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Master Thesis - MSc Data Science & Marketing Analytics

Reaching Beyond the Stars: A Comparative Review Text Mining Study on the Factors Driving Customer Satisfaction and the Presence of Social Influence in the Refurbished Smartphone Market.

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Abstract

With the increasing contribution of the refurbished market to a circular economy, this paper examines factors driving customer satisfaction and the possible existence of social influence based on review text data. The paper approaches identifying key motivators of customer satisfaction for refurbished phones compared to new phones and how a possible social influence effect exerted by previous reviews might differ between these two types of phones. Building on expectancy-disconfirmation theory and word of mouth theory, a text analytical approach is taken to contribute and examine the research question. Open-source text data is used by scraping review data on refurbished and original iPhone models from Amazon. First, a comparative sentiment analysis on review and bigram level is conducted to obtain insights on environmental, financial and product-specific motivators that could potentially drive customer satisfaction. The results of the analysis proved that consumer of refurbished phones exert higher levels of satisfaction coming from environmental and financial motivators, compared to consumers of new phones. These findings highlight the importance of optimizing marketing tactics dedicated to sustainability and the need for optimized pricing models for refurbished phones. Moreover, the result conformed the hypothesis that consumers of refurbished phones are less satisfied with the expected performance of the product-specific features, compared to consumers of new phones. This implies a shortcoming in the actual quality assurance of the refurbished model compared to what it is marketed as. In addition to the sentiment analysis, social influence within the product reviews and its difference between new and refurbished phones was tested through a nested ordered logit model, to potentially quantify the word-of-mouth theory. Results showed the existence of social influence within the reviews; however, no significant difference was found for this effect between refurbished and new phones. The findings of this paper provide unique insights on refurbished phone’s specific factors that drive customer satisfaction due to its comparative nature, contributing to the related gaps in existing research. Moreover, this paper’s contribution is identified by its methodological implications on contextual embeddings in review data and the extended usability of sentiment analysis results such that they could be recycled into the nested ordered logit model for examining the social influence effects.

Contents

1 Introduction[1]

The transition to a circular economy has been found as one of the solutions to driving economic growth and avoiding resource constraints simultaneously (Winans et al, 2017). In the theme of this, the refurbished market has adopted the concept of the circular economy, where products are given a new life and resold as refurbished. The benefits of the refurbished market are promising and catching onto consumers as well. Within the refurbished market, refurbished phones in particular are popular. The global refurbished phone market alone gained a size of 50.5 billion dollars in 2022 and is expected to increase to 172 billion dollars by 2033 (Laricchia, 2023).

To facilitate this growth, one needs to consider the optimal combinations of product specifications and price. Customer´s needs and attitudes could help reveal certain product specifications that are of importance when offering refurbished products. Past research shows a need for this, as well as consumers, have a positive attitude towards refurbished phones, yet this attitude does not often lead to an actual purchase and rather stays as an intention (Phantratanamongkol et al., 2018).

To gain actionable insights into this, a look can be taken at general existing customer feedback to research their attitude and (un)fulfilled needs after purchasing a refurbished phone. Specifically, online customer reviews could be utilized in this context and combined with machine learning methods to obtain findings beyond the numeric ratings. Specifically, text analytics is a state-of-the-art approach since it can transform unstructured text data into useful insights. Nowadays, unstructured business data consists for the majority out of text data (Gandomi & Haider, 2015). With open-text reviews, this sort of detail generates direct product feedback points across many customers, revealing the values perceived for each product specification. In addition to this, online customer reviews serve as an electronic word-of-mouth tactic where consumers voice their opinions. These opinions are easily accessible to other potential customers, leading to a possibility of social influence (Moe & Trusov, 2011).

[1] In compliance with policy Erasmus School of Economics, the GenAI tools that were used in this research are Scribbr and Grammarly for checking reference formatting and enhancement of the writing by correcting grammar, spelling mistakes and sentence structure

The data approach of modelling online customer reviews for insights into customer satisfaction has proven to make a significant impact through text analytics over the past years (Berger et al, 2020). Together with predictive machine learning methods, well-rounded research can be conducted on customer satisfaction within the refurbished market. Moreover, customer satisfaction and electronic word-of-mouth for refurbished phones could be put into perspective, by comparing it to online reviews of the original non-refurbished phones. This comparison is important as the original models and their quality set the stage for the expectations of the refurbished version. The insights into this comparison could help bridge the current gap in literature where it only focuses on the refurbished phones themselves instead of analysing them against the non-refurbished models.

Considering the objectives above, the research question for this research is therefore stated as follows:

What are the key motivators that determine customer satisfaction and how does social influence on potential customers for refurbished phones play a role compared to new phones?

It can be divided into two sub-questions for which different contributions of this research are established, namely:

1. *What factors drive customer satisfaction for refurbished phones and how does it differ from new phones?*
2. *To what extent can social influence be detected in online customer reviews of refurbished phones and how does it differ from new phones?*

The central constructs derived from the research objective are customer satisfaction with its dimensions and social influence, which form the focus of this study. These central constructs are supported by several theoretical concepts resulting in the following theoretical framework:

The first sub-question in this research focuses on defining customer satisfaction based on online reviews. In the study of customer satisfaction, the expectancy-disconfirmation theory states that satisfaction is created by the difference in expectations of a consumer prior to buying a product or service and their actual experience they have once bought (Oliver, 1980). In this research, the expectancy disconfirmation theory is particularly relevant as it enables companies to measure the quality of services or products and obtain information on the dimensions of customer satisfaction based on customer reviews (Ekhlani & Bakri, 2012). By measuring quality and gaining insights on what this specifically entails, it can be examined how to pursue satisfaction and suppress dissatisfaction. In terms of the expectancy-disconfirmation theory, improving satisfaction means aligning actual experiences with their expectations or exceeding their expectations (Oliver, 1980). Translating this to the refurbished market, a company could analyse customer satisfaction through online reviews to measure the discrepancies between experience and expectations. This could help retrieve actionable insight on how to improve their product based on this feedback. By identifying specific aspects of customer satisfaction, actionable insights can be derived on how to properly market and tailor the refurbished products that will convince potential customers to buy refurbished products.

Looking at the second sub-question, an approach is stated to detect any social influence in online reviews on potential customers, as online reviews serve as a form of electronic word-of-mouth. The social influence theory describes that the attitudes and behaviour of individuals are affected by the opinions, actions, and behaviour of others (Kelman, 1958). In addition to online reviews having the function to outline the meaning and features of customer satisfaction according to the expectancy-disconfirmation theory, the social influence theory indicates another use of online reviews which is influencing potential customers by voicing their opinion in a review. A contingent effect also has been stated, describing the theory that people who influence other people with their customer experience through reviews are also more likely to have been influenced prior to having an actual experience with a product or service (Sridhar & Srinivasan, 2012). Through analysing the customer reviews with this theory, it can research how factors such as positive word-of-mouth and recommendations by peers could influence potential customers in their purchasing decisions within the refurbished market. This theoretical construct is essential in research on the refurbished market as the existing doubts about potential customers can be susceptible to the social influence of existing customers. This could thus lead to a higher conversion rate to sales coming from potential customers being positively influenced.

Building on the social influence theory, a conceptualized subject of this is explained by the Electronic Word of Mouth Theory. It is derived from the Word-of-Mouth theory, where a customer shares their experience of a product/service with their peers through mostly informal communication (Westbrook, 1987). From that, the electronic word-of-mouth concept describes the informal communication related to a product or service, directed at (potential) customers through internet technology (Litvin et al., 2008). The theory contributes to this research as it reflects how reviews as an electronic Word-of-mouth tactic can envisage and support in detecting social influence.

The application of this framework goes beyond researching the central constructs of customer satisfaction and social influence in the refurbished phone market alone. A comparative approach is introduced where reviews of original non-refurbished phones are included as well.

Online reviews will be scraped from Amazon on refurbished phones (through their Amazon Renewed platform) and for new phones that are sold on Amazon. Specifically, English reviews will be scraped coming from the UK, US, and Indian Amazon websites. Sentiment analysis through text mining is widely used in academics to perform analyses on customer satisfaction, as this text-analytical approach can filter out noise and thus identify relevant sentiments based on open text sources (Al-Otaibi et al., 2018; Kang & Park, 2014). To research the second sub-question on the social influence effect, a logit model is utilized to test this.

Customer satisfaction has been an integral part of marketing research in the past (Bowen & Chen, 2001; Keaveney, 1995; Oliver, 2014). Additionally, gaining customer satisfaction insights through text analytics and predictive methods did not remain untouched in past academic research and has been applied to different industries (Berger et al., 2020; Chevalier & Mayzlin, 2006; Ludwig et al., 2013). However, researching customer satisfaction through text analytics remains limited until now in the context of refurbished phones. Therefore, this research contributes to take a deep dive into defining customer satisfaction through text analytics in the refurbished market. Moreover, a gap in research remains in comparing customer satisfaction dimensions from refurbished phones to the ones established from online reviews for similar original phone models that are not refurbished. The original phone model reviews serve as the status quo here, which helps to differentiate between the general customer satisfaction dimensions defined for a phone and the specific dimensions that apply to refurbished. This allows for the study to contribute with results that are unique for the refurbished phones. Lastly, a gap remains in examining the difference of social influence effects in online customer reviews between refurbished phones and new phones.

The findings of this research will showcase what exactly drives customer satisfaction, such as environmental and financial motivators but also valued product features that are derived from text analysis. The consecutive sentiment analysis then reveals how aspects drive customer satisfaction. The comparative nature of these findings allows for a clear distinction between what customers value for refurbished phones and new phones, and how one can reduce the doubtful customers that have a purchase incentive for refurbished phones but often remain with buying new phones. Moreover, once customer satisfaction aspects and their sentiment are defined, the remaining unexplained behaviour that might drive review ratings is then tested for a potential social influence effect that could be present.

2 Literature Review

This section provides an outline of previous academic literature on the refurbished market with a focus on refurbished phones and the marketing implications of refurbished products from a company perspective. With this, the gaps existing in academic research are highlighted for refurbished phones which will set the stage for this paper. An overview of the literature treated in this review section and the following theoretical framework can be found in Table 1.

A distinction needs to be made between refurbishment and remanufacturing, as they are often used interchangeably. This is not incorrect necessarily, but the definitions and distinctions will be clarified for this research. The most important distinction is that in the process of remanufacturing, the products do get restored as well but the guidelines are stricter, as remanufactured products need to meet new-like standards coming from the original product with the original specifications (Ayres et al., 1997). With refurbished products, the condition should be satisfactory and sufficient for usage but does not have to contain the exact state of the original product specifications (Ijomah, 1999).

Table 1: *Literature Table*

Authors	Methodology	Dataset	Key (Relevant) Findings
Bridgens et al. (2017)	Systematic review with multidisciplinary team	Case study on mobile phones	Challenges defined in the process of e-waste reduction comes mainly from the setup of traditional design that is not adapted to disassembly, repair, and reuse of components. Suggestions of opportunities in reducing e-waste lies in coordinating with consumer´s on how to properly dispose items and reinvent supply chain with experts.
Guide & Li (2010)	Comparative study through price auction	Two companies for participation	The study was conducted with the hypothesis that remanufactured products cannibalize new product sales. For one company was minimal overlap found and thus minimal cannibalization taking place. The second company had a higher but moderate overlap, suggesting the possible existence of cannibalized sales of new products by remanufactured products.
Ferguson & Toktay (2006)	Pricing evaluation model		It was found that regarding selling refurbished versions of a company´s own product the potential cannibalization of sales is less of a threat than the external competition created. Companies are better off according to the pricing evaluation when selling their own product refurbished than when another party does it.
Liu et al. (2016)	Life Cycle Assessment	Cylinder head production process	The process of repurposing and thus refurbishing cylinder heads through laser cladding resulted in an environmental impact reduction of 63% on the whole product life cycle.
Mugge et al. (2017)	Cluster Analysis	Online survey, 250 responses	Six customer cluster were identified together with 16 incentives, of which three groups take on incentives that motivates them to buy refurbished models based on environmental and cost saving factors. The other three groups showed less support for refurbished phones, based factors such as outdated technology and design.
Niu & Xie (2020)	Game Theory		The findings show that a brand owner always has an incentive for quality certification of products, for brand control. The remanufacturer does not always have an incentive for quality certification, especially in a situation where their demand is more uncertain. These different incentives can jeopardize a brand reputation as a company is not in control of the remanufacturer´s incentives
Seifian et al. (2023)	Sentiment Analysis	Reviews Amazon India and USA	Indian Customers are more negative towards refurbished phone versus American Customers. Indian Customers have a more financial incentive whereas American customers attain a more environmental incentive when buying refurbished phones.
Sharifi & Shokouhyar (2021)	Sentiment Analysis	25,000 tweets on refurbished phones	Tweets data show that environmental factors are more motivating than financial factors and the 3 important features are price, product warranty and quality. The most important product components are the display, camera and battery of a refurbished phone.
Van Weelden et al. (2016)	In-depth interviews	Dutch refurbished and new phone buyers	Consumer-decision process is defined, starting with a pre-purchase phase where acceptance of refurbished phones is indicated. Lack of awareness and misconception are defined as two barriers in the orientation phase. In the evaluation phase, it is found that consumers abstain from buying due to perceived risks outweighing the benefits.
Zink et al. (2014)	Life Cycle Assessment	Nokia and HTC Phones	Showing findings of the negative environmental impact of refurbishing compared to other methods. Refurbishing, general repurposing and repurposing through solar power were examined. Refurbishing resulted in the highest environmental impact

2.1 The Refurbished Market

The refurbished goods market refers to the selling and buying products that are pre-owned and partly restored to a sufficient condition. It is similar to the second-hand market, yet inspection and quality assurance play a pivotal role in the refurbished market compared to the second-hand market. Product categories range from electronics such as phones or laptops but also cover home appliances, cars or furniture. Key players in the market include manufacturers of the original product, refurbishers that specialize in buying used electronics and repurposing them, retailers that dedicate (part of their) product assortment to refurbished goods, companies or insurers that specialize in certifying the quality of refurbished goods for the customers, reverse supply chain companies that focus on connecting returned products with refurbishment facility centres, and the end customers that buy the products.

2.1.1 An Environmental Perspective

Motivated by adapting to a circular economy, the refurbished market creates a space to collect and restore products to give them a new life and sell them to customers (Rathore et al., 2011). Refurbishing products are viewed as best option of repurposing processes with relatively less drawbacks compared to other methods (Dalrimple et al., 2007).

The benefits of refurbishment as a product life extension tool come from different factors. With refurbishing products, one gains environmental benefits, such e-waste reduction, resource conservation through the collection of products and only restore the parts where needed. Liu et al. (2016) Studied a specific example of this on manufacturing cylinder heads through laser cladding. Life Cycle Assessment (LCA) is a common method that was adopted in this research to assess the environmental impact of remanufacturing products. LCA is a systematic methodology to outline the cumulative environmental impact of products and specific activities of the product life cycle and assist in defining opportunities for ecological improvement (Basket et al., 1995). Firstly, a goal and scope were defined. After, a life cycle inventory analysis and life cycle impact assessment were performed. Based on this, the authors concluded that by remanufacturing cylinder heads, the overall environmental impact over the whole life cycle of the product could be cut by 63.8%.

Existing literature also shows the negative environmental impact of refurbishing. In Zink et al. (2014), a study was conducted on smartphone reuse in ways of repurposing and refurbishing.

LCA was adopted as well in this research to assess the environmental impact of repurposing versus traditional refurbishing. The three waste management options for reusing smartphones were traditional refurbishment, repurposing using portable solar chargers and repurposing with battery power. Five indicators were defined to assess the environmental impact: global warming potential, atmospheric ozone depletion potential, acidification potential, human toxicity potential and smog creation potential. Results showed that refurbishing is the most harmful out of all three in terms of net impact on all indicators. Repurposing therefore shows a more sustainable way. Yet, repurposing is not as adaptive in a production process compared to refurbishing.

2.1.2 A Bottom-Line Perspective

With the increase of value of returned products nowadays, appropriate designation of these products can be sourced to the refurbished market. In 2013, the value of returned products in the United States was $267 billion, making it 8.6% of the total sales that year (Abbey et al., 2015). In 2020, this amount rose to $428 billion, representing now 10.6% of the total sales (National Retail Federation, 2021). Whereas returned products do not always qualify to be sold as new again, refurbishing these products could help in repurposing the return value.

Economic benefits are therefore derived from selling refurbished products as a company. By reusing materials, it is not only sustainable but also cost-effective in terms of resources when performing refurbishment.

MacArthur (2013) wrote a report showcasing the potential and real-life examples of the impact of refurbishing as part of the circular economy. Early successes of different companies are demonstrated in terms of economic growth coming from refurbishing, such as the automotive company Renault. By adopting a remanufacturing plant with several hundred employees and implementing a structured reverse logistic chain, Renault has grown its remanufacturing practices into a 200-million-euro business.

Additionally, research shows that companies gain an economic benefit due to their involvement in Corporate Social Responsibility (CSR) activities when refurbishing products. Being involved in CSR activities can improve the image of a company, increase customer acquisition and loyalty, and even attract certain investment opportunities (Branco & Rodrigues, 2006; Peloza & Shang, 2011; Piercy & Lane, 2009).

These benefits form the basis for improved strategies of companies involved in the electronics market. However, past research also argues for some drawbacks in terms of strategy.

Guide & Li (2010) hypothesized in their research how remanufactured products can cannibalize new product sales, based on existing literature. Cannibalization is referred to as the concept where a product released by a company will acquire customers at the cost of customers of products that are also offered within the same company (Copulsky, 1976). Refurbished products in this setting are considered a line extension in the company since the refurbished product belongs to the same category as the original product. They used an auction as a tool to gain insights into the possible cannibalization of new product sales by remanufactured products. Two companies participated in this study, Robert Bosch Tools and Cisco Systems. The results show that for Robert Bosch Tools, the remanufactured and new products only have minimal overlap in terms of customer segments which indicates a minimal concern for cannibalization. However, for Cisco Systems, the implications were less minimal in terms of concerns. While the availability of a refurbished product did not affect the number of bids and ending bid of new products, it did show a larger proportion of bidders that were interested in both remanufactured and new products. This suggests a certain degree of cannibalization for Cisco Systems.

Ferguson & Toktay (2006), counter this standpoint in their research on brand cannibalization. They do start their paper with the fact that companies often do not get involved in remanufacturing processes because of cost and internal cannibalization. Yet, the developed model shows that refraining from remanufacturing due to the threat of internal cannibalization brings up a bigger threat: external competition. According to their pricing evaluation model, companies are better off remanufacturing despite the rise in costs and potential cannibalization compared to not remanufacturing in a situation where another party might start selling their remanufactured products.

2.1.3 A Marketing Perspective

In cases where companies do not engage in refurbishing activities themselves, thus leaving it to independent sellers in the market, the brand reputation becomes less controlled for as their products are resold as refurbished. For the original products to be sold, internally aligned quality assurance and checks are performed to make sure that the product is sold in the condition that it is marketed for and represents the brand of the company. In the case when a product gets returned and is taken up by another player in the market such as a retailer that will sell it as refurbished, the same quality assurance and checks are not in place to guarantee the same condition that represents the brand of a company.

Niu & Xie (2020) studied the underlying incentive alignment between brand owner and remanufacturer that touches on the subject of brand reputation. Specifically, they treat the matter where a remanufacturer can receive a quality certification from the brand owner to use in promoting the product through a game theory method. The findings show that a brand owner always has an incentive for quality certification of products, as this will control the brand reputation to some extent. The remanufacturer does not always have an incentive for quality certification, especially in a situation where their demand is more uncertain. If the competition is fiercer for a remanufacturer and the demand therefore less uncertain, the method suggested that the remanufacturer is more willing to cooperate with the brand owner for quality certification, as it takes away the customer´s initial prejudice towards the refurbished products. This study hence showcases how different incentives can jeopardize a brand’s reputation as a company is not in control of the remanufacturer´s incentives.

2.2 The Refurbished Phone Market

Within the refurbished market, refurbished phones specifically have gained popularity over the years. The above-mentioned findings of the literature on the refurbished market in general also apply to the refurbished phone market. Existing research also covers phone-specific research within the refurbished market. Smartphones are a good prospect for refurbishing activities as past literature suggests an increase in negative environmental impact and a shortened product life cycle for smartphones (Bridgens et al., 2017; Zufall et al., 2020).

Bridgens et al. (2017) address the challenges and opportunities identified regarding e-waste in the transition to a circular economy, focusing on mobile phones. They shed light on the take-make-waste economy regarding phones, addressing the e-waste generated. Specifically, technical challenges need to be solved to reverse traditional industrial design that does not consider the disassembly, repair, and reuse of components. Suggestions of opportunities in reducing e-waste lie in coordinating with consumers on how to properly dispose items and with teams of multidisciplinary expertise to reinvent the supply chain loop for smartphones for a circular economy transition.

Likewise, in Zufall et al. (2020), research has been done on business model patterns that address different life cycle phases of smartphones. Analysis showed that an ideal sustainable business model for smartphones was not observed yet. This indicates the higher complexity of a fully sustainable smartphone business model.

In conclusion, research on the refurbished market is still of relevance and importance as multiple gaps remain in existing literature.

3 Theoretical Framework

In this section, the hypotheses will be conceptualized that form the basis of further analysis in this study.

3.1 Customer Satisfaction

Customer satisfaction is a common theme in this research and has varying definitions in past research. For this study, customer satisfaction will be defined as pleasurable fulfilment coming from consumption of a good (Oliver, 1999). Specifically, customer satisfaction here is the fulfilment that a customer can potentially obtain from buying refurbished or original smartphones. The aim is to also investigate the possible differences in customer satisfaction between refurbished phones and new phones. Focusing on the expectancy-disconfirmation theory, that forms the basis of measuring customer satisfaction dimensions.

Van Weelden et al. (2016) developed in their paper the factors that affect customer´s acceptance regarding refurbished phones along a four-phase decision-making process: pre-purchase, orientation, evaluation, and post-purchase. To get insights of customer on these phases, 20 in-depth interviews were held consisting out of 10 refurbished buyers and 10 non-refurbished buyers. In the pre-purchase phase, the acceptance seems promising based on the interviews. In the orientation phase, two main barriers were defined, despite the initial acceptance, a lack of awareness and misconceptions about the refurbished market. In the evaluation phase, the perceived risks of people weighed out the perceived benefits, leading to refraining from purchasing. The fourth phase, post-purchase, was not covered in this paper.

Mugge et al. (2017) performed a follow-up study on the four-phase decision-making model that was defined by Weelden et al. (2016). The paper focuses on exploring the incentives underlying the responses to refurbished phones and clustering customers in groups through a survey of 250 people, distributed through email and social media, as a response to past literature missing this specific segmentation of customers. Consecutively, a cluster analysis is performed based on the responses. The questionnaire covers four sections: response to refurbished smartphones, impact of incentives, individual differences, and demographics. 16 incentives were defined, ranging from product specifications such as upgraded battery, upgraded screen, and upgraded camera. Moreover, incentives focused on information gain such as quality certification, information on the refurbishing process and a classification system were outlined.

These incentives were matched with 6 defined clusters of customers: casual supporters, sustainability enthusiasts, conservative critics, susceptible followers, proud power users and expert techies. It was found that the groups casual supporters, sustainability enthusiasts and susceptible followers are most suitable for buying a refurbished smartphone. The reasons for that were the high interest in environmental issues and less desire for the latest technology which implies a sufficient satisfaction for buying “last year” phone models that would be refurbished. The environmental aspect specifically plays a role for sustainable enthusiasts and susceptive followers. Casual supporters do share this interest but also attach value to the cost-saving aspect of refurbished phones. These three groups represent 46% of the sample, indicating a substantive portion of the audience for the refurbished phones. The other three groups show some incentive, yet they are less willing to convert to a purchase, due to the uncertain reliability in their opinion or the fact that the refurbished model does not have the latest technology and design.

The paper above mentions environmental incentives as an important factor for purchase behaviour. Another note on the study is that it was conducted in the Netherlands, which is considered as developed country. Seifian et al. (2023) performed research investigating cross-cultural opinions between a developed and developing country on refurbished mobile phones through Amazon reviews. Specifically, the USA as a developed country and India as a developing country were used to outline the cross-cultural differences in this research. A sentiment analysis was performed on the reviews with pre-specified aspects covering product specifications such as battery, screen or camera and the aspect of environmental motivation and financial motivation. It was found that American consumers in their reviews mentions product characteristics 26.7% more on average compared to Indian customers. Indian customers mention aspects of sellers such as warranty, reputation, and packaging. The environmental motivation aspect appeared more in reviews of American customers, whereas Indian customers´ reviews shed more light on financial motivation. With this, the authors concluded that American customers, representing a developed country sample, have stronger environmental incentives compared to Indian customers, representing a developing country sample. The Indian customers were found to have stronger incentives coming from financial motivators.

Sharifi & Shokouhyar (2021), analyse consumer attitudes towards refurbished phones in their research based on 25,000 collected tweets. The defined categories for the analysis of customer opinions are environmental versus financial motivators, the main components of refurbished smartphones and refurbished phone features. Sentiment was utilized and after relational analysis on the tweets Interpretative Structural Modelling was applied. Results found that, like Seifian et al. (2023), environmental motivation was more endorsed compared to financial motivation in developed countries and vice versa for developing countries. Important aspects of a refurbished phone in general were defined by price, warranty, and quality. Specific components to be considered as significant features for refurbished phones were camera, screen, battery, performance, and storage.

3.1.1 Environmental Satisfaction

When buying a refurbished phone model instead of a new model, Mugge et al. (2017), raised a point that part of these customers cares about sustainability and are incentivized by it to buy the refurbished version. Seifian et al. (2023) stated that customers in developed countries such as the USA, which is part of the research scope in this study, tend to have more environmental reasoning to buy a refurbished phone compared to customers from developing countries. Sharifi & Shokouhyar (2021) found evidence of environmental based incentives as well in social media data coming from Twitter. These findings in existing literature thus state that environmental satisfaction gained from buying refurbished phones is a relevant and common occurring metric.

The distinction of environmental motivation is particularly important since this kind of customer satisfaction is a new form, especially with the rise of refurbished products. For other product categories, Frey et al. (2023) describe how consumers have been proven to be more inclined towards greener and environmentally friendly products, looking at their spending decisions. They tested the finding of a previous research which stated that consumers care more for sustainable purchasing if the option is available (Feber et al., 2020). The follow-up study showed that products with Environmental, Social and Governance (ESG) claims had 28% cumulative growth between 2017 and 2022, compared to 20% growth for similar products without ESG claims (Frey et al. 2023).

With the knowledge of environmental motivations being present in the refurbished market regarding purchase intention and the proved growth of products when an environmental factor was put in place, the importance of investigating the environmental motivation is highlighted.

Whereas customer satisfaction based on environmental motivation for refurbished phones is already touched on in existing research, its effect on realized purchases and the comparison to new phones remains to be studied. Therefore, the following hypothesis is formed:

Hypothesis 1a: Reviews of refurbished phones reflect higher levels of environmentally motivated satisfaction by customers than reviews of (the same) new phones.

3.1.2 Financial Satisfaction

Another type of motivation when buying a refurbished phone shown in existing literature is financial satisfaction. The casual supporter group from the segmentation model of Mugge et al. (2017) showed an additional financial satisfaction next to environmental satisfaction. Although Seifian et al. (2023) argued that developing countries often are more incentivized by financial motivators compared to developed countries, this does not necessarily imply that there is no financial or cost savings intention at all for these customers. Sharifi & Shokouhyar (2021) defined financial motivators as well based on social media data.

The reasoning for treating financial satisfaction on its own in this research is based on multiple points. The price of a product is important, as a trade-off is made between the willingness to pay of a customer and the value perceived when using the product. Specifically for refurbished phones, prices tend to vary more compared to new phones as the product can have different types of conditions such as used, fair or excellent condition which sets the expectations for the customer when buying it. The larger range of prices creates an additional decision step for the customer where they build expectations of the chosen price. As prices for new iPhones are more stable in the whole market, the absence of price variation can indicate a lower level of satisfaction that is financially motivated since it is something that cannot be altered.

The pleasurable fulfilment of buying a refurbished phone coming from a cheaper price (range) could therefore be more apparent compared to buying a new phone. Yet, this has not been proven in existing research. Hence, the following hypothesis is stated:

Hypothesis 1b: Reviews of refurbished phones reflect higher levels of more financial motivated satisfaction by customers than reviews of (the same) new phones.

3.1.3 Product-Specific Satisfaction

The past two hypotheses stated possible favourable incentives for buying a refurbished phone. Yet, they are not (directly) informative on the satisfaction from the product itself. Environmental satisfaction appears more from buying a refurbished phone in an environmentally friendly manner, which is not dependent on the performance of a product itself. The product could be completely disfunction, but the environmental satisfaction is independent from that.

Financial satisfaction is already dependent on product specification and features to a higher degree compared to environmental satisfaction. After all, the price paid by the customer gives them an expectation of how the product should function. To dive deeper into this, it is relevant to focus on the customer satisfaction derived from product-specific aspects of refurbished phones compared to new phones.

Mugge et al. (2017) defined other customer groups that care more about product-specific features. Here, customers value the latest technology and design of a product which is found more in new phones than refurbished smartphones. This argues thus for a lower level of satisfaction regarding product specifications for refurbished phones. To test this in the scope of this research, the following hypothesis is formed:

Hypothesis 1c: Reviews of refurbished phones reflect lower levels of satisfaction with product specifications than review of (the same) new phones.

3.2 Social Influence in Customer Reviews

Besides customer reviews revealing attitudes and satisfaction dimensions that serve a purpose for a company, the main reason for reviews is to inform potential customers about a product. In this case, online reviews serve as word-of-mouth tactic that exert social influence on potential customers.

Kelman (1957) states in his research that an individual (or in this case a customer) and his attitudes, subsequent actions and beliefs are influenced by others. Translating this to opinions, Myers and Robertson (1972) argue that it is a two-way street: people influence others, and were initially also influenced by other on the same topic. A specific action of social influence is carried out through word of mouth (Arndt, 1967; Whyte 1954). Electronic word of mouth is adopted in this context where reviews specifically serve as the communication between customers related to a product (refurbished and non-refurbished phones).

In research, the gap remains in examining the social influence effect in online reviews of refurbished phones. Likewise, the difference in possible social influence between reviews of refurbished phones and new phones is pending. Past literature states that people are accepting towards refurbished phones, yet converting to sale remains lower (Mugge et al., 2017; Phantratanamongkol et al., 2018; Van Weelden et al., 2016). The papers state reasons such as misconceptions regarding refurbished products or perceived benefits being outweighed by the perceived risks causing the hesitance or resistance to be buying refurbished phones. Hence, more uncertain and/or being uninformed as a potential customer is present in the context of refurbished phones. To make a buying decision on a refurbished phone in the end, customers might inform themselves through various sources such as online reviews, considering the potential drawbacks. For example, as the quality of new phones is more controlled for and known by customers, they might be less incentivized to inform about their decision through online customer reviews since there is less uncertainty around the product. When assuming that reviews are more often used for buying decisions regarding refurbished phones than new phones, as there is more uncertainty and hesitancy around it, the possible social influence effect coming from reviews might be different for refurbished phones compared to non-refurbished phones. To test this, the following hypothesis is formed:

Hypothesis 2: Reviews of refurbished phones reflect higher levels of a social influence effect than of the same (new) phones.

4 Methodological Framework

In this section, the process of data collection, preprocessing will be outlined followed up with conceptualizing customer satisfaction and its dimension and the techniques to test for social influence effects.

4.1 Data Collection

To examine the customer satisfaction and social influence effect for refurbished and new phones, review data was collected from Amazon. Specifically, the larger part of the data was scraped through the Chrome extension tool Web Scraper[2].

Within the tool, URLs are obtained that lead to English reviews of refurbished products as well as of original products on Amazon.us, Amazon.co.uk & Amazon.in. To obtain access to most products on the respective websites, postal codes are specified to define the shipping location for the products to be in the country where the reviews were scraped from, as Amazon only shows products that are available for shipping based on the indicated postal codes. Once the URLs are defined such that it shows all available and relevant iPhone models, HTML elements were identified, mapped and specified for scraping the relevant variables in this research. Two types of selectors were identified, where the first one is used to select the products on a page that were to be clicked to gain further information. Secondly, a pagination selector was defined to make sure that the scraper would consider multiple product pages. Consecutively, tags were created to navigate to the reviews of a product. Here, elements are selected such as, *review text, rating, title, review place*, *review date*, and the *product information.* Within the review, pagination elements are also defined to navigate to multiple pages of reviews for the selected product. Once all tags are defined, the scraping is initiated, and the output is returned in an Excel format.

Additionally, due to the limited product availability of new iPhone models on the Amazon websites, data from an existing dataset is available on the data.world platform[3] containing iPhone product reviews was collected to gain sufficient amount of observations. This dataset contained the same variables in the same format as the scraped review data.

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[2] https://webscraper.io
[3] https://data.world/opensnippets/iphone-11-reviews

4.2 Data Cleaning & Preprocessing

4.2.1 Data Cleaning

Once all the data is collected, it is merged into one file, where a check is performed on rows containing missing values for the review data and detection of any duplicated rows. A specific check is also put in place for Amazon reviews, as some reviews do not contain textual data but solely videos. As these reviews contain the same text string, "*Video Player is Loading*.", they are filtered out based on this specific text string. In the last step of cleaning the data, in terms of filtering for relevant observations before further preprocessing, the R package *textcat* was used to perform language detection and assign these to the reviews. One drawback of this package is that it does not always classify language correctly due to informal language or mistakes, manual inspection of the categories was also performed to check that all English reviews remain. Once the data was cleaned, the dataset contained 16,587 reviews.

4.2.2 Data Preprocessing

As the review text will form the basis for further analysis, several preprocessing steps were performed. Firstly, the characters and numbers in the *review_text* variable were reviewed and replaced or removed where necessary in cases such as excess spaces, punctuation or numbers, as they could disrupt and clutter the data (Ravi & Ravi, 2015). Additionally, a function was created to detect emojis based on a range of Unicodes and remove them from the text data.

Next, stop word removal was conducted where frequently occurring words that have little to no meaning are removed from the text data to reduce noise when performing analysis. After stop word and emoji removal, the data was checked for any remaining missing values in the data prior to any further step of analyses.

Another crucial NLP task when working with text data is part-of-speech (POS) tagging. With POS tagging, words are stemmed, and grammatical tags are assigned to its root form. With this, the ambiguity regarding the meaning of a word is reduced due to its grammatical tag and its syntactical relation to other words. To properly tag the words in the review data, reviews are split into sentences when performing POS tagging to retrieve semantic information on the words. POS tagging was therefore applied to the final dataset.

As a comparative analysis is conducted in this study between refurbished iPhones and new iPhones, it is important that both types are represented equally in the data. The occurrences of each type were assessed, and it turned out that refurbished iPhones were overrepresented in the data compared to new iPhones. Therefore, an under-sampling technique was performed with the *ROSE* R package where a random sample from the majority class (refurbished iPhones) is taken to match the number of observations of the minority class (new iPhones). The final dataset after preprocessing and balancing contains 10,884 reviews that were published between March 2017 and June 2024.

4.3 Comparative Sentiment Analysis on Customer Satisfaction

For obtaining the dimensions and levels of customer satisfaction through customer reviews, a text mining approach is often found in existing literature. To get an attitude of customer regarding certain defined topics, sentiment analysis is a viable option and widely used in academia (Seifian et al., 2023; Sharifi & Shokouhyar, 2021). Here, sentiments are to see if, on average, customers have a positive attitude towards specific product specifications such as a battery, screen, or camera of a (refurbished) phone.

4.3.1 Defining Customer Satisfaction Aspects

In this study, the hypotheses outline potential customer satisfaction based on environmental motivation, financial motivation and specific product features. To define and analyse customer satisfaction, specific words and terms need to be retrieved based on their (frequent) occurrence in that data.

For environmental motivation (hypothesis 1a) and financial motivation (hypothesis 1b), specific terms were defined based on past literature that analyzed customer satisfaction dimensions in reviews where environmental and financial motivation were part of the parameters. The following terms, shown in Table 2, were defined for further analysis of these motivators:

Table 2

Defined Customer Satisfaction Aspect for Hypothesis 1a and 1b

Aspect	Terms
Environmental Motivation	Ecofriendly, ecological, environment, recycle, sustainability, sustainable
Financial Motivation	budget, cost, deal, money, offer, price, promotion, worth

For hypothesis 1c, a different approach is taken to identify the relevant aspect and terms. As phones contain multiple product-specific features, identifying the relevant features that drive customer satisfaction in the review data was done through plotting the frequency of words that had noun tags assigned as part of the POS tagging procedure, while excluding very frequent words that are irrelevant to product specification features. This allows for a data-based approach of identifying the relevant product features mentioned in the reviews.

After having obtained the relevant customer satisfaction dimensions related to the hypotheses, mentions of these dimensions within the reviews are compared between refurbished iPhones and new iPhones.

4.3.2 Sentiment Analysis on Review level

To assess the general sentiment on a review in which an aspect occurs, a sentiment analysis is performed on the entire review by calculating sentiment scores on sentence level. The sentiment scores are calculated over the textual data by assessing each meaning of a word through a polarity function that helps identifying the expressed sentiment of a specific word in a text with the help of a lexicon dictionary. The Hu & Liu lexicon dictionary is applied here as past literature shows that this dictionary in particular performs well for product review sentiment categorisation (Khoo & Johnkhan, 2018). A valence shifter lexicon dictionary is included as well to account for negators, amplifiers and de-amplifiers.

The R package *sentimentr* is used to perform the sentiment analysis. The sentiment function of this package takes a text variable, review text in this case, and splits it into sentences with the *get_sentences()* function. Lexicon dictionaries are implemented to find the polarity values of the words used in a sentence. Additionally, valence shifters are loaded to detect any words that might alter the meaning of the polarized word with a default definition of looking for valence shifting by creating a context cluster of 5 words before and 2 words after the initial polarized word. A default amplifier weight of 0.8 is applied to assign weight to words that intensify or tone down the meaning of another word. Mathematically, the polarity score *(δ)* is defined as follow:

$$(1)\ \delta = \frac{c'_{i,j}}{\sqrt{w_{i,jn}}}$$

Where $c'_{i,j}$ represent the weighted sum of polarity scores of context clusters in which values are assigned to the polarized words while considering (de)amplifiers, negators and valence shifters. This then gets divided over $\sqrt{w_{i,jn}}$, which represents the square root of the total word count of a sentence in this case.

Once the polarity scores are assigned to each sentence, the average polarity score is calculated by each review and stored in *avg_sentiment*. Here the polarity score for all sentences within a review are summed up and divided it by the number of sentences in the review. Lastly, a variable *sentiment_review* is created where based on the average sentiment (polarity) score, the sentiment category is assigned to the review. average polarity scores higher than 0 results in a positive sentiment, lower than 0 in a negative sentiment and scores equal to 0 in a neutral sentiment.

With the defined sentiment scores and categories for each review, the distribution of the sentiment categories of reviews that have an occurrence of (one of the) customer satisfaction aspects in their text is then modelled per each aspect split by refurbished and new iPhone reviews. This supports in illustrating the sentiment towards the customer satisfaction aspects based on the overall review sentiment.

4.3.3 Sentiment Analysis on Aspect level

Where the occurrence of the customer satisfaction aspects in reviews based on the review's sentiment can give some insights regarding the hypotheses, a drawback here is that the overall sentiment of the review might not be equal to the sentiment around the aspect itself within the review. This is because one review may contain different sentiments where both positive and negative feedback is mentioned. Therefore, aspect-based sentiment analysis is performed as an additional approach in this research. Past literature vouches for this approach, as it gives insights on the specific motivations and product features based on its own context (Seifian et al., 2023; Sharifi & Shokouhyar, 2021).

For this approach, the words within the sentence of a review are split into bigrams. To further define the meaning of the words within the bigrams, an additional column *upos_bigrams* is created where Universal Part-of-Speech (UPOS) tags, are placed to capture the syntactic categories of the words in the bigrams. The values of this variable are pairs such as *(Adjective, Noun)* or *(Adjective, Verb).*

With the defined bigrams and its UPOS tags, a sentiment analysis like the one for the reviews is applied on the bigrams to obtain the sentiments. Once the sentiments are defined, columns are generated in the review data for each customer satisfaction aspect such as *financial_motivation*. If one or more terms defined as financial motivation are detected in a bigram belonging to a review, it gets assigned the corresponding sentiment of the bigram which is positive, negative or neutral. If the word does not occur in a bigram within a review, it gets NA value assigned. The resulting values in aspect-specific columns therefore represent its existence and sentiment based on the bigram in a review.

To inspect the sentiment around the customer satisfaction aspects based on the bigrams, not all bigrams and their corresponding combinations of UPOS tags will reveal relevant information. Therefore, only bigrams that have combinations representing *(Adjective, Noun), (Adjective, Verb), (Adverb, Noun), (Adverb, Verb), (Noun, Adjective), (Noun, Adverb), (Noun, Verb), (Verb, Adjective), (Verb, Adverb), and (Verb, Noun)* will be considered.

By splitting the sentences into bigrams and filtering for relevant UPOS tag combinations, it enables the model to capture the sentiment of the aspects that were initially a noun, which often do not contain sentiment on its own, by assessing its context based on the word it is used together with. The distribution of sentiment values can then be modelled per aspect and compared between refurbished iPhones and new iPhones.

4.4 Comparative Social Influence Effect Analysis

Sridhar & Srinivasan (2012) explain in their paper how to quantify social influence effects in online product ratings in the context of hotel reviews. They hypothesise that an online rating is influenced by prior online ratings of other customers. This hypothesis is tested with a nested ordered logit model, where the dependent variable represents a rating of a product and the independent variable of the average rating prior to the other rating being done and variables accounting for product specifics, sentiment of experience, rating behaviour and review specification to isolate the effect of social influence represented by the average rating of prior reviews. This was done by each hotel in the dataset, which can be translated in this set to each product that was considered for both refurbished and non-refurbished phones.

4.4.1 Nested Ordered Logit Model

A nested ordered logit model is used in this research based on the data and variable's structure. The nested ordered logit model is an extension of the ordered logit model. The ordered logit model describes an elaborated multivariate regression model with an ordinal dependent variable (McCullagh, 1980). This translates to this research for the ordinal variable *rating,* With 5 levels of one to five stars for the review data. By adopting this proportional odds model, the maximum likelihood estimation simplifies the computation and interpretation of the results in this model (McCullagh, 1980).

As the context for social influence effect is on product level, since a customer is potentially influenced on reviews that relate to the same product that they are considering buying, rather than reviews from a completely different product. Therefore, the data structure is nested since the reviews and their ratings are nested within each product for both refurbished and new iPhones. Yet, an ordered logit model would assume here that for each product the effects are equal. To overcome this assumption, nested structure is introduced into the ordered logit model. The nested ordered logit model relaxes the assumption of the proportional odds being equal across products, by assuming this only for within products or nests (Hauman & McFadden, 1984).

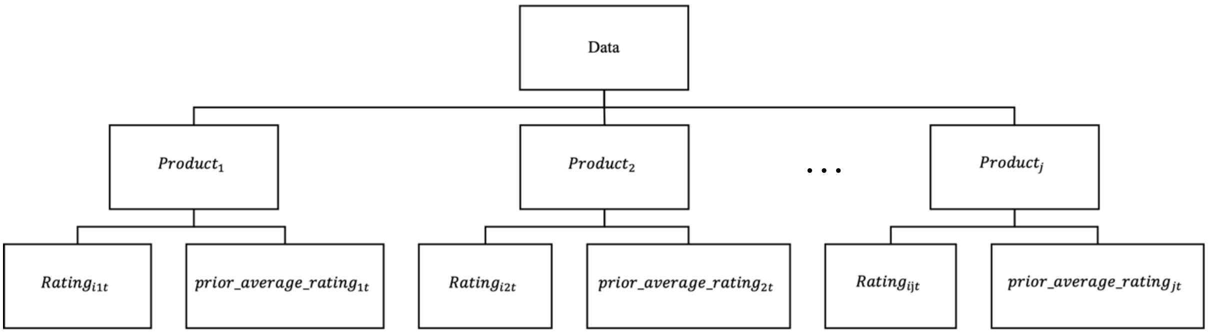
The dependent variable in this model is denoted by ordinal variable *numeric_rating* and is represented as $y_{ijt} = \{1,2,3,4,5\}$. For y_{ijt}, i represents the score given by a reviewer, for a specific phone product j defined by categorical variable *product_prefix* at a certain date *t.* As the review rating has multiple ordinal score option, the function $y_{ijt}{}^{*}$ the different ordinal score options as factors.

The independent variable of specific interest that captures the social influence effect is defined as $prior\_avg\_rating_{jt}$, which takes the average rating for reviews of a product prior to review *i.* This variable is chosen as previous research suggests that prior ratings can conceptualize the social influence of existing reviews on a new review rating (Li et al, 2020; Sridhar & Srinivasan, 2012).

A visualization of the nested structure of the data in light of the dependent and independent variable can be found in Figure 1 below.

Figure 1

Nested Structure Overview



To account for the refurbished and non-refurbished phone types, the dummy variable *refurbished_dummy* is included in the model, representing 1 if the rating is for a refurbished phone and 0 in case of a non-refurbished phone.

Furthermore, to test the difference in social influence effect denoted by *prior_avg_rating*, an interaction effect is utilized with *refurbished_dummy* to test for hypothesis 2.

To aim for an unbiased estimation in the model, several control variables are utilised. Variables coming from the initial review data such as number of words of a review (*nr_words)* & review place (*review_place*) are defined. Additionally, variables that were generated in light of the prior conducted sentiment analysis are also used. These include binary variables for the aspects, a continuous sentiment score and a categorical sentiment indication. A full overview of the control variables can be found in the appendix in Table A1.

Lastly, a random intercept u_j is included, which allows the model to only capture effects within each phone model and their reviews. With this, every product gets an intercept and thus their own baseline, allowing to account for variability between phone models.

The final model is mathematically represented as follows:

$$(2)\ y_{ijt}{}^{*} = \beta_1 prior\_avg\_rating_{jt} + \delta_1 refurbished\_dummy_{\,ij} + \gamma_1 \left(prior_{avg_{rating}}{}_{jt} \times refurbished_{dummy}{}_{ij} \right) + \theta' \boldsymbol{Z_{ij}} + u_j + \varepsilon_{ij}$$

Where $\beta_1 prior\_avg\_rating_{jt}$ represents the independent variable accounting for the prior average rating, $\delta_1 refurbished\_dummy_{\,ij}$ the dummy variable for refurbished, $\gamma_1(prior\_avg\_rating_{jt} \times refurbished\_dummy_{\,ij})$ the interaction effect, $\theta' \boldsymbol{Z_{ij}}$ represents the set of control variables and u_j represents the random intercept for each phone model.

To test the model´s performance, its pseudo-R-squared is calculated and compared to a basic version of the model that includes the interaction effect. In doing so, the change in the pseudo-R-squared represents the change in variance explained in the model by adding the difference in social influence effect between the phone types.

The nested ordered logit comes with a set of assumptions. First, the dependent variable is measured on an ordinal level. This is the case as the ratings are ordered from 1 to 5. Secondly, the independent variables need to be either categorical, continuous, or ordinal, which also holds in this model. Moreover, the data should not have any multicollinearity for the independent variables and control variables. To test this Variance Inflation Factor (VIF) will be applied once the model is run. VIF measures the inflation of variance of the estimated regressions coefficient in case the independent variables are correlated (Shrestha, 2020). The formula if VIF is represented as follows:

$$(3)\ VIF = \frac{1}{1 - R^2}$$

Where $1 - R^2$ represents a tolerance. The rationale here is that tolerance represents the proportion of variance that is not explained by other independent or control variables. The higher, the tolerance, the lower he VIF and thus less likely to have multicollinearity present for that variable (Shrestha, 2020).

5 Results

5.1 Data Exploration

Prior to discussing the results of the analyses, a data exploration table is provided in Table 3 that presents the structure of the variables of the used data.

Table 3

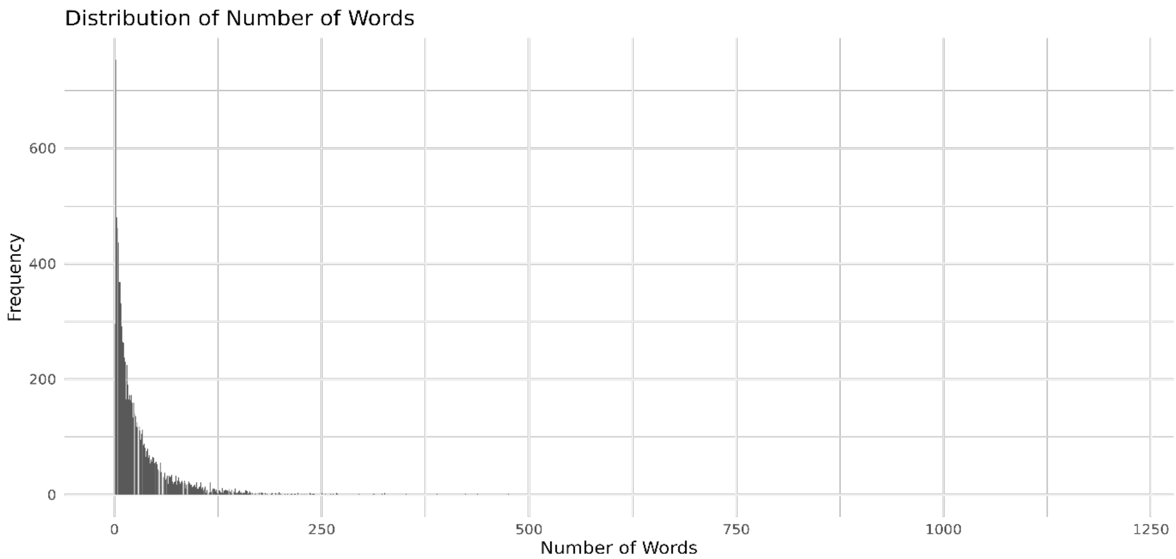
Descriptive Statistics

Numeric Variables	**Mean**	**Std. Dev**	**Min**	**Q1**	**Median**	**Q3**	**Max**
Nr_of_words_original	33.81	55.72	1	6	17	39	1,216
Numeric_rating	4.28	1.26	1	4	5	5	5
Categorical Variables							
Rating	1 Star	2 Star	3 Stars	4 Stars	5 Stars		
	1,018	298	614	1,683	7,271		
Place	India	UK	US				
	4,937	3,504	2,543				
Product_prefix	Unique count						
	60						
Type	Refurbished	New					
	5,442	5,442					
Date Variable	**Min**	**Max**					
Review_date	2017-03-06	2024-06-17					

From *nr_of_words,* it can be observed that, on average, a review contains almost 34 words. Yet, looking at the median, this lies around 17 words. This suggests a right-skewed distribution of the number of words. The fact that most of the reviews contain a small number of words could be related to the fact that there are many five-star reviews in the dataset. Here, customers might have fewer feedback points other than just indicating that it is a good product or that they are satisfied, without going into specific detail. The largest review text contains 1,216 words. The distribution plot of the number of words per review is shown in Figure 2:

Figure 2

Distribution Plot of the Number of Words per Review

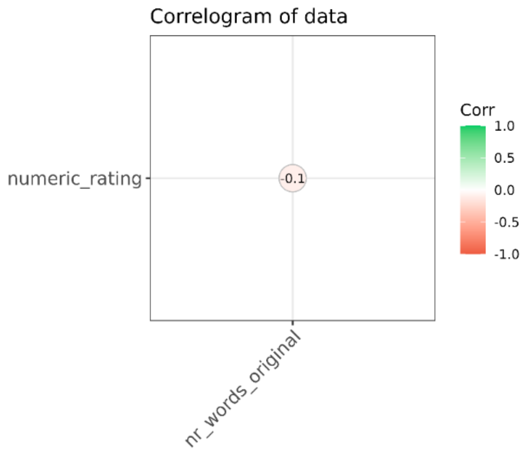


The distribution is skewed to the right, indicating that as word count increases, the number of reviews per word count decreases.

The categorical variable *rating* is also transformed into a numerical factor that represents 5 integers represented by *numeric_rating.* The ratings have an average of 4.28 and a median of 5. A correlation plot between the numeric variables is shown in Figure 2.

Figure 3

Correlation Plot Numeric Variables

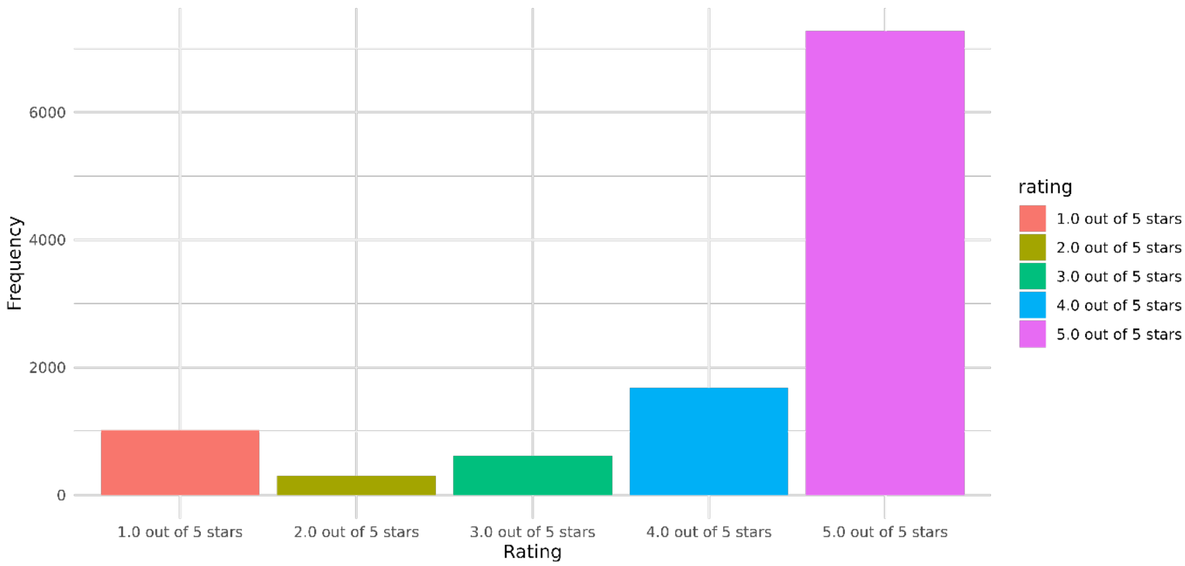


The correlation between number of words and negative rating shows a negative weak linear relationship. This indicates that a slight increase in number of words in a review causes a slight decrease in rating and vice versa. This suggests that reviews with lower ratings would contain more words than reviews with higher ratings.

The distribution of categorical variable *rating* is visualized in Figure 4 below.

Figure 4

Frequency Plot of Review Rating Categories

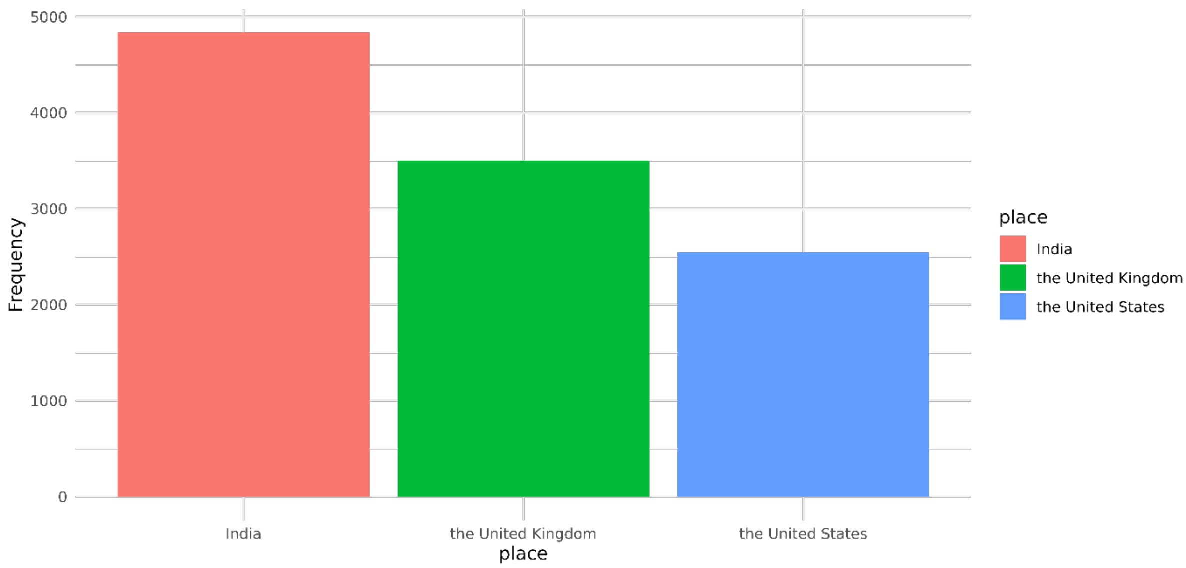


Looking at the counts of the categorical variable *rating*, the distribution among the categories takes a J-shaped form, where most reviews have a four- or five-star rating, much less two- or three-star ratings, and then peak again at a one-star rating. This phenomenon is not unknown in existing research. Product ratings in general tend to have a positive yet asymmetric skewed distribution (Chevalier & Mayzlin (2006); Eliashberg & Shugan, 1997; Liu, 2006; Hu et al., 2009). Hu et al (2009), supports this by defining to biases surrounding product reviews. The first bias is the purchasing bias, which describes the fact that people who can give a review, the buyers in this case, already have some sort of favourable attitude towards the products as they chose to buy it instead of other products (Hu et al., 2009). Secondly, the under-reporting bias would generate this j-shaped distribution, since mainly buyers that have something positive or negative to say will more likely report in a review than buyers with a more moderate attitude (Hu et al., 2009).

Place indicates the three countries from which the reviews are derived from, namely India, UK and USA. The distribution is visualized in Figure 5 below.

Figure 5

Frequency Plot of Review Countries



Product_prefix represents 60 unique products[4] that were identified, and where reviews were obtained from.

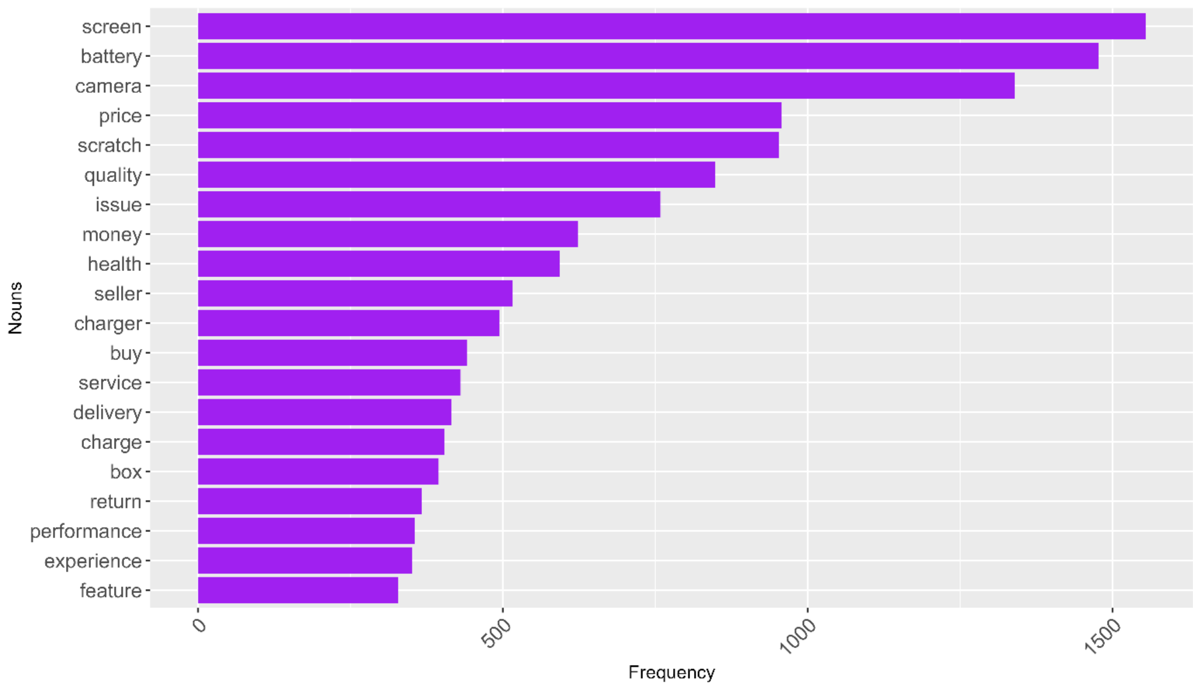
5.2 Comparative Sentiment Analysis on Customer Satisfaction Results

5.2.1 Defining Customer Satisfaction Aspects Results

To further define customer satisfaction aspects regarding product-specific features in support of hypothesis 1c, words tagged as a noun through POS tagging have been modelled by frequency to reveal the top 20 most mentioned terms in the total review data. The first iteration reviewed frequent nouns of which some of them are not considered meaningful to the analysis due to their general meaning in the context of phone reviews. Therefore, the plot was visualized while excluding words such as *phone, amazon, apple, review, love, life, pro & month*. The resulting graph can be found in Figure 6.

Figure 6

Frequency Distribution Plot of the 20 most occurring nouns in the review data



The plot suggests that the word *screen* is the most frequently used with an appearance of over 1,500 times in the review data. The last noun in the top 20 graph is the word *feature* with a frequency of less than 500 times. The terms screen, battery, camera, charge are terms

[4] Refurbished versions of a model are considered as unique products as well here.

representing possible product specification of the phones in the review data. As hypothesis 1c focuses on testing customer satisfaction between refurbished iPhones and new iPhones based on product specifications, these terms will be selected as aspects which will be used in the remainder of the analysis. The final selection of customer satisfaction aspects to be tested is presented in Table 4.

Table 4

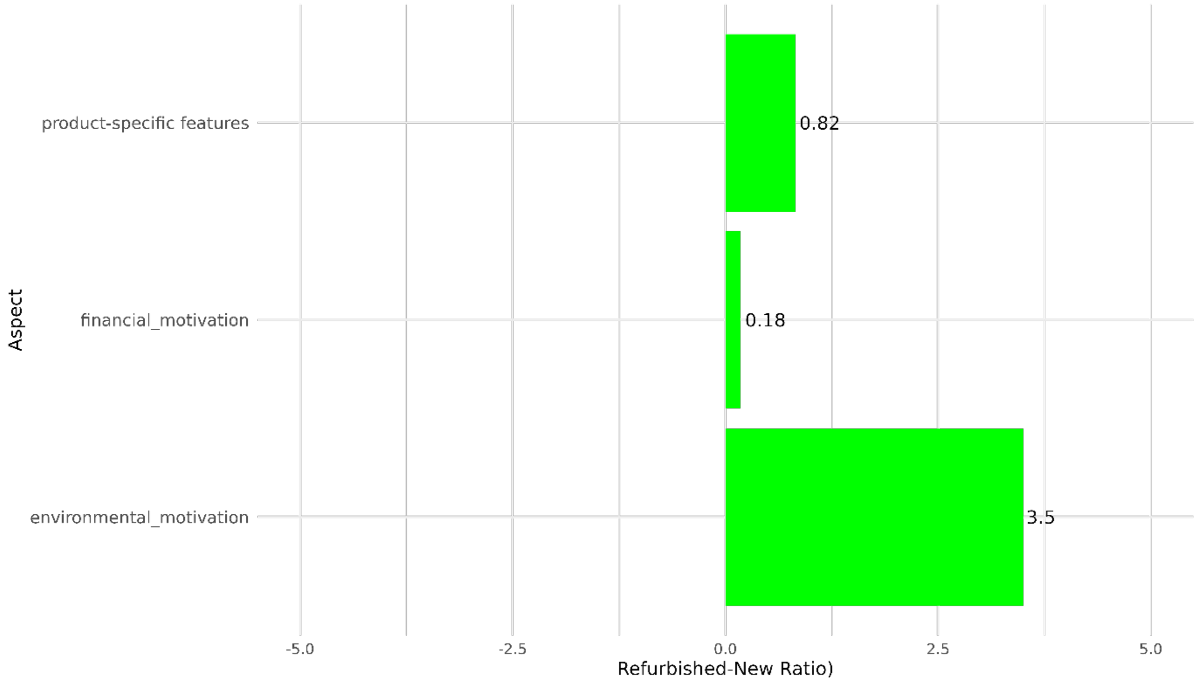
Full Overview of Defined Customer Satisfaction Aspects

Aspect	Terms
Environmental Motivation	ecofriendly, ecological, environment, recycle, sustainability, sustainable
Financial Motivation	budget, cost, deal, money, offer, price, promotion, worth
Product-Specific Features Satisfaction	Screen, battery, camera, charging

As the study follows a comparative approach, the identified aspects are plotted to compare their occurrences (or mentions) in refurbished iPhones versus new iPhones Here, a review gets scanned to check if it contains the terms that are given in Table 4. In case a term or aspect is present in a review, it gets assigned a value of 1 and else 0. Once all the reviews have been checked for the occurrence of the aspect terms, the number of refurbished iPhone reviews that contain a certain aspect gets counted. After, it is divided over the count of occurrence in reviews of new iPhone reviews for each aspect The resulting plot can be found in Figure 7:

Figure 7

Aspect Mentions Ratios Plot for Refurbished Phones over New Phones

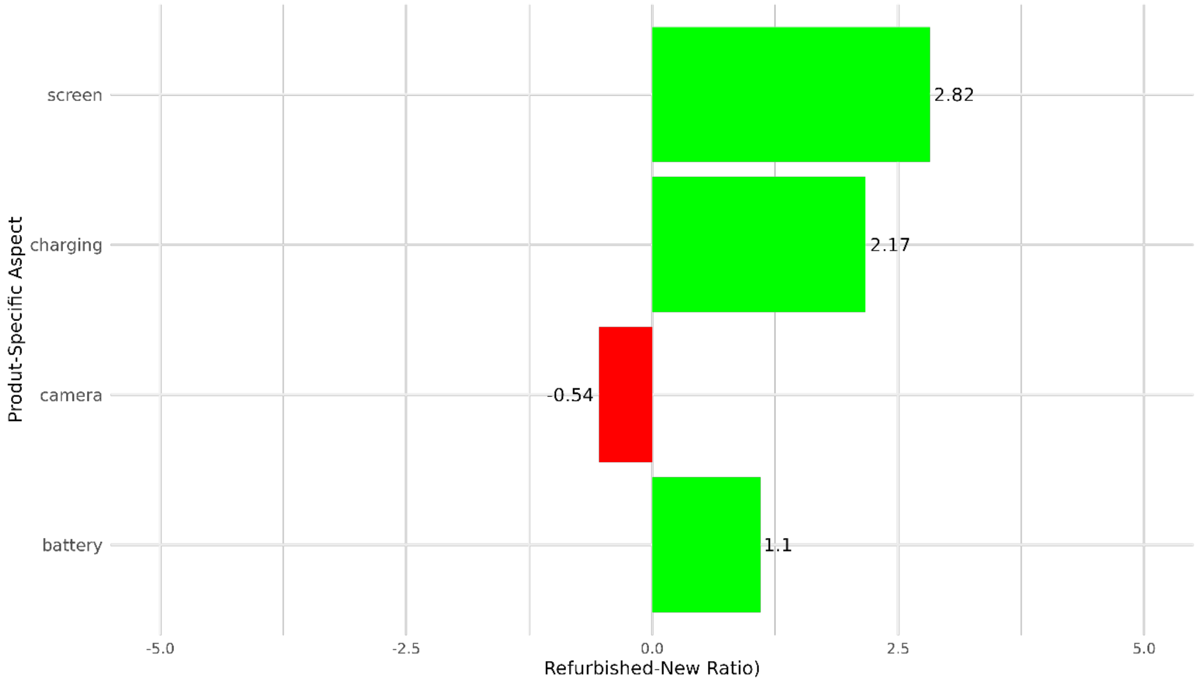


Environmental motivators appear to be more than 3.5 times present in reviews of refurbished iPhones than in reviews of new iPhones, which supports hypothesis 1a. Financial motivators also appear to be more present, around 0.18 times or by 18% more, supporting hypothesis 1b. The product specifications seem to be mentioned more often in review for refurbished phones compared to new phones.

Upon further inspection, the mentions of product specifications differ depending on the specific aspect with varying ratios. Therefore, an additional graph has been created to have a split view for each aspect which can be found in Figure 8. From now on, results of the consecutive analyses will be split by term for the product specification, and not thus aggregated like the financial or environmental motivators, due to its heterogenetic nature.

Figure 8

Product-Specific Aspect Mentions Plot for Refurbished iPhones over New iPhones



Screen, charging capabilities and battery are mentioned more often in refurbished iPhone reviews, yet the camera as an aspect appears around only half as much in the refurbished iPhone reviews compared to new iPhone reviews.

5.2.2 Sentiment Analysis on Review Level Results

Sentiment analysis was performed on each review to get a general understanding of the sentiment within the dataset. Figure 9 displays a histogram of each sentiment representing the distribution of the ratings 1 to 5. Table 5 contains the shares in percentages of a rating category by each sentiment based on the total number of reviews of all rating categories in sentiment. Additionally, a row is added to the table called Total Rating which shows the distribution of all the reviews consolidated for the defined sentiments.

Figure 9

Frequency of Ratings by Sentiments of Reviews[5]

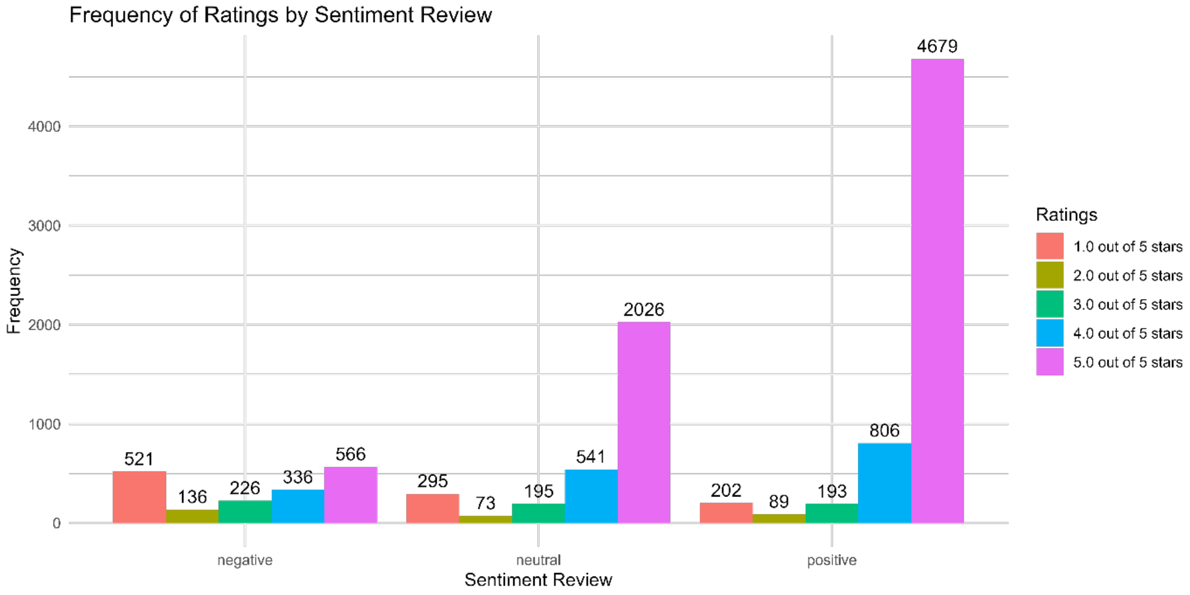


Table 5

Shares of Ratings by Segment (%)

Rating Category	Negative	Neutral	Positive
1.0 out of 5 stars	29.19	9.42	3.38
2.0 out of 5 stars	7.62	2.33	1.49
3.0 out of 5 stars	12.66	6.23	3.23
4.0 out of 5 stars	18.82	17.28	13.50
5.0 out of 5 stars	31.71	64.73	78.39
Overall Shares of Sentiment Across Ratings	**16.4**	**28.76**	**54.84**

For the positive sentiment, the four- and five-star ratings outnumber the other ratings, with a combined share of 91.82% of reviews. This is in line with expectations, as those ratings are considered as good or excellent in a one- to five-star rating. One-star ratings seem to appear more than two- or -three-star ratings even though it is a more negative rating. This could be explained by the common j-shaped distribution for product reviews (Hu et al., 2009). The

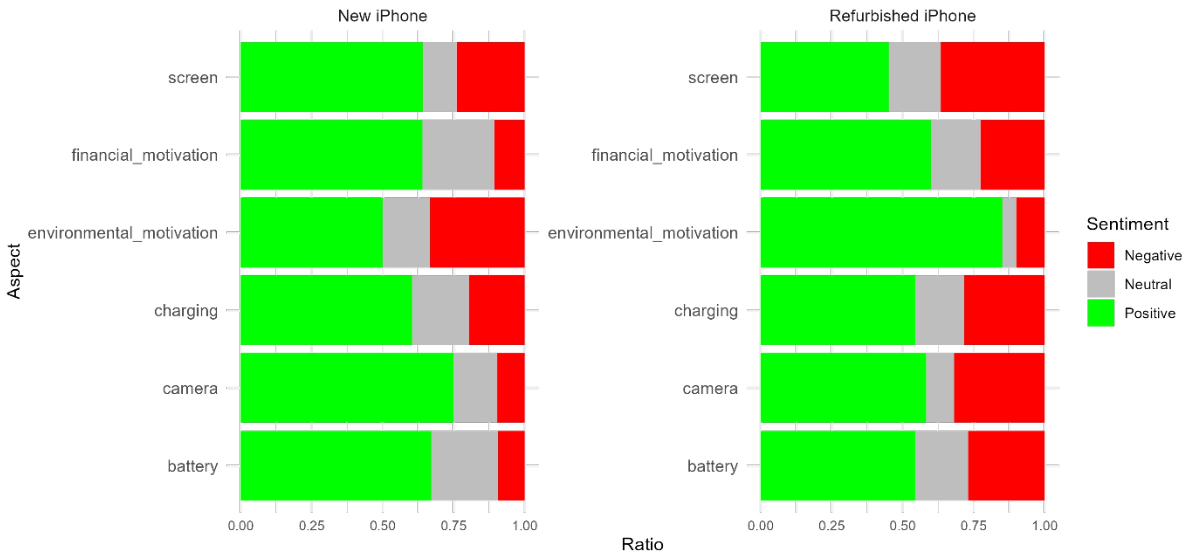
[5] As seen in the figure, some 5-star ratings ended up being classified negative after conducting the sentiment analysis. After some manual inspection, it was found that reviewers often point out some flaws such as scratches on the phone or a decreased battery life which leads to a negative sentiment in some cases. Yet, reviewers gave still a 5-star rating as they were expecting that as this was communicated upfront in the description.

neutral sentiment follows a similar distribution in terms of frequency as the positive sentiment but with fewer five-star ratings. This is also shown in the lower shares five-star reviews and higher shares for moderate review classes such as two-star and three-star rating. The negative sentiment contains the highest frequency (521) and share (29.19%) of one-star rating reviews and the lowest frequency and share of five-star reviews. Overall, 16.4% of the reviews are classified as negative, 28.76% as neutral and 54.84% as positive.

The distribution of sentiments is also split by refurbished iPhones and new iPhones and separated for each aspect, which can be found in Figure 10.

Figure 10

Distribution of Sentiments by Phone Type and Aspect on Review Level



It can be observed that for the sentiment of reviews containing environmental motivators, it carries a larger proportion of the positive reviews for refurbished phones of 85% compared to the 50% for new iPhones. Additionally, reviews for refurbished iPhones that contain environmental motivators have smaller shares of neutral (5%) and negative reviews (10%). Therefore, the data and results are in line with hypothesis 1a, which states that reviews of refurbished iPhones contain higher levels of environmentally motivated customer satisfaction compared to reviews of new phones, for sentiments on the review level.

Regarding the sentiment of reviews that contain financial motivators, reviews for refurbished iPhones have a slightly smaller share of positive reviews compared to new iPhones, 60% and 64% respectively. The reviews of refurbished iPhones appear to be less neutral with a share of 17% against the 25% portion for new iPhones and more negative. While the lower share of neutral sentiment in refurbished iPhone reviews suggests that financial motivators appear in more polarized or defined reviews, the lower positive sentiment share derived from the data indicates a different finding than what hypothesis 1b, higher levels of financially motivated customer satisfaction for reviews of refurbished iPhones, suggested.

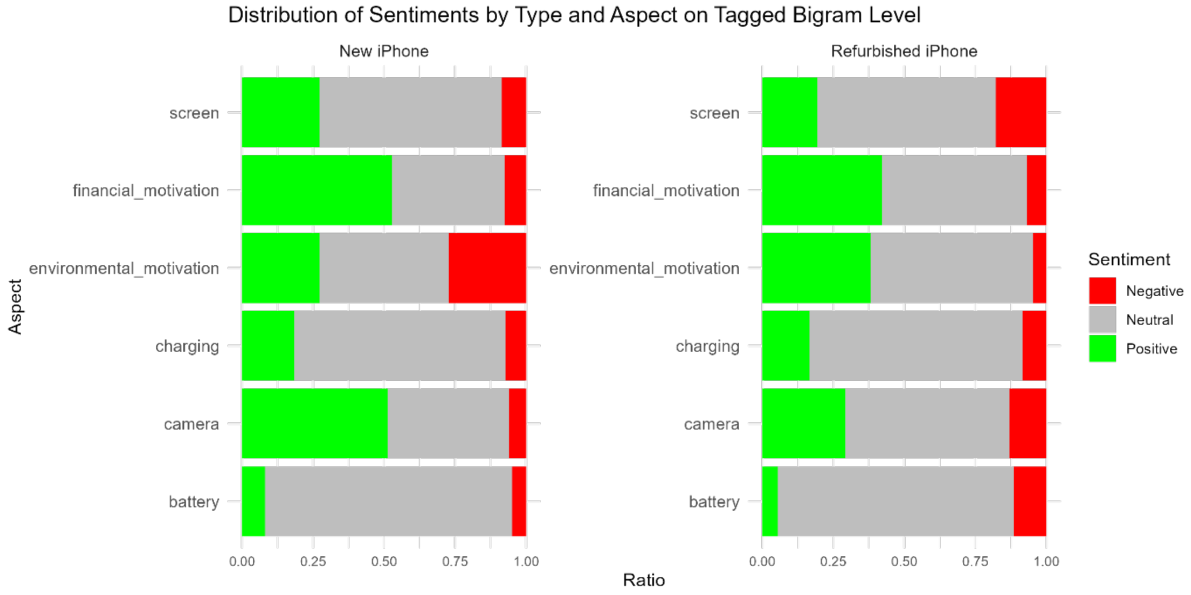
Looking at the defined customer satisfaction aspects regarding the product specifications, reviews for new iPhones show higher percentages for positive sentiment compared to reviews of refurbished iPhones. The aspect *camera* displays the highest share of positive reviews with 75%. Reviews of refurbished iPhones indicate higher levels of negative reviews, where for example 31% of all the reviews of this type that include the term camera have a negative sentiment. The results support hypothesis 1c, indicating that reviews for refurbished iPhones indicate lower levels of satisfaction coming from product-specific aspects.

5.2.3 Sentiment Analysis on Bigram Level Results

For a more comprehensive understanding of the sentiment around a specific aspect, instead of taking the review of the sentiment where the aspect is in. bigrams were created and UPOS tagged to perform this sentiment analysis. A subset of the total bigram data is created by selecting the relevant UPOS tag combinations and only selecting bigrams that contain the defined terms for the aspects, as listed in Table 4. This allows for analysing the sentiment around the words itself, instead of assessing it on the review level as a review can contain multiple sentiments. The resulting distribution of the sentiment analysis on the bigram level split by type and aspect can be found in Figure 11.

Figure 11

Distribution of Sentiments by Phone Type and Aspect on Tagged Bigram Level



Overall, analysing the sentiment of the aspect word itself, resulted in an increase in neutral sentiment classifications compared to review level sentiments.

Regarding environmental motivators, bigrams coming from review of refurbished iPhones describing these maintain a larger share of positive sentiment of 45.45% compared to the 27.27% share of positive sentiments in bigrams of new iPhones. The bigrams coming from refurbished iPhones do account for a higher share of neutral sentiments, which differ from the findings on review level. A smaller proportion of negative sentiments is demonstrated compared to new iPhones. This indicates that on aspect-specific (bigram) level, environmentally motivated satisfaction has higher levels for refurbished iPhones than for new iPhones. This finding is consistent with hypothesis 1a.

Analysing the aspects on bigram level for financial motivation shows that the proportion of positive sentiment attached to it, for refurbished iPhones, is 42.06%. This is lower compared to the 52.7% of new iPhones, which was also found on review level. The neutral sentiment around the financial motivation now has 51.14% of the total Bigram mentions for refurbished iPhones, which is higher than the 39.81% for new iPhones. The financial motivators remain to have a slightly higher proportion of negative sentiments for refurbished iPhones. 8.23% of bigrams containing financial motivation terms for refurbished iPhones had a negative sentiment whereas for new iPhones this share was 7.48%. Hypothesis 1b does therefore not state the same, as the sentiment analysis on the aspect terms for financial motivation suggest that for refurbished iPhones, lower levels of financially motivated satisfaction is derived compared to new iPhones.

Conducting sentiment analysis on the bigrams of the aspects resulted in similar figures as when analysed on review level. The positive sentiment towards all four aspects has a larger proportion for new iPhones compared to refurbished iPhones. Neutrality in sentiment did take on a larger proportion on all aspects where especially for battery, new iPhones and refurbished iPhones indicated 87% and 83.19% respectively. All four aspects had a larger part of negative sentiment for refurbished iPhones than for new iPhones. Considering the distributions of sentiment for the four aspects, hypothesis 1c that states lower levels of satisfaction coming from product-specific features is support by the sentiment analysis on the bigrams.

5.3 Comparative Social Influence Effect Analysis Results

The nested ordered logit model was run on both new and refurbished data, with the ordinal dependent variable being the numeric rating given by a reviewer for a certain product at a certain date. The assumption of no multi-collinearity remained to be tested as it uses the results of the models. Where multicollinearity is detected for a variable depends on which range the value is located in. The resulting VIF results and specifications are listed in Table B1 in the appendix. Looking at the general (unweighted) VIF, some variables do indicate multicollinearity. This could be related to the within-group variance of the products that are considered due to the nested structure. It gives an indication that ratings for the same product share common unobserved factors.

The resulting coefficients and descriptives of the nested ordered logit model can be found in Table 6.

Table 6

Coefficient Table of the Nested Ordered Logit Models

	Model 1	Model 2
Independent variable		
prior_avg_rating	0.711***	0.912**
	(0.114)	(0.305)
Interaction effect		
prior_avg_rating:refurbished_dummy		-0.248
		(0.327)
Control variables		
refurbished_dummy	-0.386	0.71
	(0.431)	(1.512)
nr_words_original	-0.004***	-0.004***
	(0.000)	(0.000)
Place		
the United Kingdom	0.238	0.224
	(0.540)	(0.542)
the United States	0.540	0.524
	(0.545)	(0.548)
Sentiment		
Neutral	0.463***	0.459***
	(0.075)	(0.075)
Positive	0.286*	0.283*
	(0.111)	(0.111)
Avg_sentiment	1.613***	1.615***
	(0.092)	(0.092)
Financial_motivation	0.317***	0.32***
	(0.059)	(0.059)
Environmental_motivation	0.102	0.097
	(0.472)	(0.472)
Screen	-0.312***	-0.313***
	(0.069)	(0.069)
Battery	0.121*	0.121*
	(0.051)	(0.051)
Charging	-0.689***	-0.69***
	(0.117)	(0.117)
Camera	-0.197**	-0.196**
	(0.074)	(0.075)
Threshold coefficients		
1|2	1.013	1.898
	(0.621)	(1.367)

2|3	1.349*	2.234
	(0.621)	(1.367)
3|4	1.893**	2.778*
	(0.621)	(1.367)
4|5	2.914***	3.799**
	(0.621)	(1.367)
Observations	10,806	10,806
Pseudo R-Squared	0.090106	0.090076
Log Likelihood	-10,069.8	-10,097.3

t statistics are presented in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Model 1 shows the result of a nested ordered logit model that is run on the independent and control variables while excluding the interaction term that accounts for a possible difference in the effect of *avg_prior_rating* between refurbished and non-refurbished phones. Model 2 represents the full model that includes the interaction term. The results for the estimation of the model show that Model 1 has the highest pseudo-R-squared (0.0901). Additionally, the interaction effect in Model 2 indicates that on average, the effect of the prior average rating changes by -0.248 when it concerns a refurbished phone. However, looking at the p-value, this coefficient is not found to be significant. This is in line with lower pseudo-R-squared value of the Model 2, since it indicates that the addition of the interaction term does not make a significant difference in the model's estimation.

The variable representing the social influence effect is *prior_avg_rating.* The coefficient has a positive value of 0.711 in Model 1, with a p-value of 0.000 and thus statistically significant. The model therefore suggests that for every unit increase in the prior average rating, the log odds of a higher rating increases by 0.711 on average for a specific phone model. Model 2 also shows a positive and statistically significant coefficient, with a value of 0.911. The dummy variable accounting for distinction between refurbished and non-refurbished phones, *refurbished_dummy,* shows a negative but insignificant effect on the ratings in Model 1. In Model 2, the coefficient for the dummy of the review rating for a refurbished iPhone has a positive value but is statistically insignificant.

For the control variables, Models 1 and 2 follow the values in terms of sign and statistical significance at a p-value smaller than 0.05. A significant negative effect a level of $p < 0.05$ is observed for *nr_words_original*, *screen, charging* and *camera.* The average sentiment score holds a high positive and significant. *Positive* & *Neutral* sentiment classification holds a large positive and significant effect on the ordinal numeric ratings compared to the reference category *Negative*.

In summary, the coefficient of *prior_avg_rating* is positive and statistically significant in both model 1 and 2 and therefore suggest a social influence effect. Yet, the interaction term between prior_avg_rating was not found to be significant. Therefore, while a social influence effect is present, hypothesis 2 is not supported by these results as there is no significant difference observed in the social influence effect between refurbished phones and new phones.

6 Conclusion

In this research, a text mining approach is used to investigate customer satisfaction and social influence in the refurbished iPhone market by answering the following research question: “What are the key motivators that determine customer satisfaction and how does social influence on potential customers for refurbished phones play a role compared to new phones?”. Two sub-questions were treated one for customer satisfaction and one for social influence effect. This was done in comparison with the normal iPhones, to capture the isolated effect that can be attributed to the refurbished aspect of the phones.

The first three hypotheses describing environmental, financial and product-specific feature motivation were answered to gain clarity on customer satisfaction. Environmental motivation and financial motivation with their related terms were defined by existing literature. Defining product specifications was done by plotting the POS-tagged nouns by frequency. From this, often mentioned product specifications were highlighted and used as terms for further analysis. A sentiment analysis on review level was run for each hypothesis to compare the sentiment of reviews. Reviews and their resulting sentiment were grouped by motivation based on the defined terms and split by phone type. The same principle was applied but on bigram level, to get the specific sentiment for a term based on its own context, rather than the general review text it occurs in.

Hypothesis 1a stated that reviews of refurbished phones exert higher satisfaction coming from environmental motivation compared to reviews of normal phones. On the review level, it was found that refurbished phone reviews indeed have higher levels of environmentally motivated satisfaction. They contain a larger proportion of positive sentiments and smaller shares of neutral and negative sentiment compared to reviews of new phones. The sentiment analysis on bigram level shows higher proportions of positive and neutral sentiments and lower shares of negative sentiment for refurbished phones compared to new phones. It can be concluded that refurbished phone reviews indeed exert higher levels of environmentally motivated satisfaction compared to new phones, both on review and bigram level.

Hypothesis 1b answers the question if reviews for refurbished phones have higher levels of financially motivated satisfaction, compared to new phones. Sentiment analysis on the review as a whole indicated smaller proportions of positive and neutral sentiments and higher levels of negative sentiments. Whereas the sentiment is more defined for refurbished phone reviews, the smaller shares of positive sentiment state that higher levels of financially motivated satisfaction are not observed in the data and thus experience more financial dissatisfaction compared to new phones. This can also be derived from the sentiments on bigram level, where neutrality is now higher, and the proportion of positive sentiments remains lower for reviews of refurbished phones.

Having detected the frequently mentioned product specification aspects, the answer derived from hypothesis 1c whether satisfaction from these aspects showcase lower values for refurbished phones can be formulated. All aspects carry a lower proportion of positive sentiments and higher share for negative sentiments for refurbished phones, on review level. Likewise, the bigram sentiment analysis shows the same results as on review level, with an increased level of neutrality. Hence, the data indeed shows lower satisfaction levels on screen, charging, battery and camera of a refurbished phone compared to a new phone.

To test for (a difference) in social influence for refurbished and new phone reviews, hypothesis 2 was set up stating that a larger effect of social influence is detected in reviews of refurbished phones. Based on previous research, this could be conceptualized by estimating the effect of prior review ratings on a review rating for a specific product. This was tested for through a nested ordered logit model to account for the nested product structure in the data and the ordinal nature of a rating. A dummy variable was added to account for the different types of products, refurbished and non-refurbished products. Prior average ratings between refurbished and non-refurbished products and an interaction term between prior average ratings and the dummy variable are denoted to test for the difference in social influence effect. Control variables such as place of review, number of words, and the previously identified sentiment and aspect variables were included, to isolate the effect of the social influence predictor. To test the full model's performance, a pseudo-R-squared is calculated and compared to a basic version of the full model.

The lower pseudo R-squared of the full model compared to the basic model and the statistically insignificant interaction term indicates that there is not a significant difference in social influence observed between reviews of refurbished and non-refurbished phone products. The average prior on its own does have a significant and positive effect across models. Yet, besides the results of a significant social influence effect, hypothesis 2 stating a larger influence effect in refurbished phone reviews does not hold.

6.1 Implications

This research contribution is defined by an innovative text-mining approach to obtain information on customer satisfaction and social influence effects for refurbished phones. This extends on existing research by evaluating reviews as on open text sources instead of survey methods used in previous studies. Moreover, this paper is unique in its set-up compared to its predecessors as it evaluates the results of the analysis on refurbished phone reviews by comparing it to reviews on the original version of the phones. Lastly, this paper's contribution is defined by creating an additional purpose for the sentiment scores besides solely interpreting them as results. They are also used in an additional model as control variables to reduce the unexplained variance of the nested ordered logit model.

An important methodological implication is derived from this paper for data scientists that seek to utilize sentiment analysis in their own research. The comparisons of sentiments on review and bigram level highlight the importance of context embeddings and definition when analysing term-specific sentiments. This is because the sentiment of a review does not always reflect the same sentiment of a part of the review, since consumers often list positive and negative opinions within the text. Additionally, this paper showcases the extended usability of sentiment categories beyond solely interpreting them. For the nested ordered logit model, sentiments were recycled and turned into relevant control variables in addition to the initial data. Plausibly, with this addition, part of the unexplained variance prior to investigating the social influence effect now could be controlled for by these new variables.

The practical implications of customer satisfaction for refurbished phones are derived from the results from hypotheses 1a through 1c. It was found environmental satisfaction is higher for refurbished phones. This points out the pivotal role of sustainability among potential customers regarding buying refurbished phones. This calls for marketing the purchase of a refurbished phone over a new phone by highlighting the positive environmental impact as a unique selling point to persuade potential customers. An example of implementation could be to obtain certain certifications[6] that ensures the customer of a sustainable refurbished product. The results showed a higher proportion of financial aspect mentions within refurbished phones, but these financial motivations were found to be more unsatisfactory for refurbished phones. This implies the presence of financial motivation, yet it did not lead to the desired satisfaction. This marks the importance of proper pricing strategies, to manage and maintain expectations for those who seek to derive financial satisfaction from buying a refurbished phone. With this, the obtained prices could be more satisfactory that can convert the now negative sentiment into a positive sentiment. Product specifications received lower satisfaction for refurbished phones compared to new phones based on the review data. In the process of selling refurbished phones, retailers could consider implementing an improved Quality Assurance step to improve the refurbished phone´s state to a more satisfactory level. This can help improve the satisfaction of customers who seek to buy refurbished phones that still maintain good quality in terms of product specifications. The original manufacturers can take this as a sign to start insourcing refurbished products and replicate their own quality assurance checks in the process to control their brand reputation

Arriving at the implications on the social influence effect, the implications on the difference between refurbished and new phones remain unavailable since no significant difference was found. However, social influence was detected in the review data. This implies a compound effect of the previously mentioned implications on customer satisfaction. Customer satisfaction of a buyer does not end once they have bought it. The difference in influence effect might not hold but the effect is present. Consumers ratings are influenced by prior ratings in a positive relationship. By improving the satisfaction dimensions, its compound effect gets exerted through the rating that serves the effect of having a positive influence on potential buyers and on potential ratings.

[6] A commonly used certificate for this is an R2 certificate. For more information, please refer to the following link: https://sustainableelectronics.org/r2/

6.2 Limitations and Future Research

This paper encountered some limitations during the research period, which can be improved on in future research.

The first limitation of this research regards the data collection of text reviews. As previously mentioned, there is limited review data available on the Amazon website for scraping for which an existing dataset was utilized from Amazon India. Even though the reviews were in English, scraping data from Amazon UK and, US and having data from Amazon India might have some cultural differences between these countries, which is stated in Seifian et al. (2023) and Sharifi & Shokouhyar (2021). As there was not accounted for country differences, a suggestion for future research would be to compare reviews of new and refurbished phone models from the same countries or similar ones to potentially get more unbiased results.

The second limitation is that in the scope of this research, reviews that are outliers in terms of the number of words per review were not taken out of the sample. Upon reflection after conducting the studies, a recommendation for future research would be to inspect and exclude outliers where possible.

The third limitation that could be optimized is the contextual embedding space used for the sentiment analysis. Whereas the bigram-level sentiment analysis gave proper results, one can observe the increased neutrality in sentiment compared to the review level. This is due to the restricted embeddings of bigrams where the meaning or sentiment of a word cannot be captured sufficiently by only their neighbouring word. A Bidirectional Encoder Representations from Transformers (BERT) model was considered in this research, as this model is effective in contextual embeddings, yet there is no updated available R package that treats a BERT model effectively. Therefore, a future research suggestion would be to adopt a BERT model instead of using bigrams for contextual embeddings with a different coding environment to potentially reduce the added neutrality on the sentiment analysis.

A fourth limitation regards the enhancement of variable selection for the nested ordered logit model that tested the social influence hypothesis. A potentially relevant addition to the variables could have been cognitive effort, which refers to acquiring knowledge and understanding the thoughts and senses behind it. The use of conceptualizing cognitive effort comes from the fact that consumers who write reviews with high cognitive effort tend to be less susceptible to the influence of others when writing a review as showed in the previously mentioned similar research in Li et al. (2020). This concept has been excluded from this research as the text mining tool, Linguistic Inquiry and Word Count (LIWC) program, was not easily retrievable to put to use in the span of this research. A future research suggestion is thus to improve the insignificant results related to hypothesis 2 by including such variables.

Lastly, a limitation which can be improved on is the detected multicollinearity in the nested ordered logit model. While here the relevant independent variable could not be removed from the model despite the multicollinearity, a future research suggestion here would be dimension reduction techniques such as Principal Components Analysis or LASSO regression to perform dimension reduction or feature selection that could combine correlated variables into one.

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8 Appendix

Appendix A

Table A1

Overview of Control Variables Used in Nested Ordered Logit Model

Name	Type	Description
Nr_words	Continuous	Number of words occurring in the original review text.
Place	Categorical	The country of which the review is from.
Sentiment_review	Categorical	Sentiment categories coming from the sentiment analysis.
Avg_sentiment	Continuous	Average sentiment score coming from the sentiment analysis.
Screen	Dummy	Dummy indicating the occurrence of the term screen in a review where 1 equals yes and 0 equals no.
Battery	Dummy	Dummy indicating the occurrence of the term battery in a review where 1 equals yes and 0 equals no.
Charging	Dummy	Dummy indicating the occurrence of the term charging in a review where 1 equals yes and 0 equals no.
Camera	Dummy	Dummy indicating the occurrence of the term camera in a review where 1 equals yes and 0 equals no.
Financial_motivation	Dummy	Dummy indicating the occurrence of financial motivation terms in a review where 1 equals yes and 0 equals no.
Environment_motivation	Dummy	Dummy indicating the occurrence of environmental motivation terms in a review where 1 equals yes and 0 equals no.

Appendix B

Table B1

VIF Values for the Nested Ordered Logit Model

Variable	GVIF	Df	GVIF^(1/(2*Df))
prior_avg_rating	1816.5	1	42.6
refurbished_dummy	1444.9	1	38.0
nr_words_original	742.3	1	27.2
place	33.2	2	2.4
sentiment_review	76.1	2	3.0
avg_sentiment	55.0	1	7.4
screen	2.6	1	1.6
battery	6.8	1	2.6
charging	4.3	1	2.1
financial_motivation	1.1	1	1.1
environmental_motivation	1.1	1	1.1
camera	1.1	1	1.0

The column GVIF indicates the general VIF value, df stands for degrees of freedom and the last column indicates the weighted VIF. A VIF of 1 indicates no correlation, a value smaller than 5 indicates moderate correlation, and from 5 up significant correlation is stated.