N.H., Harris, S.K., & Sallis, J.F. (2008). Reliability and validity of destination-specific barriers to walking and cycling for youth. *Preventive medicine*, 46(4), 311-316.
- Guo, J., Gao, Z., Liu, N., & Wu, Y. (2018). Recommend products with consideration of multi-category inter-purchase time and price. *Future Generation Computer Systems*, 78, 451-461.
- Guo, W., Liang, R.Y., Wang, L., & Peng, W. (2017a). Exploring sustained participation in firm-hosted communities in China: the effects of social capital and active degree. *Behaviour & Information Technology*, 36(3), 223-242.
- Guo, Y., Barnes, S.J., & Jia, Q. (2017b). Mining meaning from online ratings and reviews: Tourist satisfaction analysis using latent dirichlet allocation. *Tourism management*, 59, 467-483.
- Jin, J., Ji, P., & Gu, R. (2016). Identifying comparative customer requirements from product online reviews for

- competitor analysis. *Engineering Applications of Artificial Intelligence*, 49, 61-73.
- Korfiatis, N., Stamolampros, P., Kourouthanassis, P., & Sagiadinos, V. (2019). Measuring service quality from unstructured data: A topic modeling application on airline passengers' online reviews. *Expert Systems with Applications*, 116, 472-486.
- Li, X., Hitt, L.M., & Zhang, Z.J. (2011). Product reviews and competition in markets for repeat purchase products. *Journal of Management Information Systems*, 27(4), 9-42.
- Li, X., Liu, H., & Zhu, B. (2020). Evolutive preference analysis with online consumer ratings. *Information Sciences*, 541, 332-344.
- Lin, P.C., & Chien, L.W. (2010). The effects of gender differences on operational performance and satisfaction with car navigation systems. *International journal of human-computer studies*, 68(10), 777-787.
- Liu, Y., Jin, J., Ji, P., Harding, J.A., & Fung, R.Y. (2013). Identifying helpful online reviews: a product designer's perspective. *Computer-Aided Design*, 45(2), 180-194.
- Martínez-Torres, M.R. (2015). Content analysis of open innovation communities using latent semantic indexing. *Technology Analysis & Strategic Management*, 27(7), 859-875.
- Monika, R., & Jose, L.S. (2017). Mediating effect of word-of-mouth in movie theatre industry. *Journal of Media and Communication Studies*, 9(3), 17-23.
- Nasiri, M.S., & Shokouhyar, S. (2021). Actual consumers' response to purchase refurbished smartphones: Exploring perceived value from product reviews in online retailing. *Journal of Retailing and Consumer Services*, 62, 102652.
- Pang, B., Lee, L., & Vaithyanathan, S. (2002). Thumbs up? Sentiment classification using machine learning techniques. *arXiv preprint cs/0205070*.
- Raju, C.V.L., Narahari, Y., & Ravikumar, K. (2006). Learning dynamic prices in electronic retail markets with customer segmentation. *Annals of Operations Research*, 143(1), 59-75.
- Ranjan, S., & Sood, S. (2017). Online Word of Mouth Communication in Bollywood Tweet Dataset. *International Journal for Research in Applied Science & Engineering Technology*, 5(12), 1442-1449.
- Roth, A.E., & Ockenfels, A. (2002). Last-minute bidding and the rules for ending second-price auctions: Evidence from eBay and Amazon auctions on the Internet. *American economic review*, 92(4), 1093-1103.
- Sharifi, Z., & Shokouhyar, S. (2021). Promoting consumer's attitude toward refurbished mobile phones: A social media analytics approach. *Resources, Conservation and Recycling*, 167, 105398.
- Tripathy, A., Agrawal, A., & Rath, S.K. (2016). Classification of sentiment reviews using n-gram machine learning approach. *Expert Systems with Applications*, 57, 117-126.
- Wedel, M., & Kamakura, W.A. (2000). *Market segmentation: Conceptual and methodological foundations*. Springer Science & Business Media.
- Zheng, L., He, Z., & He, S. (2020). A novel probabilistic graphic model to detect product defects from social media data. *Decision Support Systems*, 137, 113369.

Received: 20-Sep-2022, Manuscript No. AMSJ-22-12581; **Editor assigned:** 22-Sep-2022, PreQC No. AMSJ-22-12581(PQ); **Reviewed:** 26-Oct-2022, QC No. AMSJ-22-12581; **Revised:** 03-Nov-2022, Manuscript No. AMSJ-22-12581(R); **Published:** 21-Nov-2022