

Exploring Consumer Sentiment and Key Satisfaction Factors in Refurbished Smartphones

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Abstract— The growing focus on sustainable consumption and the appeal of cost-effective technology have accelerated the refurbished smartphone market's expansion. Despite its role in reducing e-waste and extending product lifecycles, research on consumer perceptions and key product attributes influencing purchase decisions remains limited. This study addresses the gap by analyzing customer reviews from Amazon and eBay using a machine learning-based Refurbished Electronics Purchase Intention (RE-PI) model. Key product attributes such as Performance, Brand, Design, Utility, and Price emerged as major drivers of consumer satisfaction. Findings reveal a preference for high-performance and reputable brands, while dissatisfaction often stems from inadequate after-sales service. Customer reviews play a critical role in shaping market trends, demonstrating the potential of refurbished smartphones to support sustainable consumption within the circular economy.

Keywords-Cost-effective technology, Machine learning, Performance, Circular economy

I. INTRODUCTION

Over the past decade, the rise of the circular economy has captured significant attention from researchers, particularly regarding efforts to enhance sustainability [1]. This surge in interest has led to considerable debate and confusion across various sectors within scientific research and practice. In this article, we aim to clarify the complexities surrounding refurbished products within the context of the circular economy [2].

Extending this idea to electronic products introduces multiple stages, such as refurbishment, repair, redistribution, and recycling. In the circular economy model, refurbishment is essential for retaining the inherent value of products. The process involves taking previously used items and restoring them to their original functional state by repairing and replacing crucial components. These refurbished products are then made available to a new set of consumers. Specifically, smartphone refurbishment involves bringing a used device back to full working order by addressing issues such as defective screens or batteries, which may require cleaning, part replacement, or minor repairs. It also includes mending the cosmetic defects [3].

A smartphone is a portable device that combines traditional phone functions with enhanced computing abilities. It typically features a touchscreen, allowing users to interact with various applications, including web browsers, email, and social media platforms [3]. Modern smartphones come with additional features such as cameras, GPS, and multimedia functionalities. Communication

options often encompass voice calls, texting, and internet-based messaging. Refurbished smartphones are pre-owned devices that have been repaired, tested, and restored to their original working condition before being resold [4]. Unlike used or second-hand phones, refurbished phones typically undergo rigorous testing to ensure they meet specific quality standards. They may have had parts replaced, such as screens, batteries, or cameras, to improve functionality. As a result, refurbished phones offer consumers an opportunity to purchase high-quality devices at a cost much lesser than the brand-new ones, while also contributing to environmental sustainability by extending the lifespan of electronic products and reducing e-waste. Value can be regained from used products while stimulating a change towards more sustainable models of consumption aimed at reusing valuable resources and producing less waste through opportunities offered by the circular economy [2]. The growing demand for refurbished smartphones reflects broader consumer trends toward cost-effective and eco-friendly alternatives to brand-new technology.

The fast-paced advancements in the mobile phone industry led to frequent model updates, rendering devices obsolete quickly. Many phones are returned to manufacturers due to end-of-life cycles, warranty claims, or buyback programs [5]. Irresponsible consumption also results in improper disposal, with phones ending up in landfills and releasing hazardous substances like heavy metals. This underscores the need for regulations to ensure safe disposal. Additionally, extracting raw materials for smartphones involves extensive mining in unstable regions, contributing to large carbon footprints and energy use. Purchasing refurbished smartphones helps reduce e-waste and environmental harm, especially since some components are non-recyclable and recycling can be costly and energy-intensive.

Currently, the global market for refurbished smartphones is witnessing rapid expansion, with an annual growth rate of 18%, particularly driven by rising demand in regions like Southeast Asia and Africa. Leading companies like Apple and Samsung are solidifying their positions in the secondary market, with Samsung showing significant strides in closing the market gap. The refurbished smartphone market in Southeast Asia is anticipated to grow significantly, reaching an estimated \$12 billion by 2027. Similarly, the broader used electronics market is projected to expand at a compound annual growth rate (CAGR) of 17%, achieving a value of \$13 billion during this period [6]. This research involves collecting data from e-commerce platforms on

refurbished phones and analyzing it using the Chi-Square test for feature selection [7]. Additionally, a Multinomial Logistic Regression [8] model was employed to examine the relationship between selected product attributes and customer ratings, aiming to provide insights that support circular consumption.

II. LITERATURE REVIEW

A. Overview of Refurbished Smartphones Market

Refurbished smartphones have become a notable alternative to new devices, largely due to factors like affordability, sustainability, and enhanced quality control. Research indicates that the refurbished smartphone market is expanding quickly, with significant growth expected, particularly in regions such as India, Latin America, and Southeast Asia. According to IDC, the worldwide market for second-hand smartphones, including certified refurbished and pre-owned devices, saw shipments reaching 225.4 million units in 2020, reflecting a 9.2% growth from 206.5 million units in 2019. Moreover, IDC forecasts that by 2024, shipments of used smartphones will increase to 351.6 million units, with an anticipated compound annual growth rate (CAGR) of 11.2% between 2019 and 2024 [9].

Refurbished smartphones are carefully inspected, repaired, and certified to ensure functionality. Many consumers are drawn to them for their lower prices, offering premium features at affordable rates. This trend supports sustainable consumption and the global move toward a circular economy [10].

B. Consumer Preferences and Motivations

Several factors influence the decision to buy refurbished smartphones. Studies show that consumers prioritize affordability, environmental impact, and brand reliability [11]. Consumer behavior theories like the Technology Acceptance Model (TAM) and Expectation-Confirmation Theory (ECT) help explain satisfaction with refurbished devices. TAM highlights the importance of perceived usefulness and ease of use, while ECT suggests satisfaction occurs when post-purchase experiences meet or surpass expectations [12].

Research also underscores Generation Z's role in boosting demand for refurbished smartphones [13]. Gen Z, known for their strong environmental awareness, tends to favour refurbished products because they align with sustainable consumption habits. Furthermore, studies highlight growing trust in online platforms that specialize in selling refurbished smartphones, such as Amazon Renewed, Back Market, and eBay, which offer warranties and certified quality assurances.

C. Importance of Customer Reviews and Ratings

Customer reviews and ratings are essential for assessing the performance and quality of refurbished smartphones [14]. They offer valuable insights into user experiences, presenting a rich source of unstructured data that captures both the positive and negative features of products. The expansion of e-commerce platforms, propelled by rapid digitalization, is transforming the customer experience overall. In an era where consumer confidence is crucial,

surveys indicate that 95% of shoppers read online reviews prior to making a purchase, and 58% are willing to pay a premium for products from brands with positive reviews [15].

Reviews often address key factors like battery life, design, camera quality, and overall performance, which are essential attributes for refurbished smartphones. Studies on sentiment analysis of reviews have shown that customer satisfaction is significantly impacted by the product's condition, pricing, and after-sales services [16]. However, customer reviews can be biased, making it challenging to differentiate between genuine and manipulated feedback.

D. Product Attributes in Refurbished Smartphones

Refurbished smartphones are assessed based on various attributes, such as technical performance, physical condition, and value for money. Research examining product attributes has identified the following factors as crucial in shaping consumer decisions:

- Technical Performance: Consumers prioritize battery life, camera quality, processing speed, and software updates. Research indicates that while refurbished smartphones may fall slightly short of new devices in these areas, advancements in refurbishment processes have resulted in improved technical consistency [12].
- Physical Condition: The aesthetic condition of the phone, including scratches and screen quality, is frequently discussed in reviews. Studies reveal that even minor cosmetic flaws can have a considerable effect on customer satisfaction [17].
- After-Sales Service: Warranty periods, customer support, and return policies are crucial factors that influence reviews. A study found that products with longer warranties and more flexible return policies generally receive higher customer satisfaction ratings [18].

III. METHODOLOGY

The proposed framework is structured into four distinct phases, each contributing to the identification of optimal features to assess the performance of refurbished smartphones in terms of their success or failure. The four phases include Data collection, Data Pre-processing with word cloud and sentiment analysis, Chi-square-based Feature selection coupled with Multinomial logistic regression. An overview of the methodological process is illustrated in figure 1.

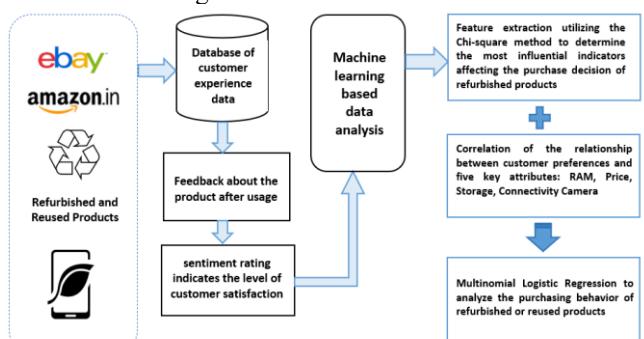


Fig.1 Work Flow diagram for the proposed Approach

A. Data collection

For the analysis of customer opinions and sentiments toward remanufactured mobile phones in the USA and India, data were collected from eBay [19] and Amazon [20]. These are widely recognized in these markets and offers a significant sample of customer reviews on refurbished products. Both platforms provide valuable insights into consumer preferences and attitudes in these regions. These platforms are prominent e-commerce sites offering a wide range of third-party refurbished mobile phones, making them reliable sources for analyzing online consumer sentiment. To strengthen the robustness of the findings, we focused on mobile phones available on both eBay and Amazon, specifically selecting products refurbished by well-established brands with a substantial global presence in the mobile phone market.

We used the web scraping tools Data Miner and Octoparse to extract detailed information on refurbished phones, including six key purchase-influencing attributes: Phone Name, Price, Rating, RAM, Storage, Screen, Camera, Operating System, Processor, Connectivity, and Brand. Initially, ratings from eBay showed a bias, so additional data from Amazon was collected to balance the dataset. A total of 2,517 phones were included in this analysis, with all datasets saved in CSV format for further study.

B. Data preprocesing

Data pre-processing is an essential first step in building effective machine learning models. This phase ensures that raw data is converted into a standardized and interpretable format. The dataset contained missing values, errors, or outliers that, if not managed correctly, can lead to misleading outcomes. To mitigate this, missing numerical values are replaced with the median or mode of their respective fields. Following these pre-processing steps, the cleaned dataset was ready for subsequent sentiment analysis.

C. Word cloud and sentiment analysis

Word cloud was used as a visual tool to display text data, where the size of each word indicates its frequency or importance. It highlights key textual elements effectively. In this analysis, word clouds are employed to showcase the most frequently mentioned features and their significance within the product review section [21]. The frequent occurrence of specific words helps identify the reviewers' opinions on various topics. Words that consistently refer to particular attributes were extracted from consumer reviews for further analysis. These word clouds were generated using a bag-of-words method, where each set of words corresponds to a distinct attribute. The collections were created utilizing the TF-IDF score, which measures the significance of a word [22]. Term Frequency (TF) indicates the word's frequency in a particular review, while Inverse Document Frequency (IDF) measures how rare the word is across all reviews. The formula for calculating TF-IDF is presented in equation 1.

$$TF - IDF = TF(i, j) \times IDF(i)$$

$$= \frac{\text{Term frequency in review comment } j}{\text{Total words in review comment } j} \times \\ \log_2 \left(\frac{\text{Total number of review comments}}{\text{Number of review comments with term } i} \right) \quad (1)$$

Sentiment refers to a personal or subjective view that can be either positive or negative. Sentiment Analysis [16] involves using computational methods to study people's opinions, feelings, and attitudes about specific topics or entities. Reviews often reflect individuals' thoughts about a person, event, or subject. The primary goal of SA is to identify opinions, analyze the underlying sentiment, and determine whether it is positive or negative.

D. Chi-square based feature selection

The Chi-Square test is a valuable analytical tool that provides significant insights into the characteristics of research data. This method reveals the degree of difference between the observed value (O) and the expected value (E) and chi-square score (χ^2). It helps to determine whether a feature's influence on the outcome is due to chance or if it genuinely impacts the result based on its observed frequencies. The Chi-Square test is extensively applied in disciplines like biological research and genetics [7], showcasing its efficiency in selecting relevant features. The Chi-Square test was applied to identify features with the strongest correlation which is calculated using Equation 2:

$$\chi^2 = \sum \frac{(O-E)^2}{E} \quad (2)$$

The resulting model after feature selection was named as 'Refurbished Electronics Purchase Intention (RE-PI) model'. The representation of this model is shown in Eq. (3).

$$y = \frac{1}{1 + \sum_{k=1}^m e^{-(a_k + \sum_{i=1}^n b_i x_i)}} \quad (3)$$

E. Multinomial logistic regression

Multinomial Logistic Regression, sometimes referred to as Softmax Regression due to its use of the softmax hypothesis function [8], is a supervised learning algorithm suitable for various tasks, such as text classification. In this study, sentiment was classified into three categories: positive, neutral, and negative, with sentiment acting as the dependent variable for the logistic regression analysis. Consumer reviews were transformed into an attribute dataset, which was then used to build a multinomial logistic regression model. The objective of this model was to identify patterns in combinations of attributes that influenced specific ratings.

IV. RESULTS

The analysis included a statistical summary of 28,351 reviews, which were grouped by sentiment according to star ratings. Reviews rated with 4 or 5 stars were classified as positive, those with a 3 star rating were labelled as neutral, and reviews with 1 or 2 stars were marked as negative. The

The distribution of sentiments showed 15,337 positive reviews, 3,959 neutral reviews, and 9,055 negative reviews.

The word cloud showcases six primary attributes: Performance, Price, Design, Brand, Utility, and Service, as seen in Figure 2.

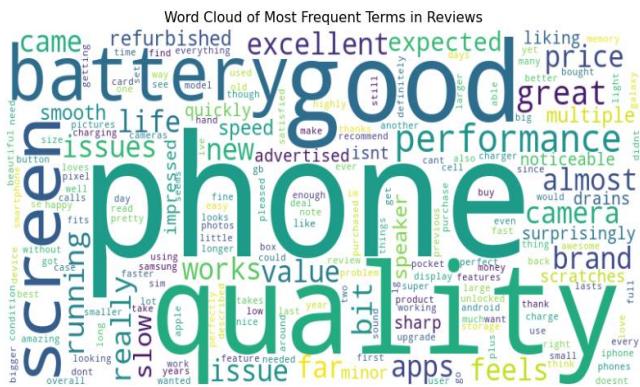


Fig.2 Word Cloud highlighting attributes

Frequently appearing terms in the word cloud indicate how these attributes influence star ratings and overall perceptions of refurbished products. Key terms linked to product features were identified and marked as distinct elements during the analysis. Reviews often touched on multiple attributes, revealing diverse consumer experiences with different product aspects. To analyze attributes, the word cloud was utilized to extract relevant features from each review. A bag-of-words approach was applied to record the frequency of individual and combined attribute appearances, along with their corresponding sentiment types, as summarized in Table 1.

In the frequency analysis, indicative words or features were identified to highlight specific attributes within the reviews and comments. The frequency of attributes was determined individually and in combination, categorized into positive (4-star and 5-star ratings), neutral (3-star ratings), and negative (1-star and 2-star ratings) sentiments. These frequencies were further analyzed to associate specific attributes with sentiments and gain insights into consumer perceptions.

According to Table 1, 'Performance' is the most frequently mentioned attribute in the dataset, with a total count of 10,272. It significantly contributes to positive sentiment, appearing in 5,502 reviews with "4 and 5 stars." 'Brand' is the second most discussed attribute, having an overall frequency of 7,750 and being associated with positive sentiment in 3,741 instances. The third most prevalent attribute is 'Design,' which appears 6,008 times and is linked to positive sentiment in 3,313 cases.

Table 1. The occurrence of positive and negative reviews.

Pe	Br	De	Pr	Ut	Se	f	f_{a,s}	%	f_s	%	f_z	%
Pe	Br	De	Pr	Ut	Se	10272	5502	53.56	2833	27.58	1937	18.86
Pe	Br	De	Pr	Ut	Se	7750	3741	48.27	1606	20.72	1403	18.10
Pe	Br	De	Pr	Ut	Se	6008	3313	42.75	2866	36.98	1571	20.27
Pe	Br	De	Pr	Ut	Se	5836	2776	47.57	1369	23.46	1271	21.78
Pe	Br	De	Pr	Ut	Se	5521	3751	67.94	1960	35.51	701	12.70
Pe	Br	De	Pr	Ut	Se	5157	2808	54.45	1005	19.49	1344	26.06
Pe	Br	De	Pr	Ut	Se	3718	2403	64.63	835	22.47	488	13.13
Pe	Br	De	Pr	Ut	Se	3012	1921	63.78	642	20.72	467	15.51
Pe	Br	De	Pr	Ut	Se	2980	1360	45.64	897	30.10	627	21.04
Pe	Br	De	Pr	Ut	Se	2928	1232	41.45	1323	45.18	373	12.74
Pe	Br	De	Pr	Ut	Se	2917	1249	42.67	1223	41.90	445	15.24
Pe	Br	De	Pr	Ut	Se	2874	1267	44.08	911	31.70	696	24.22
Pe	Br	De	Pr	Ut	Se	2790	1673	59.96	418	14.98	699	25.06
Pe	Br	De	Pr	Ut	Se	2750	1393	50.65	811	29.49	546	19.85
Pe	Br	De	Pr	Ut	Se	2723	1401	51.45	268	9.84	1054	38.71
Pe	Br	De	Pr	Ut	Se	2682	1675	62.45	453	16.89	554	20.66
Pe	Br	De	Pr	Ut	Se	2669	1320	48.72	846	31.71	503	18.87
Pe	Br	De	Pr	Ut	Se	2633	1521	57.77	318	12.08	744	28.26
Pe	Br	De	Pr	Ut	Se	2628	1257	47.83	825	31.39	546	20.78
Pe	Br	De	Pr	Ut	Se	2618	1292	49.35	1062	40.57	264	10.08

**Overall Frequency of Ratings from 1 to 5; f; Combined Frequency of Ratings 4 and 5; f4,5; Frequency of Rating 3; f3; Combined Frequency of Ratings 1 and 2; f1,2; Performance Attribute; Pe; Brand Attribute; Br; Design Attribute; De; Price Attribute; Pr; Utility Attribute; Ut; Service Attribute; Se; ** The bolded terms represent the attributes being assessed

When analyzing attribute combinations, the most frequent pair is 'Performance' and 'Brand,' appearing 3,718 times and showing a positive sentiment in 2,403 reviews. Similarly, 'Performance' and 'Utility' occur 2,972 times and contribute to positive sentiment in 1,232 comments from the analyzed data. These insights emphasize the key attributes that strongly influence both positive and negative sentiments in reviews. A visual representation is provided in Figure 3.

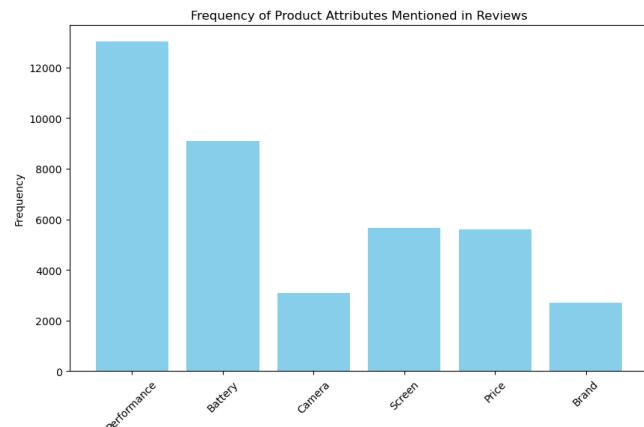


Fig.3 Product attribute frequency distribution

The Chi-Square test was applied to identify features with the strongest correlation to the outcome, based on the p-values derived. A p-value below 0.05 indicates a significant association between the variables. Key features were selected based on their p-values, as illustrated in Table 2. In the feature selection process, 10 features were chosen in total, with the top 5 being ‘RAM,’ ‘Price,’ ‘Storage,’ ‘Connectivity,’ and ‘Camera.’

Table 2. Features and their attributes

Feature	Attribute	p-value
RAM	Performance	0.000
Price(in \$)	Price	7.76×10^{-129}
Storage	Utility	1.47×10^{-123}
Connectivity	Utility	2.29×10^{-45}
Camera	Performance	2.31×10^{-36}
Processor	Performance	1.20×10^{-5}
Brand	Brand	2.12×10^{-5}
Operating System	Utility	1.66×10^{-3}
Screen	Design	7.04×10^{-1}
Rating	Utility	7.55×10^{-1}

This study employs logistic regression to develop decision models using available datasets, where the classification process involves mapping inputs to corresponding categories through a mathematical function.

In this model, attributes are represented by x , and n is the total count of attributes, which in this study is 6. The variable y indicates the sentiment. Additionally, in Equation 3, m represents the sentiment categories: positive, negative, and neutral. The model achieved an accuracy rate of 93.3% in predicting sentiments.

Table 3 outlines the performance metrics for the Multinomial Logistic Regression model applied to the dataset. It includes Precision, Recall, Accuracy, F1 Score. The model achieved an overall efficiency score of 0.450 in identifying true positive instances, among other measures.

Table 3. Measures of multinomial logistic regression

Algorithm	Precision	Recall	Accuracy	F1 Score
Multinomial Logistic Regression	0.910	0.915	0.933	0.912

However, Table 4 shows the efficiency of true negative cases is relatively low at 0.467, suggesting that the model does not struggle to accurately detect negative sentiments.

The efficiency for identifying False Negative cases is 0.025, that implies a low level of misclassification where positive sentiments are incorrectly labeled as non-positive. On the other hand, the False Positive efficiency stands at 0.030, indicating a lower rate of incorrectly labeling neutral or negative sentiments as positive, which may affect the overall precision of the model.

In future research, alternative methods or models may be explored to enhance sentiment analysis, particularly in improving the detection of negative sentiments, which

appears to be a challenge in this analysis. This approach could provide a more balanced and accurate understanding of customer ratings and reviews for refurbished phones or similar products.

Table 4. Efficiency of performance measures

Performance measures	Efficiency
True-positive	0.450
False-positive	0.030
True-negative	0.467
False-negative	0.025

V. DISCUSSION

Results from four distinct machine learning models have been presented, along with explanations concerning consumer preferences for refurbished products. The frequency analysis provided important insights into product features, reflecting customer experiences with refurbished items, particularly smartphones. While some insights are specific to smartphones, several general patterns emerged at the attribute level in the review analysis of refurbished products. Key attributes like "Performance," "Brand," and "Utility" were found to have the greatest impact on positive customer sentiment. For instance, "Performance" was mentioned 10,272 times in reviews, with 5,502 of those expressing positive feedback. This indicates that many users had favorable opinions about "Performance." Due to the strong performance of refurbished smartphones, users showed more positive feedback on this attribute compared to others. The term "Brand" appeared 7,750 times, with 3,741 comments reflecting positive sentiment, while "Utility" was mentioned in 5,521 reviews, with 3,751 of those being positive.

Consumers have high expectations for the performance of refurbished phones, and meeting these expectations often leads to positive reviews and ratings. However, the attribute 'Service' recorded the highest negative sentiment at 26.06%. This may stem from customer dissatisfaction with after-sales support provided by refurbished phone retailers like ReCell, TechRevive, and PhoneWorld. Issues such as limited warranties, slow response times, inadequate customer support, and challenges in securing replacements or repairs likely contribute to this negative feedback. To boost customer satisfaction, resellers could improve their service by offering longer warranties, quicker support, and clearer return or repair processes that better align with customer expectations. When analyzing attribute combinations, 'Performance' and 'Brand' were frequently mentioned, appearing 3,718 times in comments, with 2,403 of these reflecting positive sentiment—indicating that high-performing, branded refurbished products receive favorable feedback 64.63% of the time. Likewise, 'Performance' and 'Design' appeared 3,012 times, with 1,921 positive mentions. These findings suggest that focusing on key attributes, aside from 'Service,' can enhance positive sentiment and increase the likelihood of successful sales.

A. Inferences

The suggested model is distinctive as it focuses specifically on refurbished products, particularly smartphones, as the central topic of analysis. It aligns with the concepts of 'Reuse' and 'Refurbish' within the framework of the circular economy. This method proves valuable in identifying key factors that influence customer satisfaction in the realm of refurbished consumer electronics. In this study, a multinomial logistic model was employed to examine the chosen features of refurbished products. The findings from this study could provide valuable insights for industry players to adapt their product strategies, enhancing customer satisfaction and boosting competitive advantage. Furthermore, the model can classify potential buyers of refurbished products, making it a potential tool for integration into e-commerce product recommendation systems.

VI. CONCLUSION

To conclude, this study's machine learning analysis of consumer reviews identifies key attributes like Price, Utility, Design, and Brand as the primary factors influencing consumers' intentions to purchase refurbished smartphones. Frequency analysis further highlights that Performance, along with Price, Brand, Design, and Utility, are commonly mentioned in customer feedback. In contrast, Service holds limited relevance in consumer sentiment, likely due to lower expectations for after-sales support for refurbished products.

The findings indicate that consumers rely significantly on reviews and ratings, along with brand trust, in their decision-making processes. Price and Utility are strongly linked to positive consumer sentiment, while Service shows a negative correlation, suggesting that buyers consider a mix of attributes when choosing refurbished smartphones.

Addressing key aspects of consumer behavior in the refurbished market, this research supports sustainable development by encouraging responsible consumption and extended product lifespan. Future research could build on these insights by using alternative methods, examining reverse logistics, and exploring how consumers handle refurbished products. Other factors, like product type and manufacturing date, could further clarify purchase intentions, enriching our understanding of the refurbished market. This study provides a foundational approach to leveraging consumer feedback to anticipate purchasing behavior and optimize strategies in the refurbished product sector.

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Declarations

No conflict of interest exists between the authors.

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