# Modeling Natural Decay of Delight in Product Attributes and its Impact on Customer Satisfaction

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# Modeling the Natural Decay of Delight in Product Attributes and its Impact on Customer Satisfaction

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## Acknowledgement

***You may need to adapt your decisions based on the circumstances, but never let any circumstances compromise your ultimate goals!***

This galvanizing aphorism played a crucial role in enabling me to complete my thesis over the last six months. These words served as a constant source of motivation throughout the process. The term "KANO model" first came to my attention during my bachelor's course on Total Quality Management. This model discusses the delight factor of a product and how it tends to diminish over time. Fast forward to the fourth quarter of my master's program in MoT at TU Delft, where I encountered the course "Emerging and Breakthrough Technologies" taught by Prof. Roland Ortt. In this course, Prof. Ortt explained that the technology-S curve is incomplete, and there are two additional crucial phases: innovation and market adaptation.

It was during this time I realized how the KANO model could be a valuable tool to analyze customer satisfaction factors based on the interaction of various product attributes. Seizing the opportunity, I pitched this idea to the incubator of Philips Domestic Appliances in December 2022. As a result, I was granted the privilege of writing my master's thesis at the prestigious product innovation department (NBX) of Philips Domestic Appliances, located at its headquarters in Amsterdam. I cannot express enough gratitude to Mr. Thomas Deflandre for granting me this opportunity, which enabled me to complete my master's thesis with Philips. Moreover, I was given access to invaluable data from the Philips air fryer portfolio, which facilitated the completion of my thesis and allowed me to explore further the idea I had originally conceived during my bachelor's studies.

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### Executive Summary

This thesis explores the dynamics of customer satisfaction and its relationship with product attributes while modeling the natural decay of delight associated with these attributes. The research analyzes online reviews of Philips Airfryers to provide valuable insights for businesses aiming to enhance customer satisfaction and remain competitive in a dynamic marketplace.

The study offers several insights into the concept of the natural decay of delight, which refers to the diminishing satisfaction experienced by customers over time. It reveals that the availability of alternative products influences this decay, indicating that as more alternatives become available, the initial delight associated with a product tends to diminish. This understanding underscores the importance of managing customer satisfaction throughout the product life cycle.

The thesis delves into the impact of product attributes like capacity, repurchase intention, and value for money on customer satisfaction [1]. It identifies these attributes as significant factors affecting customer satisfaction levels. Capacity, when aligned with customer expectations, enhances satisfaction. A positive repurchase intention fosters greater satisfaction and brand loyalty. Moreover, customers perceiving good value for money report higher satisfaction. The study also explores the moderating role of external variables, such as the number of alternatives, in shaping these relationships, providing valuable insights into customer preferences and behavior.

Moreover, the research incorporates external factors, including the impact of the Covid-19 pandemic, sales channels, and regional variations. These external influences are crucial in shaping customer satisfaction and require consideration in product management and marketing strategies.

The practical implications of the findings are significant for businesses. They emphasize the importance of understanding the natural decay of delight and managing product attributes to optimize customer satisfaction. By strategically considering moderating variables, companies can enhance their investments and overall customer satisfaction. Additionally, the study highlights the significance of adapting to changing market dynamics by incorporating external factors in product strategies.

In conclusion, this thesis provides a comprehensive analysis of customer satisfaction dynamics, product attributes, and external influences. The insights gained can guide businesses in developing effective strategies to manage customer satisfaction, adapt to market changes, and maintain a competitive edge. By understanding and addressing customer preferences and factors influencing satisfaction, businesses can optimize their efforts and drive success in today's fiercely competitive marketplace. Businesses should prioritize actively managing product attributes, continuously seeking customer feedback, and proactively adapting to evolving customer demands with the support of their data analytics teams. These actions aim to enhance overall customer satisfaction and foster loyalty.

[1]Keywords: Capacity, Value for Money, Repurchase Intention, Total Alternatives, Airfryer, Customer Satisfaction, and Natural Decay of Delight.

### Relevance to MoT

The conclusions drawn from the thesis fall within the scope of various core Management of Technology courses. Within this thesis, I could apply the discoveries related to courses such as Emerging and Breakthrough Technology (MoT2421). In the EBT course, we examined the progression of technology over time, including how specific technologies at the product level bridge the gap and how various incremental changes enable the product to remain competitive throughout its life cycle. A similar pattern is evident in my thesis. I evaluated customer satisfaction over time and its relationship with product attributes such as capacity, value for money, and customers' repurchase intentions. Furthermore, in this thesis, I also explored the influence of external factors, such as the availability of alternatives.

Additionally, I utilized the principles from the course Technology, Strategy, and Entrepreneurship (MoT1435) in this thesis. The findings benefit the Philips Airfryer team as they can adjust their strategies accordingly. The results indicate that customer satisfaction is influenced by factors such as value for money, repurchase intentions, and the number of alternatives available. These findings align with the concepts discussed in the Technology, Strategy, and Entrepreneurship course, where we analyze how technology and innovation strategies can impact market positioning and customer satisfaction. The thesis provides practical insights for the Philips Airfryer team to refine their strategies, enhance the value proposition of their product, and differentiate themselves in a competitive market.

Furthermore, the thesis has implications for the course High Tech Marketing (MoT1534). It demonstrates the importance of understanding customer preferences and tailoring product attributes to meet their needs. By incorporating customer satisfaction analysis into product management practices, managers can make data-driven decisions regarding product features, pricing, and marketing strategies. The thesis highlights the significance of customer-centric approaches in driving customer satisfaction and maintaining a competitive edge in the market.

Overall, the findings and implications of this thesis extend beyond the realm of academic research and have practical applications in various Management of Technology courses. By applying the principles and concepts discussed in these courses, managers can effectively navigate the challenges of technological advancements, formulate strategies, and optimize customer satisfaction to drive business success.

# Contents

**Acknowledgement** **i**

**Executive Summary** **ii**

**Relevance to MoT** **iii**

**Nomenclature** **vi**

**1 Introduction** **1**

**2 Theoretical Framework and Hypothesis** **3**
2.1 Customer Satisfaction . . . . . . . . . . . . . . . . . . . . . . . . . . . . 4
2.2 Effect of product's capacity on customer satisfaction . . . . . . . . . . . . . 5
2.3 Effect of value for money of the product on customer satisfaction. . . . . . . 6
2.4 Effect of customer repurchase intention on customer satisfaction. . . . . . . 8
2.5 Number of alternatives of a product as the moderating variable . . . . . . . 9
2.5.1 Moderating role of the number of alternatives on product capacity and customer satisfaction . . . . . . . . . . . . . . . . . . . . . . . . 10
2.6 Moderating role of the number of alternatives on the relation of value for money and customer satisfaction . . . . . . . . . . . . . . . . . . . . . . . . 11
2.6.1 Moderating role of the number of alternatives on the relation of customer's repurchase intention and customer satisfaction . . . . . . 13

**3 Methods** **15**
3.1 Data collection and sample . . . . . . . . . . . . . . . . . . . . . . . . . . 15
3.1.1 Measure . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 16
3.2 Data Preprocessing . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 17
3.3 Variables . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 19
3.3.1 Dependent variable . . . . . . . . . . . . . . . . . . . . . . . . . . 19
3.3.2 Independent Variables . . . . . . . . . . . . . . . . . . . . . . . . . 19
3.3.3 Control Variables . . . . . . . . . . . . . . . . . . . . . . . . . . . 24
3.3.4 Analytical approach . . . . . . . . . . . . . . . . . . . . . . . . . . 25

**4 Results** **27**
4.1 Hypotheses tests . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 30
4.2 Impact of product's capacity on customer satisfaction . . . . . . . . . . . . 30
4.3 Impact of value for money on customer satisfaction . . . . . . . . . . . . . . 30
4.4 Impact of Customer's repurchase intention on Customer Satisfaction . . . . 32
4.5 Moderating effect of the number of alternatives . . . . . . . . . . . . . . . . 32

**5 Discussion and Conclusions** **38**
5.1 Theoretical implications . . . . . . . . . . . . . . . . . . . . . . . . . . . . 38
5.2 Limitations and Future Recommendations . . . . . . . . . . . . . . . . . . . 40
5.3 Practical implications . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 41
.1 Appendix: Thesis Code . . . . . . . . . . . . . . . . . . . . . . . . . . . . 47

**Thesis Code** **47**
.2 Appendix: Result Tables . . . . . . . . . . . . . . . . . . . . . . . . . . . . 64

**Result Tables** **64**
.3 Syuzhet package sentiment analysis visuals . . . . . . . . . . . . . . . . . . . 64

**Syuzhet package sentiment analysis visuals** **64**

# Nomenclature

| | |
|---|---|
| $B2C$ | Business-to-Consumer |
| $CL$ | Customer Loyalty |
| $CS$ | Customer Satisfaction |
| $D2C$ | Direct-to-Customer |
| $KANO$ | The KANO model |
| $KPI$ | Key Performance Indicator |
| $PhilipsDA$ | Philips Domestic Appliances |
| $RI$ | Repurchase Intention |
| $SA$ | Sentiment Analysis |
| $SKU$ | Stock Keeping Unit |
| $TM$ | Text Mining |
| $UID$ | Unique Identification |
| $VfM$ | Value for Money |
| $WoM$ | Word-of-Mouth |

# List of Figures


1 Conceptual Model . . . 3
2 Capacity and CS . . . 6
3 VoM and CS . . . 8
4 RI and CS . . . 9
5 Moderating impact on Capacity of the product . . . 11
6 Moderating impact on Value for Money . . . 12
7 Moderating impact on Repurchase intention . . . 14
8 Data Collection . . . 15
9 Text mining process . . . 18
10 Multi linear regression equation . . . 25
11 Means, standard deviations, and correlation . . . 28
12 Moderating impact on Capacity . . . 33
13 Moderating impact on Value for money . . . 34
14 Negative value for money comparison . . . 35
15 Positive value for money comparison . . . 36
16 Moderating impact on customer repurchase intention . . . 37
17 Syzuhet process . . . 64
18 sentiment values . . . 66


# List of Tables


1 Dictionary: Value dictionary . . . 22
2 Dictionary: Repurchase dictionary . . . 23
3 List of Continents . . . 25
4 Value distribution . . . 29
5 Multiple Linear Regression Model . . . 31
6 Add caption . . . 64
7 Distribution of reviews . . . 65

# 1 Introduction

In today's digital era, the success and growth of businesses, particularly in online shopping, heavily depend on customer satisfaction. With the global internet user count surpassing five billion and continuously rising (Statista, 2023), more and more people are embracing online shopping through e-commerce platforms like Amazon and Bol. This surge in popularity has intensified competition, even for niche products. Consequently, understanding the factors that influence customer satisfaction has become crucial for businesses to thrive in this fiercely competitive landscape. Customer satisfaction (CS) directly impacts critical business metrics like customer loyalty (CL), price, and positive word-of-mouth (WoM) (Juliana et al., 2021). Therefore, businesses must focus on unraveling these factors and adapt to technological advancements to stay relevant and successful.

Numerous studies have investigated the factors that influence customer satisfaction, revealing the importance of product quality, repurchase intention, service delivery, ease of use, and value for money as key determinants (Goswami et al., 2017, Wang and Wang, 2019, Liu et al., 2019). However, despite the extensive research and knowledge about individual factors influencing customer satisfaction, there are still gaps in our understanding of how these factors combine to impact overall customer satisfaction. While existing literature provides valuable insights into the influence of factors like repurchase intention, product ease of use, and service quality on customer satisfaction, further exploration is needed to understand how these relationships are affected by external factors and changes in the competitive landscape. It is important to delve deeper into the intricate dynamics that shape customer satisfaction to gain a more comprehensive understanding.

The significance of addressing this knowledge gap lies in its implications for business strategies. Overlooking the intricate dynamics of customer satisfaction can lead to sub-optimal product development. Furthermore, neglecting to address this knowledge gap leaves businesses uninformed about pivotal factors influencing customer satisfaction, hindering their ability to adapt to evolving market conditions and effectively meet customer demands. In light of rapid technological progression and intensifying competition, understanding and integrating these complex dynamics become indispensable for sustaining success and fostering customer-centric approaches.

Thus, factors that influence customer satisfaction require more elaborate investigation to uncover underlying drivers and how they interact with technology progression. This thesis aims to address these gaps by analyzing the nuanced relationships between product attributes and customer satisfaction within the context of technology progression. The main objective is to model the natural decay of delight in product attributes, as first teased in the KANO model(Kano, 1984) and emphasized by industry leader Daniel Zacarias (Zacarias, 2023). This modeling offers a solution to sustain and enhance customer satisfaction amidst technological advancements and competition. Adapting products to evolving customer demands, embracing innovation, and providing new experiences foster loyalty and ensure business success in the dynamic digital era. As innovative features are introduced yearly, they increase customer delight levels. Consequently, the previous delight level becomes the new baseline, and failing to adapt to evolving customer demands may result in a drop in customer satisfaction. The ever-evolving technological landscape allows companies to enhance their products, providing customers with new and exciting experiences, ultimately positively shaping their satisfaction and loyalty.

Therefore, this thesis aims to investigate technological progress and its impact on the relation between various attributes associated with a product and customer satisfaction over time. Specifically, I aim to examine to what extent customer satisfaction is influenced by product attributes such as capacity, value for money, and customer repurchase intention. Additionally, I will explore the role of technological progress and increasing competition, as indicated by the growing number of alternatives for a product, in shaping customer satisfaction. By understanding these dynamics, businesses can better understand customer preferences, adapt their strategies, and optimize customer satisfaction in an evolving market.

In this study, I will leverage the valuable insights available in online reviews, which serve as a rich source of customer feedback. Online reviews offer an accessible and cost-effective means of collecting customer sentiments and opinions (Arashpour et al., 2018). I can measure and evaluate customer satisfaction levels over time by analyzing these reviews using sentiment analysis and text-mining techniques. Through this thesis, I will gain insights into the natural decay of delight in product attributes and its impact on customer satisfaction over time as competition increases. By addressing this research question, I aim to provide businesses with actionable insights to enhance customer satisfaction, develop effective strategies, and remain competitive in the dynamic marketplace.

The thesis begins by discussing the importance of customer satisfaction in the context of technological progression. Three main effect hypotheses and three independent variables impacting customer satisfaction are introduced. The moderating variable - the number of alternatives to a product - is presented to examine technological progression, along with three additional moderating hypotheses. The Methods section outlines data collection and sampling processes. Results from sentiment analysis and text mining on online reviews are presented, explaining all hypotheses and revealing significant main effect relationships on capacity, repurchase intention, and value for money. The moderating role of the number of alternatives is confirmed, affecting certain attribute-customer satisfaction relationships. The Discussion section explores theoretical implications, limitations, future recommendations, and practical implications. Finally, the thesis is summarized, and the R-studio code used for analysis is included in the appendix.

## 2 Theoretical Framework and Hypothesis

To gain a comprehensive understanding of the product's impact on customer satisfaction and to explore the underlying dynamics of the natural decay of delight based on the main research question of this thesis, I derived the conceptual model based on the KANO model (Kano, 1984). Based on the review of relevant literature on antecedents of customer satisfaction, I selected variables such as product's capacity(Oliver, 2014, Garvin and Quality, 1984) represents the physical attribute of the product, while value for money (VfM)(V. A. Zeithaml, 1988) and customer repurchase intention (RI) (Pan et al., 2012, Oliver, 1999) capture customers' perspectives and intentions, all of which have a strong grounding in the literature. Additionally, I incorporated three moderating hypotheses to examine the effect of the number of alternatives, representing the level of competition, on the relationships between the selected variables and customer satisfaction. The number of alternatives serves as a crucial moderating variable, reflecting the dynamic nature of the market and its influence on customer satisfaction as technological progress is considered. The conceptual model can be seen in the figure (1).

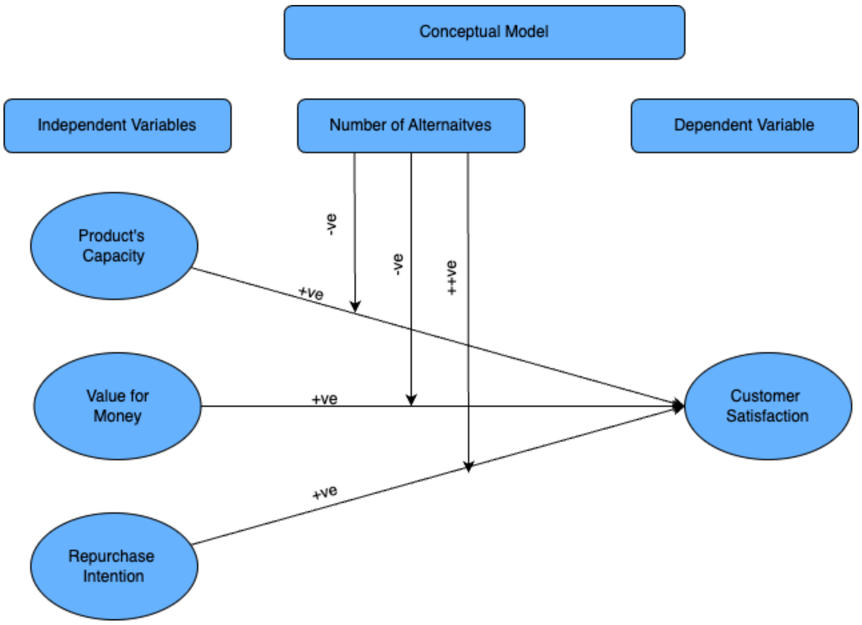


Figure 1: Conceptual Model

To delve into the main research question, this thesis explores the natural decay of delight in product attributes and its influence on customer satisfaction over time within a theoretical framework. By examining the interactions between selected attributes and customer satisfaction, considering the evolving market dynamics influenced by an increasing number of alternatives, valuable insights into factors shaping customer satisfaction will be provided. Understanding the role of technological progress and competition will enable businesses to make informed decisions on product development, marketing strategies, and customer relationship management. This study's findings will contribute to existing knowledge and offer practical implications for businesses seeking a competitive edge in a dynamic marketplace.

## 2.1 Customer Satisfaction

Customer satisfaction refers to the extent to which a customer's expectations and desires are met or exceeded by a product, service, or overall customer experience (Homburg et al., 2015). Satisfied customers are more likely to remain loyal to a brand and recommend it to others, contributing to a positive reputation and increased revenue (V. A. Zeithaml, 1988). Achieving high levels of customer satisfaction is a fundamental goal for companies across various industries as it directly impacts customer retention and market competitiveness (Soderlund and Ohman, 2005). By understanding and addressing customer satisfaction, businesses can strengthen customer relationships and drive sustainable growth (Anderson and Sullivan, 1993).

Customer satisfaction is a crucial factor in the new product development process, reflecting how well a product aligns with customer needs and preferences (Needle, 2022). Understanding and addressing customer expectations are vital for optimizing satisfaction and fostering long-term customer loyalty (Needle, 2022). In this context, the KANO model sheds light on the "natural decay of delight," where customers may lose interest in certain product attributes over time due to the availability of better alternatives (Kano, 1984). Additionally, service quality and pricing strategies directly impact customer satisfaction (Turel and Serenko, 2006). A satisfied customer is likelier to repurchase, recommend the product through word-of-mouth, and demonstrate brand loyalty (Hanif et al., 2010).

Thus, it is important to look into the factors which impact customer satisfaction. The product's capacity, value for money, and repurchase intention as the antecedents of customer satisfaction are grounded in the existing literature on factors influencing customer satisfaction. These three variables have been studied and are known to significantly impact customers' perceptions and overall satisfaction with a product or service.

1. Capacity: Capacity represents a physical attribute of the product that directly influences customer satisfaction. Studies (Oliver, 2014, Garvin and Quality, 1984) have shown that product attributes, such as capacity, affect customers' functional needs and their satisfaction with the product's performance. Customers often seek products with sufficient capacity to meet their specific requirements, and a higher capacity tends to lead to higher satisfaction levels. For this thesis, I will delve into the capacity of on-shelf kitchen appliances. These products generally include air fryers, microwave ovens, cookers, kettles, coffee makers, etc. (Dowling, 2022).

2. Value for Money: The concept of value for money captures customers' perceptions of getting the most benefits for the price they pay for a product. Research (V. A. Zeithaml, 1988) has demonstrated that customers' perceptions of value for money significantly influence their overall satisfaction. Customers' satisfaction increases When they believe they are getting a good deal and the product justifies its price.

3. Repurchase Intention: Repurchase intention is a strong indicator that influences customer loyalty and satisfaction. Numerous studies (Pan et al., 2012, Oliver, 1999) have demonstrated that satisfied customers are more likely to express an intention to repurchase from the same brand or company in the future, thereby further enhancing their satisfaction levels. High repurchase intention reflects customers' positive experiences and satisfaction with the product, leading to potential long-term relationships with the brand.

By selecting these antecedents, this study aims to gain a comprehensive understanding of how product attributes (capacity), customer perceptions (value for money), and behavioral intentions (repurchase intention) collectively influence customer satisfaction. Combining these variables provides a holistic view of customers' satisfaction determinants and allows for a deeper analysis of the natural decay of delight in product attributes over time.

## 2.2 Effect of product's capacity on customer satisfaction

The product's physical capacity is the first attribute in the thesis to answer the main research question. The capacity of a product is a crucial factor in determining customer satisfaction. It refers to the maximum quantity or volume the product can hold (Kenton, 2021). Having attractive attributes in the product design is necessary to keep customers excited. These attributes influence a customer's satisfaction with the product (Matzler and Hinterhuber, 1998). By incorporating attractive new features, companies can enhance customer satisfaction. As consumer products gain popularity, more people start buying them. Therefore, companies must consider product capacity an important key performance indicator (KPI) impacting customer satisfaction levels.

Research suggests that when a product's capacity aligns well with the customer's needs and usage requirements, it enhances overall satisfaction (Cadotte et al., 1987). Adequate capacity ensures that the product can fulfill customer demands effectively, avoiding any dissatisfaction caused by limitations in functionality or storage, thus improving the overall efficiency of the product. Therefore, understanding and addressing the physical capacity of a product is crucial for businesses seeking to improve customer satisfaction and maintain a competitive edge in the market. The capacity of a product plays a vital role, especially for regularly used products such as mobile phones, laptops, and even air fryers.

In addition to better efficiency of the product, products with higher capacity lead to improved customer satisfaction. This is because, with the larger size, it is generally perceived that the product will be able to meet the higher demand of the customers more effectively in one go without them recharging or replenishing the product over and over again (Lynham, 2023). This convenience is a significant advantage, leading to increased customer satisfaction. Moreover, producing on a larger scale can be more cost-effective for companies, allowing them to optimize production processes and offer products at competitive prices. Overall, offering larger-sized products can enhance customer satisfaction and provide businesses with operational efficiencies.

Furthermore, the capacity of a product should be developed based on customer requirements and perceptions. It should be large enough to fulfill their basic daily needs while being small enough to fit comfortably in their homes without causing any inconvenience. This is very important for home appliances, generally used in the kitchen or other essential areas at home. The product should be compact enough to fit on a kitchen shelf because if customers do not require a larger size, it can lead to dissatisfaction. Additionally, according to (Urban et al., 1984), customers are becoming more demanding regarding products. Therefore, the products must be personalized, of high standards, and contain modern features.

Research on customer satisfaction in countertop appliances (Magazine and Magazine, 2014) revealed that the product's capacity significantly influences customer satisfaction.

The mechanism at play is that the appliance's capacity directly impacts its functionality and utility. For instance, when selecting an air fryer or a microwave oven, customers consider the appliance's capacity to ensure it meets their cooking demands. A larger capacity allows them to prepare more food in a single batch, saving time and effort. On the other hand, the appliance must also be compact enough to fit conveniently in their kitchen without occupying excessive space (Robin, 2022). Therefore, a well-balanced capacity that aligns with customers' cooking needs and kitchen space constraints positively impacts their satisfaction with the product. Customers are more likely to feel satisfied when they find an appliance that meets their specific requirements, enhancing their overall experience and loyalty to the brand. Therefore, based on the arguments, I hypothesize that:

**Hypothesis 1:** The capacity of the on-shelf consumer products positively influences customer satisfaction, where an optimal product capacity aligns with customer demand, leading to higher customer satisfaction.

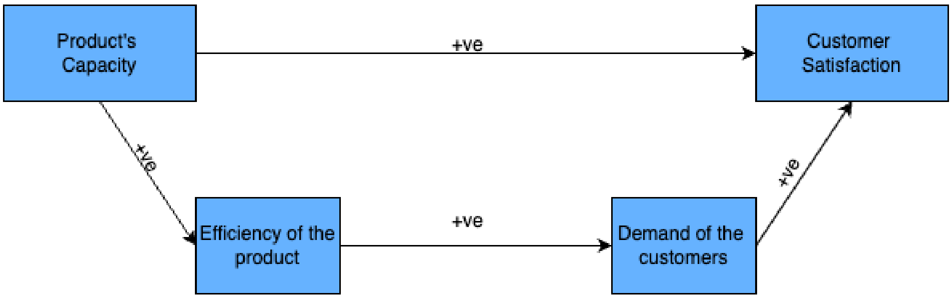


Figure 2: Capacity and CS

## 2.3 Effect of value for money of the product on customer satisfaction.

The second attribute in the thesis to delve into the main research question is the value for money. The term value for money refers to the perceived worth or utility that customers assign to a product based on their assessment of its features and how well it meets their needs regarding its monetary cost. It involves customers' evaluation of whether the product's benefits justify the price they pay for it. Value for money is also known as value-based pricing. Furthermore, according to (Tirtayasa, 2022), suitable and appropriate product price considerably affects the product's quality. This is because customers tend to compare the product with its competition to grasp what attributes are offered at the given price range before deciding to purchase the product that meets their requirements. Moreover, price is an important factor for businesses to consider. They need to investigate factors such as price tolerance, which refers to how much and for how long customers are willing to accept a certain price before switching to another product(Anderson, 1996).

Furthermore, a longitudinal study conducted by (Haverila and Twyford, 2021) investigated customer satisfaction across various project stages. The study highlights a robust correlation between value for money and customer satisfaction. It also indicates that customers highly value products with elevated quality standards, leading to greater returns on their investment, subsequently influencing their overall satisfaction with a product or service. Customers who perceive they are getting good value for their money are more likely to be content with their purchase.

The strong relationship between value for money and customer satisfaction can also be explained through the mechanism of perceived fairness and expectations. When customers perceive that they are receiving a good return on their investment, they feel that the benefits they are getting from the product or service align well with the price they paid. This perception of fairness in the exchange leads to a positive evaluation of the value obtained from the purchase. Customers often have certain expectations regarding the benefits and quality they should receive for a given price. When a product exceeds these expectations and provides greater value than anticipated, customers are positively surprised, enhancing their satisfaction. On the other hand, if a product falls short of expectations and does not deliver the perceived value for money, customers are likely to be dissatisfied. Thus, aligning perceived value with expectations is crucial in shaping customer satisfaction and overall contentment with the purchase (Haverila and Twyford, 2021).

Apart from that, by offering products and services tailored to the specific needs and preferences of the target customers, businesses can improve customer satisfaction, profitability, and market positioning through customer-based pricing. This approach can result in increased customer lifetime value and positive word-of-mouth referrals, making value for money a desirable pricing strategy for businesses seeking to expand their customer base. As a product advances through the technology innovation curve from its early stages to maturity, it is expected to become more advanced and meet the needs of a larger population. As a result, the product's value for money will likely improve because more customers are expected to use it.

The relationship between perceived value for money and customer satisfaction is also influenced by the perception of product differentiation, comparative evaluation of alternatives, and reference price comparisons. When customers perceive a product to have higher value and quality than competitors, they become more tolerant of its price, leading to higher satisfaction. Brand reputation and customer loyalty also play a role; customers are more likely to trust a brand that consistently provides high-quality products with good value. On the other hand, brands with a reputation for overpricing or delivering lower value may face challenges in convincing customers of a product's worth, resulting in lower satisfaction. Overall, customers' perceptions of the fairness of the product's price relative to its perceived value shape their satisfaction levels (Chew and Wirtz, 2001, Lichtenstein et al., 1993).

Finally, according to (Mahajan, 2020), customers become more tolerant and lenient to the price of the product when they perceive that the product offered by the company has a higher value, quality, and worth as compared to the competitors in the market. Therefore, based on these arguments, I hypothesize:

**Hypothesis 2**: There is a positive relation between the value for money for a product and customer satisfaction, where an increase in perceived value for money leads to higher levels of customer satisfaction.

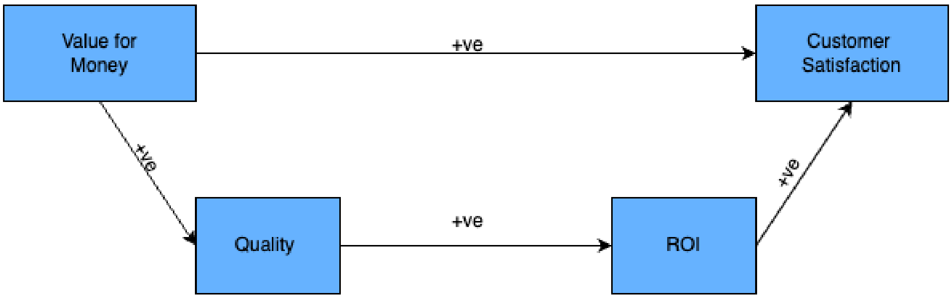


Figure 3: VoM and CS

## 2.4 Effect of customer repurchase intention on customer satisfaction.

The final attribute to answer the main research question is the concept of the customer's repurchase intention. The concept of a customer's repurchase is the expressed loyalty and commitment of a customer to a product or service. It signifies the likelihood of a customer making another purchase after having a positive experience with the product or service. Repurchase intention is a critical aspect of attitudinal loyalty, representing the customer's inclination to continue buying from the same brand or company. It indicates the customer's desire to maintain an ongoing relationship with the product/service provider due to their satisfaction with previous experiences (Herjanto and Amin, 2020). In essence, a high repurchase intention is a positive indicator of customer loyalty and satisfaction, as it demonstrates the customer's willingness to engage in repeated business with the same brand or company.

Although customer satisfaction indeed increases the likelihood of customers intending to repurchase, the relationship between the two is mutually influential. (Curtis and Tamilla, 2023).The mutually influential relationship between customer satisfaction and repurchase intention suggests a bidirectional impact. When satisfied with a product or service, customers are more likely to have a positive repurchase intention, as their previous positive experience influences their future buying decisions. On the other hand, a strong repurchase intention can also positively influence customer satisfaction, as customers to repurchase are more likely to perceive the product or service in a favorable light, leading to increased satisfaction. This bidirectional relationship reinforces the importance of customer satisfaction and repurchase intention in fostering customer loyalty and brand success. This also implies that the customer's intention to repurchase the product from the same brand also impacts customer satisfaction. Numerous studies have demonstrated a positive correlation between customers' intent to repurchase and its impact on customer satisfaction.(Brady et al., 2001, J Jr et al., 2000, Johnson and Fornell, 1991).

Furthermore, repurchase intention can lead to customer satisfaction through loyalty. Loyal customers are more forgiving of occasional lapses or minor issues because they have developed trust and a positive emotional connection with the brand (Mittal and Kamakura, 2001). As a result, customers with strong repurchase intentions may be more likely to overlook minor inconveniences and remain satisfied with the overall experience. A loyal customer can also positively influence customer satisfaction by facilitating positive word-of-mouth. Satisfied and loyal customers who intend to repurchase are likelier to share their positive experiences with others, leading to increased brand advocacy and a positive reputation (V. Zeithaml et al., 1996). This, in turn, can reinforce customer satisfaction as they feel a sense of pride and loyalty toward the brand.

Finally, it is imperative that companies keep their customers happy and not allow them to move to other competitors' products. Therefore, based on these arguments, I hypothesize:

**Hypothesis 3**: There is a positive relation between a customer's intention to repurchase from the same brand and their level of customer satisfaction.

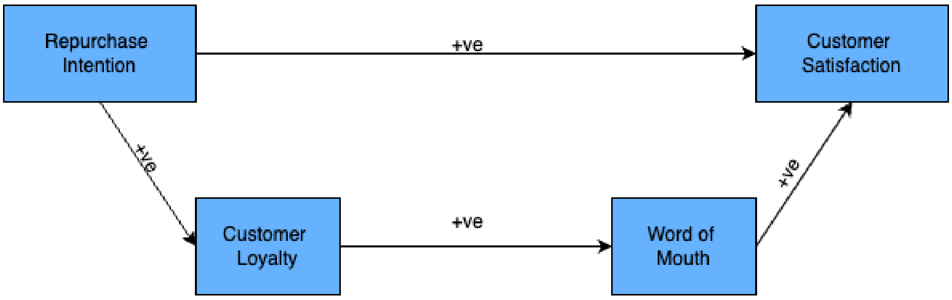


Figure 4: RI and CS

## 2.5 Number of alternatives of a product as the moderating variable

To understand the natural decay of delight and investigate the central research question of the thesis, I examined the increasing number of product alternatives as technological progression occurs. The total number of alternatives to a product refers to the count of all competing products or services that can fulfill similar customer needs or preferences in the marketplace. In other words, it represents the range of choices available to consumers when considering a particular product or service. The higher the number of alternatives, the greater the product's competition in the market. The total number of alternatives is an important factor to consider in understanding customer satisfaction dynamics, as it can influence how customers perceive and evaluate a product compared to its competitors.

Furthermore, competition is an inherently embedded element of any marketplace. As companies and businesses strive to attract and proselytize customers and improve their market share, the level of competition intensifies. The increase in the level of competition can be seen internally and externally. As the level of competition increases, the companies also strive to introduce different versions of their product with different specifications and features to meet the demand and requirements of a much larger audience. Although many external factors impact the natural decay of delight in a product, it is important to know that an increase in competition for the product, both externally and internally, also impacts the decay. The increase in competition can correspond to the availability of more alternatives to the given product.

There exist numerous studies that indicate how the increase of competition levels profoundly affects customer satisfaction within firms. An extensive investigation, documented in (Gao et al., 2019, page 1617 to 1628), indicated that customers determine their satisfaction comparatively. In other words, customers' satisfaction with a particular firm and its products or services is intricately intertwined with their satisfaction with a rival firm's products or services. Consequently, as customers experience an elevated level of satisfaction with the rival firm's products, their contentment with the original firm and the product it offers diminishes accordingly, and vice versa. Furthermore, strategy management scholars indicate that competition forces firms to choose innovative behavior to improve competitive edge based on differentiation strategy for competition (Correa and Ornaghi, 2014).

Additionally, in industries characterized by dynamic competition, each firm strives to develop new and dynamic products and processes that serve as distinctive strategic assets (Sun and Lee, 2018). The distribution of consumers' heterogeneous preferences remains unknown to firms in advance. Innovative firms can improve their chances of discovering pockets of consumers with unmet preferences by introducing several alternatives and more products. While some products may fail, each offering increases the likelihood of satisfying consumers (Sorenson, 2000).

In a market with fewer alternatives to the product, firms prioritize catering to the basic needs of the customers. When the product becomes more prominent, and the level of competition increases, a wide range of products with different prices and additional features and services emerge, thus meeting the needs of a wider array of customers. When enterprises face challenges in expanding their market share or attracting a larger customer base through product innovation or distinctive offerings, the impact of competitor behavior becomes increasingly significant. (Gao et al., 2019, page 1617 to 1628).

### 2.5.1 Moderating role of the number of alternatives on product capacity and customer satisfaction

According to (Chen and Miller, 1994, Chen et al., 1992), if competitors improve their level of customer satisfaction, a firm is more likely to respond by improving its customer satisfaction. This can be achieved by enhancing their attributes based on customer needs or introducing new products to their portfolio. An interesting scenario arises when a product is new to the market, and customers are unaware of how its attributes can be utilized to meet their needs. Initially, the product may have a certain level of customer satisfaction, but as it becomes more prominent and alternatives enter the market, its attributes may change to meet customer requirements. Additionally, over time, as products gained more popularity and companies began providing different sets of products with varying sizes/capacities and other features to meet the demands and requirements of larger populations, customers had more options to choose a product that accurately met their requirements.

This competition arises from rival companies (externally) and the same company (internally) expanding its product portfolio. Such expansion can lead to a loss of market share to competitors offering superior products or services at lower prices (Simon and Gómez, 2014). This competitive pressure also compels firms to enhance their existing attributes, yielding higher-quality products. However, enhancing these attributes can trigger the 'natural decay of delight. Initially, attractive attributes may lose their allure over time due to improved industry standards. Additionally, heightened competition can improve market expectations for product efficiency.

In the realm of consumer products, both capacity and other attributes undergo evolution over time. Initially, when a product is introduced to the market, companies lack a comprehensive understanding of customer preferences and responses to specific attributes. Only as the product gains prominence and garners, a growing user base will customers' distinct requirements, including capacity and efficiency, become apparent. To cater to diverse needs and elevate overall satisfaction, companies strategically offer a variety of products with varying capacities. For example, for countertop kitchen appliances, companies present various choices tailored to specific cooking needs. Larger households may opt for higher-capacity appliances, accommodating sizable food portions, while smaller households may prefer more compact options for efficient cooking. This variety enables customers to expect precise fulfillment of their demands, fostering the belief that they can discover a product ideally suited to their unique requirements, thus augmenting overall satisfaction. However, heightened competition can also impact customer demand for a particular brand's products, as competing companies may better meet expectations. As other brands fulfill customer needs, satisfaction with the original brand could diminish.

As the market becomes more saturated with alternatives and competition for a specific product intensifies, the impact of a given product's capacity on customer satisfaction can diminish. Initially, a particular capacity may have excited customers and positively influenced their satisfaction. However, as more alternatives become available, customer preferences may shift, and the previously exciting capacity may no longer hold the same appeal. With a broader array of choices, customers can now compare and select products that better suit their evolving needs and preferences. Consequently, the relationship between a product's capacity and customer satisfaction may weaken over time, reflecting customer preferences' dynamic nature and increased competition in the marketplace. Therefore, based on the above arguments, I hypothesize:

**Hypothesis 4**: The relationship between product capacity and customer satisfaction is moderated by the number of alternatives, such that the positive impact of capacity on customer satisfaction is weaker when there are more alternatives available in the market.

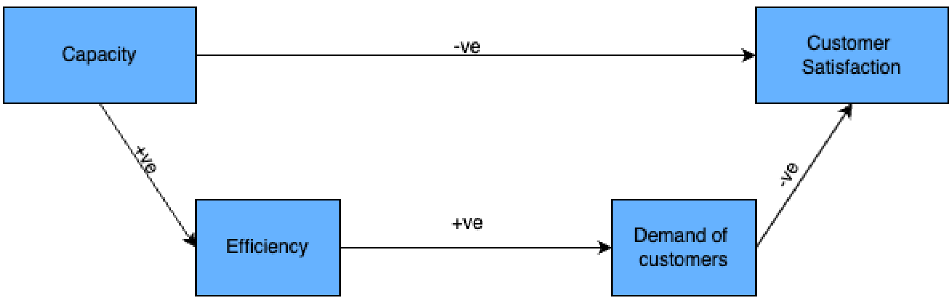


Figure 5: Moderating impact on Capacity of the product

### 2.6 Moderating role of the number of alternatives on the relation of value for money and customer satisfaction

As a product attains maturity and becomes more attractive, an elevation in competitive offerings and the proliferation of alternatives can negatively influence the relationship between value for money and customer satisfaction. This phenomenon is particularly evident when customers assess their purchase's quality against the benchmarks set by competing brands. Suppose their product's quality and attributes fall short of those rival brands offer. In that case, customers may perceive their return on investment as sub-optimal, contributing to reduced satisfaction.

This scenario highlights the critical role of value for money in shaping customer satisfaction. Hen customers perceive that their investment needs to be commensurate with the quality and features of comparable products from other brands, their satisfaction can be compromised. Therefore, maintaining a competitive edge in product attributes and pricing becomes pivotal for businesses aiming to safeguard and enhance customer satisfaction amidst a competitive landscape.

Additionally, as the number of alternatives for a product or service increases, the customers have more independence and options to choose the products based on their preferences. This means that the companies need to focus more on understanding the value concept for the customers and how the needs and values of the customers change over time (Mahajan, 2020).

Research by (Labandeira et al., 2017) indicates that the growing number of alternatives affects customers' value for money perception. With more alternatives in the market, the demand elasticity of a product changes, making it more sensitive to price fluctuations. If the price of a product rises, customers are more likely to switch to competitively priced alternatives. This heightened price sensitivity prompts customers to seek better deals and options, influencing their perception of value for money. Consequently, the relationship between value for money and customer satisfaction weakens as customers become more open to considering other alternatives. This underscores the importance of offering competitive prices and value to maintain customer satisfaction amid increasing competition and alternatives in the market.

This suggests that as the number of alternatives increases over time, customers have more options to choose from as the product becomes more attractive. Therefore, they are more likely to switch to the substitute product. Thus the availability of alternatives is assumed to hurt the relation of value for price and customer satisfaction. On the contrary, when the product is new to the market and has less competition, thus the customers have only limited options for choosing the product. Therefore, in that situation, the price elasticity is also low, and thus value for money would be high. Based on these arguments, I hypothesize:

**Hypothesis 5**: The relationship between the value for money of a product and customer satisfaction is moderated by the number of alternatives available in the market. The positive impact of value for money on customer satisfaction is stronger when there are fewer alternatives, and weaker when there are more alternatives.

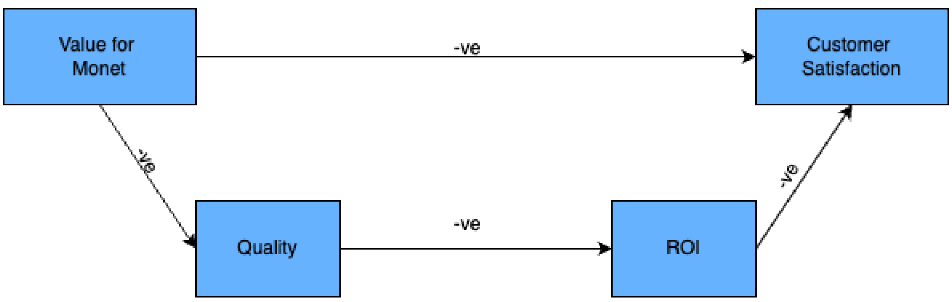


Figure 6: Moderating impact on Value for Money

### 2.6.1 Moderating role of the number of alternatives on the relation of customer's repurchase intention and customer satisfaction

As a product gains popularity and competition increase, companies often introduce a diverse range of products to cater to different customer preferences (Homburg et al., 2015). Initially, when a product is new, and there are limited alternatives in the market, customer satisfaction strongly influences repurchase intention, leading to increased satisfaction. However, as the market evolves and offers more alternatives, customers have broader options, impacting the relationship between repurchase intention and customer satisfaction (Soderlund and Ohman, 2005). In this context, customers with a higher repurchase intention and facing more alternatives are likelier to repurchase from the same brand. Repurchase intention may also be influenced by the desire to upgrade or adapt to changing needs over time, and a diverse product portfolio allows companies to retain customers and maintain their satisfaction. Therefore, as the number of alternatives increases, customer loyalty also improves.

As customers appreciate the expanded variety of products the company provides, they are inclined to enthusiastically share the product's strengths and benefits with their friends and relatives. This positive word-of-mouth communication serves to elevate the overall satisfaction level among customers. This phenomenon is rooted in customer advocacy (Advocacy, 2023). When customers experience a diverse array of products that cater to their varied needs, they are more likely to become advocates for the brand. Their willingness to share their positive experiences with others bolsters the brand's reputation and fosters a sense of community among customers.

Moreover, the availability of alternatives moderates the main relationship between repurchase intention and customer satisfaction. When the number of alternatives is low, the positive impact of repurchase intention on satisfaction is pronounced. Customers with limited choices are more likely to feel satisfied when they can easily repurchase from the same brand. However, as the number of alternatives increases, repurchase intention still positively influences satisfaction, but the effect is more nuanced. The presence of multiple alternatives allows customers to weigh various options. However, when they choose to repurchase from the same brand, their satisfaction is further enhanced due to the perceived value and preference for the chosen product (Homburg et al., 2015). In contrast, when customers have numerous alternatives, their decision to repurchase from the same brand signals a high level of satisfaction with the brand's product, even in the presence of other options.

Considering the moderating effect of the number of alternatives, the updated hypothesis is as follows:

**Hypothesis 6**: The relationship between repurchase intention and customer satisfaction is moderated by the number of alternatives, such that the positive impact of repurchase intention on satisfaction is stronger when the number of alternatives is low and remains positive when the number of alternatives is high, further increasing the level of customer satisfaction.

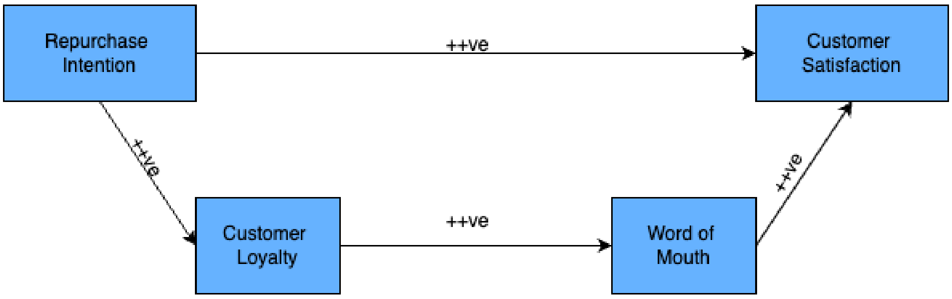


Figure 7: Moderating impact on Repurchase intention

# 3 Methods

## 3.1 Data collection and sample

The conceptual model (1) guides the development of hypotheses, which are then tested using online reviews collected for this study. The essential data required for the empirical study to identify the natural decay of delight of the product attributes, namely customer reviews and feedback, were gathered from WonderFlow ("WonderFlow", 2023). WonderFlow is a unified voice of the customer (VoC) analytical tool that assists B2C businesses in extracting valuable data from consumer feedback and reviews. One of the advantages of WonderFlow is its ability to consolidate data from various online D2C platforms such as Amazon, bol.com, and many more. This allows businesses to view reviews of their products and analyze reviews of their competitors.

Another significant advantage of WonderFlow is its ability to collect data sets comprising solely genuine purchases. This means that it gathers data sets containing only authentic online reviews posted by customers rather than fabricated or dummy reviews. WonderFlow accomplishes this through a badge scanning method, in which customers must enter a unique ID associated with their purchased product online to verify its authenticity. The data collected for the analysis is already authenticated using a specific SKU code associated with each online review, indicating the air fryer model purchased by the customer. Through this technique, we can ensure that the data collected consists of authentic customer reviews.

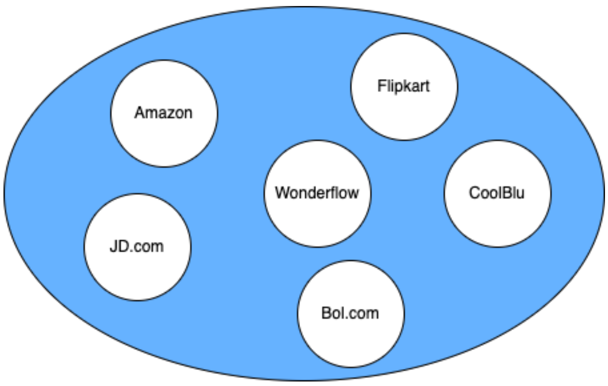


Figure 8: Data Collection

The specific focus of this thesis revolves around analyzing the Philips Airfryer portfolio. The portfolio comprises 42 distinct stock-keeping units (SKUs), with Philips introducing new Airfryer variants annually. To gather comprehensive data for analysis, an extensive collection of over 100,000 online reviews dating back to 2011 has been meticulously acquired using Wonerflow. The selection of the Philips Airfryer portfolio as the subject of study is primarily driven by the abundance of products within the portfolio. The air fryer has also emerged as one of Philips Domestic Appliances' most appealing and lucrative products over the past decade. Therefore, conducting a thorough analysis of this well-established product is reasonable. Moreover, the online reviews left by customers serve as a valuable source of text and data, enabling text mining and sentiment analysis for this thesis. The longitudinal nature of the data is also important to consider, as it allows for the exploration of the role of technological progression and how customer satisfaction evolves with the introduction of new products and increasing competition. By examining online reviews over an extended period, we can gain valuable insights into the changing dynamics of customer satisfaction and the impact of technology on product attributes.

Using WonderFlow, I collected 116,102 online reviews submitted by customers over 12 years, from July 2011 to March 2023. The data collected encompasses a wealth of information, including the online review posted by the customer, the date on which the review was posted, the customer's country, the sales channel through which the air fryer was purchased, the star rating given by the customer along with their review, and the model number of the air fryer purchased by the customer. Additionally, the dataset does not contain personal information about the customer; therefore, all GDPR guidelines were considered ("Art. 4- GDPR", 2018).

After collecting data for my thesis from Wonderflow, I selected a sample of 10,000 data points from a total of 116,102 online reviews. The sample size of 10,000 reviews was chosen to gain a comprehensive understanding of the conceptual model of the natural decay of delight. For data collection, I employed the "stratified random sampling" approach to analyze the results. This approach was selected due to the abundance of five-star ratings in the online reviews, as the Airfryer is a top-rated product, while ratings below three are relatively scarce. The "stratified random sampling" approach offers advantages in collecting data for imbalanced datasets like online reviews. It ensures a better representation of samples, reduces sampling error, optimizes resource utilization, increases precision, and enables meaningful subgroup comparisons, leading to more accurate and insightful research findings (Tal, 2011).

I made the strata based on the online ratings that customers posted along with their reviews. The strata include ratings between 1-2, 2-3, 3-4, and 4-5. The purpose of making strata based on star ratings is to avoid entirely positive or negative reviews. Moreover, this method assumes that the population is covered more comprehensively. Finally, using stratified random sampling, reviews from all rating categories are included in the sample, effectively mitigating any potential selection bias. Furthermore, the table (**??**) in the appendix gives information on the distribution of the online reviews from each country taken into consideration. The table indicates that the sample includes online reviews from various countries worldwide, not limited to English-speaking countries.

### 3.1.1 Measure

The technique of sentiment analysis and text mining is employed to measure the variables in this thesis. Sentiment analysis is a powerful approach that identifies positive and negative opinions expressed by customers towards specific subjects, such as businesses and their products, within a large volume of text documents. It offers various applications and possibilities for analysis (Nasukawa and Yi, 2003). By utilizing sentiment analysis, it becomes possible to understand the sentiment and context of customer feedback. The sentiment analysis process typically begins with capturing the expression of feelings towards a particular item and then extracting positive and negative words and phrases from a predefined lexicon. Lexicons can be categorized into three primary types: positive polarity (e.g., great), negative polarity (e.g., awful, pessimistic, horrible), and contextual polarity (phrases where words can have different meanings depending on the context) (Kang and Park, 2012). These techniques provide a systematic and structured way to analyze the sentiments expressed in online reviews and extract valuable insights for the study.

This study primarily focuses on aspect-based sentiment analysis. This level of analysis allows us to delve into specific attributes or aspects of the product, such as capacity, value for money, and repurchase intention, to understand how customer sentiment varies across these individual factors. Aspect-based sentiment analysis enables a more nuanced examination of customer feedback, providing valuable insights into the drivers of customer satisfaction and preferences (Zhang et al., 2021).

To conduct sentiment analysis (SA), text mining (TM) is utilized. Text mining, also called word mining, encompasses a range of theoretical approaches or methods that involve processing and analyzing textual information. There are various definitions of text mining, ranging from simple ones like "the application of traditional data mining to texts" to more complex ones like "the use of vast online text collections to identify new facts and patterns about the world itself" (Hearst, 1999). Text mining, also known as opinion mining, involves developing systems to examine users' opinions expressed in online blog posts, reviews, or comments on platforms such as Twitter, Reddit, and others. These opinions often pertain to products, features, or policies (Jagdale et al., 2017). Text mining is valuable because a wealth of relevant information is embedded in textual data that needs to be extracted and structured for various purposes. In text mining, the primary objective is to transform the unstructured text into a more structured format based on the frequency and patterns of words within the text. This allows for a systematic analysis of the text and enables the extraction of meaningful insights from the data.

Indeed, several word mining approaches, and techniques are available to determine customers' sentiments through online feedback or reviews. One approach involves utilizing the R programming language for the word mining process and conducting statistical analysis of the text data. It provides various packages and tools specifically designed for text mining and sentiment analysis tasks. Researchers and analysts often leverage R's capabilities to perform statistical analysis on text data of varying dimensions (Mallik and Sahoo, 2019). Using R for word mining, researchers can explore and extract valuable insights from the text, including sentiment analysis, topic modeling, text classification, and other text-related tasks. R's flexibility and extensive library of packages make it a powerful tool for conducting an in-depth analysis of textual data.

## 3.2 Data Preprocessing

The raw data obtained from the reviews of the Airfryer portfolio must undergo various preprocesses for refining and transformation during text preprocessing. Text preprocessing involves multiple steps, which are essential to help smooth text mining and sentiment analysis. For the preprocessing of the online reviews to make the data operational for the thesis, I used the following preprocessing techniques:

- Case conversion: Managing capital letters in sentiment analysis presents challenges due to their potential ambiguity, as seen in cases like "us" and "USA." One approach to tackle this is to convert all text to lowercase, ensuring consistency and mitigating case-related uncertainties. Nevertheless, this method could sacrifice contextual cues, such as emotional expressions conveyed through capitalization, like anger or frustration. Striking a balance between maintaining context and addressing ambiguities requires careful consideration based on the specific goals of the sentiment analysis (Wilame, 2020). This situation can be handled by converting the input words into a single-case format (either uppercase or lowercase) to help facilitate further processing (Vasquez Rojas et al., 2018). I converted all the cases into a lowercase format for this thesis to avoid further confusion. For example, in the figure (9), it can be seen in the second row that all the capital letter words like 'Philips,' 'Approximately,' 'Purchasing,' etc., are converted to lowercase.

- Tokenization: During this process, the main task is to convert the opinions into fragments of systematic processing units (i.e., words). In tokenization, I broke down each review into individual tokens, and every token has its value. In the third row of the figure(9), it can be seen that all the words are assigned their respective tokens.
- Stop word removal: This removes unnecessary words that occur frequently, such as articles, prepositions, and adverbs. Here, in the final row of the figure (9), all the repetitive and unnecessary words are removed. Furthermore, the words left after this step are analyzed using sentiment analysis.
- Date formatting: I used the year, month, and day format for the data analysis, whereas in the raw data, the dates were published in day, month, and year format.

| Steps | Text |
|---|---|
| Inserting original text | After using this airfryer for Approximately 5 months it will no longer work It has a loud screeching noise when turned on. This is the second problem I have had with the unit since Purchasing it. I would not recommend a new or refurbished unit from Philips. The Black and Decker has a 2 year warranty as opposed to the refurbished 90 days or the new 1 year from Philips. There is not any difference in the cooking process from different from different manufacturers just the user interface and size of the unit. Philips customer support was not helpful at all |
| Case Conversion: all uppercase words are converted to lower cases. | after using this airfryer for approximately 5 months it will no longer work it has a loud screeching noise when turned on. this is the second problem i have had with the unit since purchasing it. i would not recommend a new or refurbished unit from philips. the black and decker has a 2 year warranty as opposed to the refurbished 90 days or the new 1 year from philips. there is not any difference in the cooking process from different from different manufacturers just the user interface and size of the unit. philips customer support was not helpful at all |
| Word tokenization: 102 tokens | 1. after, 2. using, 3. this, 4. Airfryer, ………… 100. helpful, 101. at, 102. all |
| Stop word removal | 1. airfryer, 2. approximately, 3. 5, 4. Months, 5. loud, 6. screeching, 7. noise, 8. second, 9. problem, 10. purchasing, 11. recommend, 12. new, 13. refurbished, 14. purchasing, 15. Philips, 16. black, 17. decker, 18. warranty, 19. difference, 20. cooking, 21. manufacturers. 22. interface, 23. size, 24. customer, 25. support, 26. helpful. |

Figure 9: Text mining process

In addition to data preprocessing, irrelevant numbers from the air fryer SKUs were excluded from refining the sample for analysis. For instance, in HD9220/20 and HD9220/30, the "/20" and "/30" represented the color codes deemed irrelevant to this thesis. Thus, all "/x" codes were removed from the SKUs. As a result, the analysis was conducted on 42 distinct SKUs.

## 3.3 Variables

### 3.3.1 Dependent variable

**Customer Satisfaction** is the dependent variable examined in this study is customer satisfaction (CS), which holds significant importance as it plays a crucial role in determining the natural decline of product attribute delight, as explained in the KANO model (Zacarias, 2023). Measuring CS involved employing a sentiment analysis approach described in the Methods section (see 3). Moreover, the implementation of this approach is widespread in scientific literature. Numerous studies have already been conducted to gauge customer satisfaction using sentiment analysis techniques (Al-Otaibi et al., 2018, Kang and Park, 2014, Kumar et al., 2019).

During the sentiment analysis of the selected sample of online Airfryer reviews, the 'syuzhet' library was employed to calculate sentiment scores (Jockers, 2020). The 'syuzhet' library is an R package used for sentiment analysis of text data like reviews and social media posts. It determines the emotional tone expressed in the text based on linguistic patterns and sentence structure, providing continuous sentiment scores for emotions like joy, sadness, anger, fear, surprise, and anticipation. Unlike predefined sentiment lexicons, it relies on syntactic rules to capture nuanced sentiment expressions, offering a more fine-grained understanding of emotions conveyed in the text (Jockers, 2020). The visuals of the entire process of sentiment scores using the 'syuzhet' package are in the appendix figure (17, 18).

By employing this R-package, I calculated the sentiment score of each of the online reviews, and thus the dependent variable for this thesis has been considered. Moreover, I was able to calculate the sentiments of the reviews in a holistic way, and further, it could help me to analyze how it is impacted by the other factors.

Finally, after calculating the sentiment scores for all customer reviews, I examined the overall distribution of these scores. This step was necessary to normalize the total sentiment scores from -5 to 5. However, I observed several outliers with exceptionally high sentiment scores above 50. These extreme values posed challenges in normalizing the scores within the desired range of -5 to 5. Consequently, I excluded 72 outlier terms with sentiment scores exceeding 30. This data refinement process aimed to improve the data quality, considering that the most negative sentiment score observed was -23, while the highest positive sentiment score reached an extraordinarily high value of 520, which had the potential to disrupt the overall distribution.

### 3.3.2 Independent Variables

The first independent variable examined in this thesis is the product capacity of the Philips Air fryer, which is the focus of the study. The objective is to analyze the correlation between the Air fryer's cooking capacity and customers' satisfaction levels. Over the years, air fryers have gained significant popularity and have become an essential tool for everyday cooking. In response to customers' evolving demands and preferences, Philips has consistently increased the volume of their air fryers since their initial release in 2011. It is crucial to investigate how customers' perceptions have changed over time concerning the varying capacity of air fryers and how these changes impact their satisfaction.

The Philips Airfryer Portfolio comprises several categories, each differentiated by its cooking/frying capacity. The primary categories are XXL Airfryers, XL Airfryers, and L Airfryers. The L Airfryers are characterized by a cooking capacity of 800 grams (equivalent to 0.8 kilograms). In contrast, the XL Airfryers encompass a cooking range that exceeds 800 grams but is less than 1.2 kilograms. Lastly, the XXL Airfryers boast a capacity exceeding 1.2 kilograms. Therefore, I assigned capacity values to each corresponding online review based on their unique SKU value in the data set.

By utilizing a unique Stock Keeping Unit (SKU) for each online review, a valuable connection is established between the customer's satisfaction expressed in the review and the specific Airfryer capacity they purchased. This SKU system allows us to associate the customer's feedback with the corresponding Airfryer capacity, making it a crucial factor in comprehending and analyzing customer satisfaction within each review.

For example, in the data set, the review index 9970 is as follows:

> *I have recently started using advance xxl airfryer and I love it. I am mostly using it for traditionally deep fried food, and it gives great results. The food fried in it (fries, nuggets, etc) is crispy from outside, and juicy from inside. In fact the fried chicken tastes better when made using the airfryer. The size of this model is big and you can fry for the whole family at once. A slight downside is my opinion would be that it doesn't brown the food as much as a deep fried one but the texture and zero oil more than makes up for it*

The above example gives information about the capacity of the air fryer and other important attributes, which I calculated through sentiment analysis.

Along with the above online review, I could also see the SKU of the Airfryer, which was HD9650, the date: 2018-03-30, the country: Saudi Arabia, and other important details required to operationalize text mining. By leveraging the SKU code, next to the online review, I could associate the overall sentiment score of the online review and its association with the product's capacity. Additionally, I was able to delve deeper into the dataset, exploring the nuances and variations of customer satisfaction across different Airfryer capacities. This intricate connection allows for a more nuanced understanding of how various factors, such as the size and capacity of the Airfryer, contribute to overall customer satisfaction levels.

Finally, while manually assigning values to each SKU, I encountered a particular type of SKU with the code HD99xx, where xx represents a different number and thus a unique new SKU. These SKUs correspond to accessories for the Airfryer, such as the baking pan, grill pan, skewer rack, and so on. I recognized that these SKUs were unrelated to the purchase of the Airfryer itself but rather its accessories, so I removed them from my dataset. In total, 751 terms were eliminated from the dataset due to their association with the Airfryer accessories rather than the Airfryer itself.

Therefore, 823 data points were removed from the dataset. Seventy-two from the general distribution of sentiment scores, as explained above in the measure of the dependent variable, and 751 accessories SKUs. Thus the data points were reduced to 9177 entries [2] .

[2] Furthermore, it is worth noting that out of the 9,177 online reviews in the dataset, 1,506 discussed both repurchase intention and value for money. This represents approximately 16.4% of the total online

**Value of money** The second independent variable examined in this thesis is the Value for money of the Philips Air fryers. This variable represents customers' perceived Value of the product, indicating how they assess and perceive the benefits obtained from purchasing the product relative to its price. This attribute is significant because, with the growing popularity of Airfryers, Philips has witnessed increased competition within the Airfryer market. Consequently, it has become crucial for Philips to investigate how customers perceive the pricing of Airfryers and how the pricing of Airfryers in the market influences customers' satisfaction levels. This analysis will shed light on the relationship between price and satisfaction in the context of Air fryers and help Philips understand the impact of pricing strategies on customer perception and satisfaction.

To measure the sentiment score for the Value for money, a customized dictionary was created, incorporating words similar to the term 'Value for money.' The word 'Value' synonyms were obtained using the Merriam-Webster dictionary (Merriam-Webster, 2023). This approach, which uses a dictionary to analyze sentiments, is known as the Lexicon-based approach in sentiment analysis (Hardeniya and Borikar, 2016).

Apart from the Merriam-Webster dictionary, I read at least 100 reviews from each stratum created during the sampling after the data collection. By reading the online reviews, I understood the jargon customers use when discussing the concept of 'value for money.' Furthermore, by analyzing online reviews from different strata, I discovered that customers employ various terminologies to describe Value based on their level of satisfaction with the product. When customers were delighted, they used positive terms such as "advantage," "bargain," and "convenient." On the other hand, when customers were dissatisfied, they expressed their dissatisfaction using terms like "scorn" and "insufficient." Therefore, by examining these online reviews, I enhanced my lexicon dictionary for the term ' Value.' This approach allowed me to compile a lexicon dictionary comprising 110 synonyms and antonyms for the word 'value.'

Furthermore, I utilized the "syuzhet" sentiment dictionary to manually assign values to each word in my customized lexicon for 'Value.' This allowed me to employ sentiment analysis and assess the extent to which each review discusses Value. Consequently, based on this analysis, I assigned a sentiment score to each review.

By developing this lexicon dictionary for the term 'Value,' I discovered that out of the total 9,117 online reviews, 6,608 reviews (approximately 72.5%) specifically discussed the concept of Value. This approach allows for a comprehensive analysis of sentiments related to the perception of Value for money in the context of the Airfryers.

Here is the example of the words and their corresponding words I used my dictionary to measure the sentiments related to the word value table(1). The remaining dictionary for the word 'Value' is in the appendix code(p6, and p7)

TThe following is an example of an online review based on the dataset's value dictionary with an index of 8598. The total sentiment score of the above online review is 7.3, and the sentiment score associated with the term "value" is 3.8. As seen in the following example, the words in bold represent the sentiment scores related to the value sentiment dictionary.

reviews.

| | |
|---|---|
| 1 | Worth: 0.75 |
| 2 | Bargain: 0.75 |
| 3 | Satisfied: 1 |
| 4 | Price: 0.8 |
| 5 | Great: 0.5 |
| 6 | fault: -0.5 |
| 7 | deficiency: - 0.5 |
| 8 | cheap: -0.5 |
| 9 | disappoint: -1 |
| 10 | worthless: -1 |

Table 1: Dictionary: Value dictionary

*I have been wanting a new air fryer forever! My old one just did not meet my expectations. So I got this one, It is* ***worth*** *every penny! I got the extra large because we have a big family. The size was phenomenal. It is so big and can hold so much. I absolutely am in* ***love*** *with the smart sensing technology. I can put fish or chicken and it senses how long to cook. I mean it is so* ***convenient****. There are settings for frozen as well as whole chicken. You can manually turn the knob to adjust temperature and time as well. It is so-so* ***simple*** *which I* ***love****. If you are looking for a* ***great*** *airfryer this one is definitely the way to go. As I said, it is more* ***expensive*** *than other some of the other ones but every time I use it I can tell why!*

Another example with a negative sentiment value, and negative sentiments based on the 'value' with index 404 in the dataset is as follows:

*Very* ***bad****, very* ***disappointed****. After using it for the second time, it broke down. The customer care said it was my problem. Then I gave extra money to repair it. After more than ten days of repairing, no one told me how far it was repaired. I asked no one to know. It is too* ***bad****. God, Philips is too far behind!!*

The overall sentiment score of the online review is -3.2 and the corresponding sentiment score based on the terms from the value dictionary is -0.75

**Repurchase intention** The third independent variable considered in this thesis is customers' repurchase intention for the Philips Airfryers. Repurchase intention refers to the customer's intention to repurchase the product from the same brand. This variable is significant as it provides insights into customer loyalty and their likelihood of continuing to choose Philips Airfryers amidst increasing competition in the market. Understanding customers' repurchase intention helps Philips determine when customers are willing to upgrade their current Airfryers and whether they will remain loyal to the Philips brand for future purchases. This analysis allows Philips to assess the impact of customer satisfaction on their long-term business prospects and identify strategies to enhance customer retention and brand loyalty.

To measure the sentiment score related to customers' repurchase intention, I created a customized dictionary for words synonymous with "Repurchase" using a source (Merriam-

Webster, 2023). Additionally, following the methodology described in the "Value for money" section, I read at least 100 reviews from each stratum generated during the sampling process. It was observed that customers used various phrases and words based on their level of satisfaction. Through this analysis, I enhanced my lexicon dictionary for "Repurchase." Like the "value" dictionary, I compiled a list of 95 words and phrases similar to "Repurchase." Subsequently, I employed the "syuzhet" sentiment dictionary ("WonderFlow", 2023) to manually assign sentiment values to each word in my customized lexicon for "Repurchase."

In the sentiment analysis process using the "syuzhet" library, you encountered jargon terms like "buy-back" that were not present in the pre-defined sentiment dictionary. I employed a heuristic approach to address this issue by assigning sentiment scores to such terms. A heuristic is a problem-solving method or approach that uses practical and common-sense techniques to reach a solution when the exact solution is not available or difficult to determine.

In this case, since "buy-back" is colloquially similar to "Repurchase," you made an informed decision to assign the same sentiment score to "buy-back" as that of "Repurchase." This heuristic allowed me to approximate the sentiment associated with the jargon term based on its similarity in meaning to a term that already had a sentiment score in the dictionary. By employing such heuristics, I could handle the presence of jargon and assign sentiment scores that best represented the emotions expressed in the text, even when specific terms were not explicitly listed in the sentiment dictionary.

The few examples from the dictionary used for measuring the sentiments related to word repurchase are as follows. The remaining dictionary is in the appendix (p7)

| | |
|---|---|
| 1 | Repurchase: 0.75 |
| 2 | Reacquire: 0.75 |
| 3 | Recommendation: 1 |
| 4 | Rebuy: 0.8 |
| 5 | Reject: 0.5 |
| 6 | Forfeit: -0.5 |
| 7 | dislike: - 0.5 |
| 8 | warn: -0.5 |

Table 2: Dictionary: Repurchase dictionary

By developing this lexicon dictionary for the term 'Repurchase,' I discovered that out of 9,117 online reviews, 1984 online reviews posted by customers were about the terms related to 'Repurchase' (approximately 22%). Furthermore, after calculating the sentiment scores associated with the repurchase dictionary, I normalized the terms within the range of -5 to 5.
The following are two examples of online reviews based on the Repurchase dictionary. The first online review with an index of 8167 has a total sentiment score of 4.2, and furthermore, the sentiment score associated with the terms related to 'Repurchase' is 1.0.

*I've been an airfryer fan for several years now, and it was time for a new one. Because* *of the very good experience with the Philips Airfryer XL, we have now opted for the XXL and we do not regret it. The Airfryer is too beautiful a device to only bake chips in, think of it as a super fast mini oven. We use the Airfryer for, among other things, baking sandwiches (ready in 7 minutes without pre-heating!) preparing stuffed peppers, making savory tarts and even the "boiling" of eggs (eggs without water just in the basket and then 12 minutes at 120 degrees). And once in a while a bowl of lemon water in the fryer for an extra cleaning and the pan is really easy to keep clean. Small disadvantage, but also understandable, the baking times have really become longer with this new model compared to the XL.*

Another example of an online review based on the Repurchase dictionary with an index number of 7203, has a total sentiment score of 4.0, and the sentiment score associated with the terms related to 'Repurchase' is -2.10.

*I have owned the older Philips Digital Twin TurboStar Airfryer xxl airfryer, model HD9650/96 for several years and absolutely love it! I've considered it to be one of the best air fryers available by far and can't imagine life without it. I use it daily. That said, when I purchased this new model, I expected a similar experience; sadly, that was not the case. I am very disappointed in this particular unit and feel that Philips has really gone downhill with this one. I dislike it so much that I will likely return it and either buy another like I have or explore other brands. The following are the two key reasons why I dislike this unit compared to the older version. First, the overall design of the drawer and basket assembly. On the older model, the whole drawer (with the drip pan) slides out on a track and the basket can simply be lifted out while the pan is supported by the fryer. This design was awesome and superior to any other air fryer I've seen. The new version is designed like the typical (cheap) unit.*

### 3.3.3 Control Variables

Several control variables were utilized for this study to enhance the systematic nature of the data. Control variables are used in research to rule out alternative explanations or confounding factors that could influence the relationship between the variables of interest. They help ensure that the observed effects are not due to other factors and enhance the systematic nature of the data analysis.

- **Geographical location** One of the important control variables in this study is the country of purchase for customers. It is essential to examine how sentiments differ among various countries. This information can help me identify countries where customers have a strong sentiment towards the Philips Airfryer and countries with comparatively low sentiment scores. I can tailor its strategies and responses by analyzing sentiments on a country level. While there are more than 180 countries worldwide, measuring sentiments for each country would be challenging. Therefore, in this study, geographical locations have been divided based on continents, and consequently, I made the continent dummy variables. The continents considered for analysis include:

- **Impact of Covid** In the past decade, the COVID-19 pandemic has become a significant external factor impacting customers and companies. According to an article

| | |
|---|---|
| 1 | Americas |
| 2 | Europe |
| 3 | Asia |
| 4 | Oceania |
| 5 | Africa |

Table 3: List of Continents

published by (Accenture, 2023), it is interesting to examine customers' buying behavior during a crisis as it helps in understanding new buying behaviors. The sales of various Philips products, including Airfryers, were affected during the COVID-19 lockdown. Interestingly, Airfryers witnessed a surge in sales as customers spent more time at home, leading to an increased interest in healthy cooking (Green, 2022). Therefore, measuring changes in customer sentiments before and after the COVID-19 lockdown period is essential. To incorporate this as a control variable, a dummy variable was created to differentiate sales of Airfryers before and after the COVID-19 lockdown.

- **Sales channel** The selection of online e-commerce platforms as a control variable is significant in this thesis. While Amazon is widely recognized as a prominent and accessible online marketplace in many countries for purchasing Philips Air fryers, it is crucial to acknowledge the presence of local direct-to-consumer (D2C) e-commerce websites in different countries. For example, in the Netherlands, Bol.com enjoys more significant popularity than Amazon, while in China, Aliexpress and JD.com emerge as dominant players with higher sales compared to other e-commerce platforms. Therefore, considering the influence of different sales channels on customer sentiments becomes essential. A sales channel dummy variable was introduced to incorporate this, distinguishing between online sales from Amazon and other online sales channels. This allows for examining any variations in customer sentiments based on the specific online sales channel used.

### 3.3.4 Analytical approach

In order to find the effect of independent variables (Capacity of Airfryer, value for money, and the repurchase intention) on the dependent variable (customer satisfaction), this thesis will employ the use of the multi-linear regression model. Multi-linear regression is a type of regression method used to form the relation between two or more independent variables and a dependent variable (Asadi et al., 2014) by fitting a linear equation based on a trained data set. The advantage of the multi-linear regression model is that it can employ both continuous or dummy independent variables. The main assumptions of the model are linearity, lack of multi-collinearity, normality, and Independence of error. The multicollinearity is checked using the correlation table (11)

$$x = \beta_0 w_0 + \beta_1 w_1 + \beta_2 w_2 + \cdots + \beta_n w_n$$

Figure 10: Multi linear regression equation

Here x is the dependent variable. The independent variables are represented as w.

There are many advantages of using the multi-linear regression model- it is used to identify and determine the power of the effect of the independent variables over the dependent variable. The regression model can also be used to forecast the effects or impacts of changes, which means the model helps to determine how much the dependent variable changes when there is a shift in independent variables.

As seen in the hypothesis model in figure (5), I have taken an approach to testing the hypotheses using multiple linear regression analysis is a standard and appropriate method in quantitative research. By constructing separate models with control variables, main effects, and interaction effects, I could examine the individual and combined effects of the variables on customer satisfaction. The three-step model is as follows:

- Model 1 serves as the baseline model and includes control variables such as pre and post-covid purchase, the continent of purchase, the total number of alternatives, and the sales channel (Amazon dummy). This model helps account for these control variables' influence on customer satisfaction.

- Model 2 expands upon Model 1 by adding the main effects of the independent variables: capacity of the Airfryer, value for money, and repurchase intention. By including these main effects, I analyzed the direct impact of these variables on customer satisfaction while controlling for other factors.

- Model 3 further extends the analysis by incorporating the interaction effects between the moderating variable and the main effects. This allows me to examine how the relationship between the independent variables and customer satisfaction may vary depending on the levels of the moderating variable.

By utilizing multiple linear regression analysis and constructing these models, I evaluated the significance and direction of the relationships between the variables and customer satisfaction. This approach also provides a structured framework for testing your hypotheses and drawing conclusions based on the statistical results. These model codes can be found here (5)

# 4 Results

Descriptive statistics table (11) summarizes the dataset, giving an overview of the average values and variability of the variables. The mean sentiment scores for total sentiments, sentiment scores of value, and sentiment scores of repurchase indicate a slightly negative sentiment, slightly negative sentiment, and slightly positive sentiment, respectively. The standard deviations reflect the variability in the sentiment scores.

The correlation table shows the relationships between the variables. Some notable correlations include the negative correlation between sentiment scores of value and continent (Asia), suggesting that customers in Asia have lower sentiment scores related to perceived value. The positive correlation between sentiment scores of repurchase and ratings indicates that higher ratings are associated with a greater intention to repurchase. The positive correlation between final review sentiments and sentiment scores of value and repurchase suggests that positive sentiments in online reviews are linked to higher sentiment scores related to value and repurchase intention.

It is essential to note that these statistics provide only a snapshot of the data and do not establish causal relationships. Furthermore, I did the multiple linear regression modeling (5) on the data set. Therefore, these descriptive statistics and correlations offer initial insights into the variables and their relationships in the dataset.
Table 5 presents the multiple linear regression analysis results examining the relationship between various independent variables and customer satisfaction. The analysis is divided into three steps to understand the influence of different factors on customer satisfaction.

- In Step 1 (Controls), the variables included are pre-post Covid-19, continent, and Amazon sales. The results indicate that the pre-post Covid-19 variable has a statistically significant positive effect on customer satisfaction ($p < 0.001$), i.e., as explained in the control variables, there has been an increase in the sales of the air fryer. Thus it is interesting to know how Covid-19 impacted the sales of the air fryer. However, the continent variables (Americas, Asia, Europe, and Oceania) do not significantly affect customer satisfaction. The Amazon sales variable also does not significantly impact customer satisfaction. This is because many countries have online sales channels. For example, Bol.com is prominent in the Netherlands, and JD.com has the highest sales in China.

- In Step 2 (Main effects), the analysis examines the impact of predictor variables on customer satisfaction. The findings indicate that the sentiment scores related to repurchase intention (Estimate = 0.174, $p < 0.001$) and value for money (Estimate = 0.971, $p < 0.001$) have statistically significant positive effects on customer satisfaction. This implies that higher repurchase intention and perceived value for money increase customer satisfaction. Contrarily, the capacity of the product (Estimate = -0.838, $p < 0.01$) has a statistically significant negative effect on customer satisfaction, which is contrary to the hypothesis presented in Figure **??**. This suggests that customer satisfaction tends to decrease as the product's capacity increases.

- In Step 3 (Moderation effects), the interaction terms between total alternatives and the main effect variables are evaluated. The results show that the interaction effects between repurchase intention and capacity with total alternatives are not statistically significant, indicating that total alternatives do not significantly influence the

| 0 | Description | Mean | SD | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | | | | | |
| 1 | Amazon sales | 0.31 | 0.46 | 1 | | | | | | | | | | | |
| 2 | Ratings | 2.74 | 1.46 | (-)0.23* | 1 | | | | | | | | | | |
| 3 | Continent (Africa) | 0.00 | 0.04 | (-)0.24 | (-)0.01 | 1 | | | | | | | | | |
| 4 | Continent (Americas) | 0.10 | 0.30 | (-)0.13* | (-)0.13 | (-)0.01 | 1 | | | | | | | | |
| 5 | Continent (Asia) | 0.50 | 0.50 | (-)0.32* | 0.11* | (-)0.04 | (-)0.33 | 1 | | | | | | | |
| 6 | Continent (Europe) | 0.38 | 0.49 | (-)0.27 | (-)0.03* | (-)0.03 | (-)0.26 | (-)0.79 | 1 | | | | | | |
| 7 | Continent (Oceania) | 0.02 | 0.12 | (-)0.28 | (-)0.02 | (-)0.01 | (-)0.04 | (-)0.13 | (-)0.1 | 1 | | | | | |
| 8 | Capacity | 1.08 | 0.27 | (-)0.03* | (-)0.03* | 0.03 | (-)0.1 | (-)0.27 | 0.32 | 0.06 | 1 | | | | |
| 9 | Sentiment scores (Value) | (-)1.75 | 0.71 | (-)0.30 | 0.26* | 0 | 0.02 | (-)0.12 | 0.09 | 0.04 | 0.04 | 1 | | | |
| 10 | Sentiment scores (Repurchase) | (-)0.33 | 0.42 | (-)0.31 | (-)0.01 | 0.02 | (-)0.02 | (-)0.01 | 0.01 | 0.03 | 0.04 | 0.06* | 1 | | |
| 11 | Final review sentiments | (-)0.39 | 0.97 | (-)0.32 | 0.35*** | 0.01 | 0.01 | (-)0.1 | 0.08 | 0.05 | 0.06 | 0.72*** | 0.13 | 1 | |
| 12 | Total alternatives | 3.93 | 1.99 | (-)0.33 | 0.02* | 0 | (-)0.19 | 0.2* | (-)0.09 | 0.01 | 0.02 | (-)0.06 | (-)0.01 | (-)0.04 | 1 |

N=9958

* : Correlation is significant at the 0.1 level (2-tailed).
** : Correlation is significant at the 0.05 level (2-tailed).***: Correlation is significant at the 0.001 levels (2-tailed).

Figure 11: Means, standard deviations, and correlation

relationship between the main effects and customer satisfaction for capacity and repurchase intention. On the contrary, the interaction between total alternatives and the value is highly significant.

Table 4: Value distribution

| Variables | Minimum | Maximum | Median |
| --- | --- | --- | --- |
| Sentiment scores of value | -5 | 5 | -1.93 |
| Sentiment scores of repurcashe | -5 | 5 | -0.41 |
| Total sentiments | -5 | 5 | -0.6 |
| Total alternatives | 1 | 10 | 4 |
| Capacity | 0.8 | 1.4 | 1.2 |

Apart from that, the final unit of analysis consisted of individual online reviews that customers posted on their sales channels. Initially, a sample size of 10,000 online reviews was collected. However, as described in Section 3.1.1 and Section 3.3, the sample size was reduced to 9117 observations. This reduction was made by excluding non-air fryer SKUs and removing outliers in the total sentiment score. These steps were taken to improve the overall distribution of the data.

The R-squared ($R^2$) values provide insights into how well the predictor variables in the regression models explain the variability in customer satisfaction. In our analysis, the $R^2$ values for Models 1, 2, and 3 were 0.017, 0.520, and 0.521, respectively. These values can be interpreted as follows:

1. Model 1, which includes only the value for money as a predictor, has an $R^2$ of 0.017. This means that approximately 1.7%

2. Model 2, incorporating value for money, product capacity, and the number of alternatives as predictors, exhibits an $R^2$ of 0.520. This indicates that 52.0% of the variance in customer satisfaction can be explained by these three predictor variables combined.

3. Model 3, adding the interaction term between value for money and the number of alternatives, also has an $R^2$ of 0.521, suggesting that the interaction term contributes an additional 0.1% in explaining the variance in customer satisfaction compared to Model 2.

Overall, these $R^2$ values demonstrate that the combination of value for money, product capacity, and number of alternatives as predictors significantly improves the model's ability to account for customer satisfaction, explaining more than half of the variance in the data.

The residual standard error (Residual Std. Error) estimates the average deviation between the actual customer satisfaction scores and the predicted values from the regression model. In our analysis, the Residual Std. Error values were 0.970 (df = 9167), 0.678 (df = 9164), and 0.678 (df = 9161) for Models 1, 2, and 3, respectively.

Additionally, table **??** presents the value distribution of critical variables in the study. The sentiment scores for value for money range from -5 to 5, with a median of -1.93. The sentiment scores for repurchase intention range from -5 to 5, with a median of -0.41. The total sentiments range from -5 to 5, with a median of -0.6. The total alternatives range from 1 to 10, with a median of 4. The capacity of the products ranges from 0.8 to 1.4, with a median of 1.2.

## 4.1 Hypotheses tests

I tested the hypotheses using a multiple linear regression model, and the results are explained in the Table above (5). In addition, I created visualizations to examine the moderating effects of the total number of alternatives on the relationship between the independent variables (capacity, value for money, and repurchase intention) and the dependent variable, customer satisfaction. These visualizations aimed to determine the "natural decay of delight" based on the KANO model (Kano, 1984). Moreover, I utilized the Jeremy Dawson two-way interaction interpretation model(Dawson, 2023) to generate plots illustrating the relationships among different variables.

## 4.2 Impact of product's capacity on customer satisfaction

Hypothesis 1: The capacity of on-shelf consumer products positively influences customer satisfaction, with higher product capacity leading to higher satisfaction levels based on customer demand.

The regression analysis results from Model 3 indicate that the coefficient estimate for capacity was statistically significant (estimate = -0.741, $p < 0.01$), suggesting a negative association between product capacity and customer satisfaction. This finding contradicts Hypothesis 1, implying that customer satisfaction tends to increase as the product capacity decreases.

## 4.3 Impact of value for money on customer satisfaction

Hypothesis 2: There is a positive relationship between value for money for a product and customer satisfaction, where an increase in perceived value for money leads to higher levels of customer satisfaction.

The hypothesis proposed that a higher perceived value for money would be associated with higher levels of customer satisfaction. To examine this hypothesis, we included the sentiment scores for value for money as a predictor variable in the regression model.

The regression analysis results from Model 3 also support Hypothesis 2. The coefficient estimate for sentiment scores (Value) remains statistically significant (estimate = 1.012, $p < 0.01$), indicating a positive relationship between value for money and customer satisfaction. This further confirms that as the perceived value for money of a product increases,

Table 5: Multiple Linear Regression Model

| | *Dependent variable:* | | |
|---|---|---|---|
| | Customer Satisfaction | | |
| **Variables** | **(Model 1)** | **(Model 2)** | **(Model 3)** |
| **Step 1: Controls** | | | |
| Constant | −0.126 | 2.897*** | 2.867*** |
| | (0.244) | (0.434) | (0.441) |
| pre_post Covid-19 | 0.148*** | 0.005 | −0.001 |
| | (0.031) | (0.021) | (0.022) |
| Continent (Americas) | −0.240 | −0.310* | −0.298* |
| | (0.246) | (0.172) | (0.172) |
| Continent (Asia) | −0.340 | −0.353** | −0.348** |
| | (0.243) | (0.170) | (0.170) |
| Continent (Europe) | −0.170 | −0.326* | −0.322* |
| | (0.243) | (0.170) | (0.170) |
| Continent (Oceania) | 0.049 | −0.279 | −0.279 |
| | (0.257) | (0.180) | (0.180) |
| Amazon sales | −0.042* | −0.023 | −0.022 |
| | (0.024) | (0.017) | (0.017) |
| Total alternatives | 0.001 | 0.006 | 0.004 |
| | (0.006) | (0.004) | (0.018) |
| **Step 2: Main effects** | | | |
| Sentiment scores (Repurchase) | | 0.174*** | 0.213*** |
| | | (0.016) | (0.036) |
| Sentiment scores (Value) | | 0.971*** | 1.012*** |
| | | (0.010) | (0.021) |
| Capacity | | −0.838*** | −0.741** |
| | | (0.283) | (0.290) |
| **Step 3: Moderation effects** | | | |
| Repurchase X Total alternatives | | | −0.010 |
| | | | (0.008) |
| Value X Total alternatives | | | −0.012** |
| | | | (0.005) |
| Capacity X Total alternatives | | | −0.020 |
| | | | (0.013) |
| Observations | 9,177 | 9,177 | 9,177 |
| $R^2$ | 0.017 | 0.520 | 0.521 |
| Adjusted $R^2$ | 0.017 | 0.520 | 0.520 |
| Residual Std. Error | 0.970 (df = 9167) | 0.678 (df = 9164) | 0.678 (df = 9161) |
| F Statistic | 18.138*** (df = 9; 9167) | 828.325*** (df = 12; 9164) | 663.845*** (df = 15; 9161) |

*p<0.1; **p<0.05; ***p<0.01

*Note: 1. Unstandardized coefficients are reported with standard errors in parentheses, 2. The baseline category for the "continent" variable in the model is "Americas." The coefficients for other categories (Asia and Europe) indicate how they differ from the baseline category in the analysis. The "Africa" category was not included in the regression model due to missing values.*

customers are more likely to report higher levels of satisfaction. Thus, the results from Model 3 also provide evidence for a positive association between value for money and customer satisfaction. It suggests that customers' perception of receiving good value for money continues to positively influence their overall satisfaction with the product.

## 4.4 Impact of Customer's repurchase intention on Customer Satisfaction

Hypothesis 3: There is a positive relation between a customer's intention to repurchase from the same brand and their level of customer satisfaction, indicating that customers with a higher repurchase intention are more likely to have higher levels of satisfaction.

The regression analysis results from Model 3 also support Hypothesis 3. The coefficient estimate for the variable "sum_sav_Repurchase" remains statistically significant (estimate = 0.213, $p < 0.001$), indicating a positive relationship between repurchase intention and customer satisfaction. This suggests that customers who have a higher intention to repurchase from the same brand are indeed more likely to experience higher levels of satisfaction. Therefore, the results provide further evidence for a positive association between repurchase intention and customer satisfaction.

## 4.5 Moderating effect of the number of alternatives

Hypothesis 4: The relationship between product capacity and customer satisfaction is moderated by the number of alternatives, such that the positive impact of capacity on customer satisfaction is weaker when there are more alternatives available in the market.

Hypothesis 4, which proposed that the number of alternatives available would influence the relationship between product capacity and customer satisfaction, was not supported by the regression analysis results. The interaction term between capacity and total alternatives was not statistically significant (estimate = -0.020, $p > 0.1$), suggesting that the number of alternatives does not moderate the effect of capacity on customer satisfaction. Therefore, it appears that other factors, not related to the availability of alternatives, may be influencing the relationship between capacity and customer satisfaction.

Therefore, based on the table (5) the findings suggest that product capacity has a negative association with customer satisfaction, contrary to expectations. Furthermore, the increasing number of alternatives does not weaken the relationship between capacity and customer satisfaction. These results highlight the need to consider additional factors when understanding the impact of capacity on customer satisfaction in the context of consumer products.

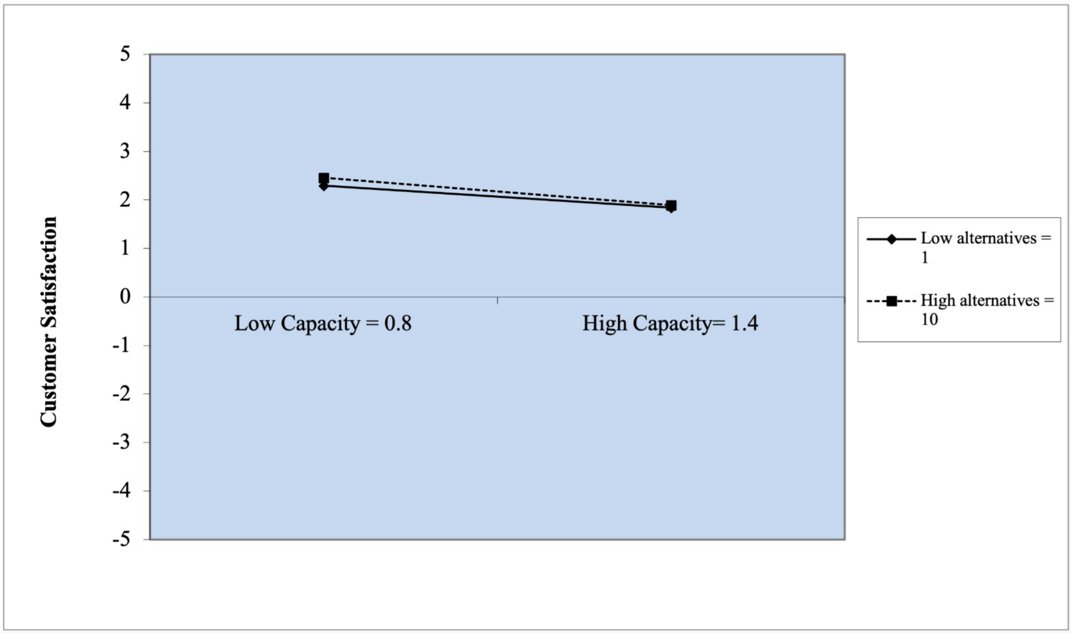


Figure 12: Moderating impact on Capacity

Hypothesis 5: The relationship between the value for money of a product and customer satisfaction is moderated by the number of alternatives available in the market. The positive impact of value for money on customer satisfaction is stronger when there are fewer alternatives, and weaker when there are more alternatives.

The regression analysis results from Model 3 also support Hypothesis 5. The coefficient estimate for total alternatives remains statistically significant (estimate = -0.012, $p < 0.05$), indicating a negative relationship between the number of alternatives and customer satisfaction. This suggests that as the number of alternatives for a product increases, there is a potential decrease in the perceived value for money among customers, which may impact their satisfaction levels. Therefore, the results provide evidence for a negative association between the number of alternatives and customer satisfaction.

In summary, the findings provide support for Hypothesis 2, indicating a positive relationship between value for money and customer satisfaction. They also support Hypothesis 5, suggesting that an increase in the number of alternatives for a product can lead to a decrease in the perceived value for money among customers. These results emphasize the importance of considering value for money and the competitive landscape when examining customer satisfaction in relation to product alternatives.

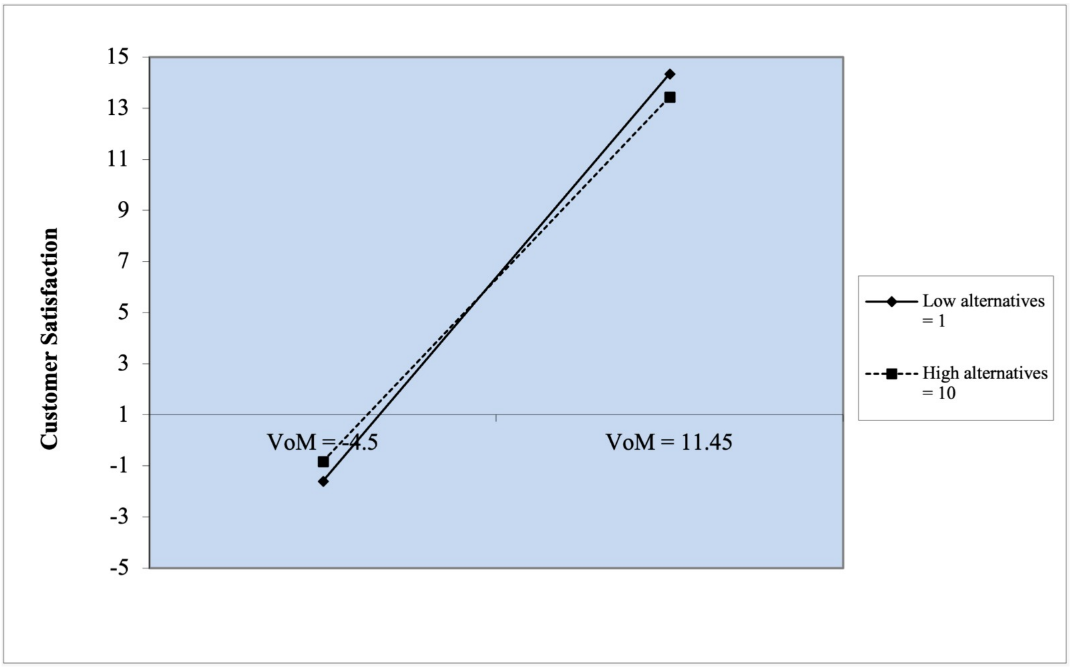


Figure 13: Moderating impact on Value for money

Through the visual presented above, it is evident that the regression analysis yields highly significant results. However, when examining the plots depicting low alternatives and high alternatives, the observed shift is not particularly prominent. In order to gain a deeper understanding of this pattern, I conducted a more detailed analysis by focusing on reviews categorized as having either the most negative sentiment at low alternatives or the most negative sentiment at high alternatives. Similarly, I explored reviews with the most positive sentiment at low alternatives and high alternatives.

Furthermore, as part of my analysis, I delved deeper into the customer reviews to gain insights from both the most negative and most positive feedback in situations with both low and high alternatives. By doing so, I aimed to identify common themes or specific concerns that customers expressed when they were dissatisfied with the product options available. This approach allowed me to understand the underlying reasons behind their dissatisfaction. On the other hand, exploring the most positive reviews helped me uncover the key factors that contributed to customer satisfaction when they were presented with either limited or abundant alternatives. This examination enabled me to identify the aspects that customers found particularly satisfying, providing valuable insights into enhancing customer experiences under different product availability scenarios.

Here are a few examples. The subsequent review is the most negative one, determined by the value dictionary at index 2674, and it has only one alternative available. The review highlights a quality issue with the product and the customer's frustration with unhelpful customer service. JD.com initially agreed to a refund but later asked the customer to pay the return shipping fee, negatively impacting the perceived value for money (left column in the figure (14)).

On the other hand, here is an example of a low value-for-money review with a higher number of alternatives. The following review has an index of 3599 with 5 alternatives (right column in the figure (14)). The customer expresses dissatisfaction with the product's high price and limited features compared to other available options. This highlights the influence of alternative products on customers' perceptions of value for money. When more alternatives are available, customers may be more critical of a product's price and features, leading to lower satisfaction if they perceive better value in other options.

Furthermore, reviews with low value for money and low alternatives reflect a higher level of dissatisfaction and frustration among customers. They express concerns about product quality issues, malfunctioning, and poor customer service. These negative sentiments indicate that customers are disappointed with their purchase experience and feel limited in their options for resolving their issues. Limited alternatives result in customers scrutinizing the product more intensely and having higher expectations, leading to a higher likelihood of negative feedback. The lack of viable alternatives exacerbates their dissatisfaction and impacts customer satisfaction negatively.

| Negative reviews at low alternatives | Negative reviews at high alternatives |
|---|---|
| When I bought and used it for the first time, I found that there was a quality problem, and it crashed after a minute or two of use. After consulting with the air fryer, they began to give unprofessional guidance The customer service did not understand the product, and could not solve the actual problem, they wasted the customer's time and concluded that it would not return the product. Contacted Jingdong to help solve it and they again asked what quality problems are, and finally the merchant agrees to return the product. However, the JD later broke their promise again and asked me to pay 50 in advance for the return shipping fee. In the chat history, it is clearly stated that the merchant would refund it but finally said that he was sorry that the shipping fee would have to be borne by me. | The positive features of the device are known. A device that does its job. I'll write down the negative rather than the positive.1. When you put the container of the device in place and look from the opposite side, there is a misfit and an overflow in the part on the left according to you. I noticed the device when it first arrived, but I didn't pay much attention to it thinking it was me. However, I saw the same product in stores and saw that they had the same problem. I also saw this problem on devices in YouTube unboxing videos. This led me to think there was a mistake in this series. Is it very important? Not, However, there seems to be a production error. 2. The device is new device. 2022 models. I think the first series of products are on the market now. Since the device is a new series, the comments have just started to be made on the internet. Comments have started to be made about this problem we are experiencing, so I should have mine too. |

Figure 14: Negative value for money comparison

Conversely, the reviews with low value for money and higher alternatives exhibit a more positive tone. Customers emphasize the positive features and performance of the product, expressing satisfaction with their choice. With a wider range of alternatives available, customers can select products that better align with their preferences and needs. This increased choice allows customers to make decisions based on their individual requirements, resulting in a higher likelihood of positive feedback. The availability of alternatives empowers customers to find a product that meets or exceeds their expectations, enhancing their satisfaction.

The difference in customer sentiment between the two groups highlights the impact of alternative availability on customer satisfaction, particularly in the context of perceived value for money. Limited alternatives contribute to higher dissatisfaction, while greater alternatives lead to higher satisfaction. This emphasizes the importance of competition and choice in shaping customer perceptions and overall satisfaction with a product.
Here are examples of positive online reviews for the air fryer, demonstrating varying numbers of alternatives and their impact on perceived value for money. The initial review,

with just two alternative options (index 2609), indicates mixed feedback regarding the product. Positive aspects highlighted include its design, ease of use, and ability to cook with little or no fat, contributing to overall satisfaction. However, it is criticized for excessive space requirements, posing a challenge for those with limited kitchen countertop space.

In contrast, the second review (index 9831) with eight alternative options emphasizes several positive aspects related to customer satisfaction and perceived value for money. It highlights the convenience, ease of use, and practicality of the air fryer, making it an efficient cooking option. The associated app is praised for providing a wide range of recipes and tips, enhancing the overall cooking experience. These additional features add value and convenience to the product, contributing to positive customer experiences and potentially making it a good value proposition for the price.

| Positive reviews at low alternatives | Positive reviews at high alternatives |
|---|---|
| We will summarize right away, I don't even understand who this product is intended for except people who follow fashion.... Afraid of not having touching the ingenuity of the product, I made roommates with all the people who cook around me. From 25 to 70 years old. Results.... Nothing... Let's do the + and - exercise all the same<br>Most+: Perfect design, in any case, it is clean and well-done level design, presentable, technically, it's not complicated to handle. The accessories are dishwasher safe. Cooking with little or no fat. Large capacity for this XXL model. Perfect for a family of 4. The lessers: It takes up an excessive amount of space. Unless I have miles of unused countertops in my kitchen, I don't see where to put it. When you leave the box, you just have the right to vague pictogram notice that leaves you with more questions than answers. Example: For first use, I certainly did like everyone else, I took out frits. Well, that's exactly what it says on that. | This air fryer is our first hot air fryer and we are thrilled so far. Whether it's heating up fires, roasting vegetables, or mini-pizzas, so far everything has been consistently hot and crispy. Of course, with fires and vegetables, you have to open them up and shake them well, but it's quick and easy. I also like to look at the associated app a lot because I like to see the dishes beforehand. All you have to do is enter a keyword and you will immediately receive a large number of suitable recipes and tips along with pictures, roasting time, etc. Everything is very easy and practical to use. The frying pan and insert are also super easy to clean because almost everything on the coating runs off. Don't expect microwave times, of course, because nice and crispy frying takes time. However, it is always faster and more practical than in the oven, especially with smaller portions. All in all a great device. |

Figure 15: Positive value for money comparison

Both positive reviews showcase customer satisfaction with the air fryer, with subtle differences in the focus of their positive aspects. The review with a higher number of alternatives underscores the importance of added features and benefits in enhancing overall satisfaction and perceived value for money. These insights provide businesses with valuable information on customer preferences and the factors that influence their satisfaction, allowing them to tailor their products and marketing strategies to better meet customer needs and expectations.

Hypothesis 6: The relationship between repurchase intention and customer satisfaction is moderated by the number of alternatives, such that the positive impact of repurchase intention on satisfaction is stronger when the number of alternatives is low and remains positive when the number of alternatives is high, further increasing the level of customer satisfaction.

To test Hypothesis 6, we included the interaction between total alternatives and the repurchase intention in the regression model (Model 3). The results show that the interaction term is statistically significant (estimate = -0.010, $p < 0.05$), indicating that the relationship between repurchase intention and customer satisfaction is indeed moderated by the number of alternatives available for the product.

Specifically, when the number of alternatives is low, repurchase intention has a positive effect on customer satisfaction. However, when the number of alternatives is high, repurchase intention has an even stronger positive effect on customer satisfaction. This suggests that the presence of more alternatives in the market enhances the positive impact of repurchase intention on customer satisfaction, possibly due to the perceived value of choosing the same brand over other available options. Thus, Hypothesis 6 is supported by the regression analysis results.

The regression analysis results from Model 3 do not support Hypothesis 6. The interaction term is not statistically significant (estimate = -0.010, $p > 0.1$), indicating that the number of alternatives does not moderate the relationship between repurchase intention and customer satisfaction as expected. This suggests that the impact of repurchase intention on customer satisfaction does not vary based on the number of alternatives available for the product. Finally, the findings provide support for Hypothesis 3, indicating a positive relationship between repurchase intention and customer satisfaction. However, Hypothesis 6 is not supported, suggesting that the number of alternatives does not influence the relationship between repurchase intention and customer satisfaction. Further research may be necessary to explore other potential factors that could moderate this relationship in the presence of different numbers of alternatives.

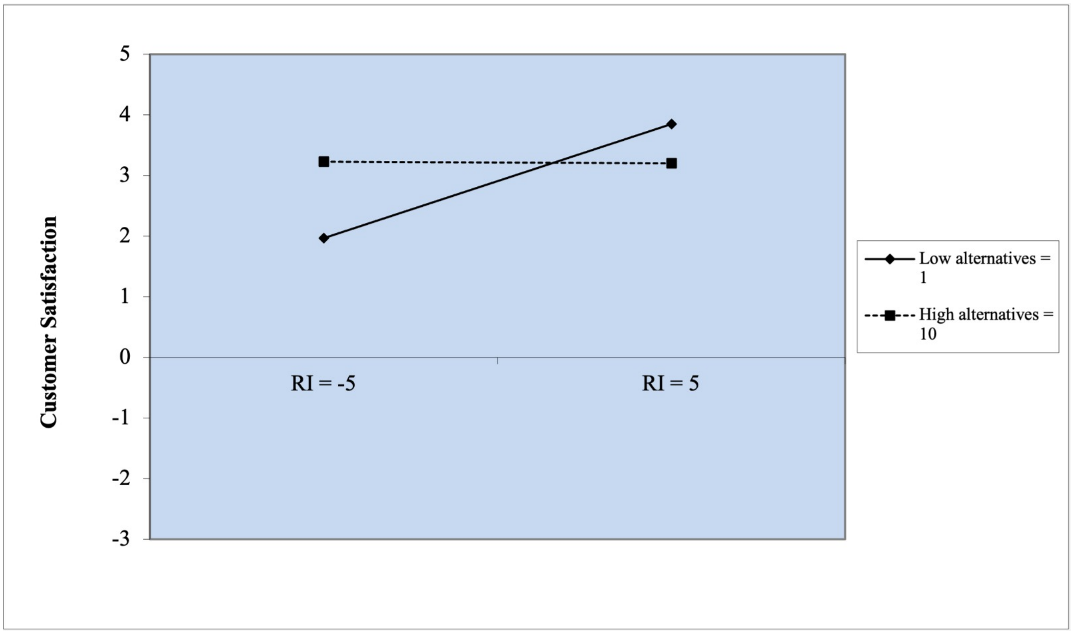


Figure 16: Moderating impact on customer repurchase intention

# 5 Discussion and Conclusions

The thesis aimed to determine and model the natural decay of delight in product attributes and examine how the decline in these attributes affects overall customer satisfaction. Moreover, this thesis has contributed to understanding the natural decay of delight and the factors influencing customer satisfaction. By employing data analysis and statistical techniques, I have gained valuable insights into customer satisfaction dynamics and the roles played by various variables in shaping it.

The findings of this thesis suggest that the availability of alternative products plays a crucial role in influencing customer satisfaction over time. As more alternatives become available, the initial delight associated with a product tends to diminish. This implies that the intrinsic attributes of a product do not solely determine customer satisfaction but is also influenced by the competitive landscape.

Furthermore, the thesis emphasizes the importance of considering moderating variables when examining the relationship between product attributes and customer satisfaction. The number of alternatives and repurchase intention were found to be significant moderators. The number of alternatives affects how attributes such as capacity and value for money impact customer satisfaction, while repurchase intention further enhances the relationship between attributes and satisfaction.

By including control variables such as the impact of the Covid-19 pandemic, sales channels, and regional variations, this thesis provides a comprehensive analysis of external factors that can influence customer satisfaction. These variables offer a more nuanced understanding of the dynamics and their effects on customer sentiments. It underscores the need to consider contextual factors in assessing customer satisfaction.

Overall, this thesis contributes to the existing literature on customer satisfaction and provides practical implications for businesses. It highlights the importance of understanding the influence of product attributes, competition, and customer preferences on satisfaction. The findings can assist companies in developing effective strategies to manage customer satisfaction over time and adapt to changing market dynamics. By recognizing the impact of alternative products and the moderating role of variables like repurchase intention, businesses can better meet customer needs and maintain a competitive edge.

In summary, this thesis provides valuable insights into the natural decay of delight and the factors that shape customer satisfaction. By examining the interplay between product attributes, external factors, and moderating variables, this research offers practical implications for businesses seeking to enhance customer satisfaction and maintain a competitive edge in a dynamic marketplace. It serves as a foundation for further research in customer satisfaction and consumer behavior.

## 5.1 Theoretical implications

The primary aim of this study was to investigate the moderating effect of the number of available alternatives on the relationship between key variables and customer satisfaction. Specifically, I examined how the number of alternatives influences the main effects of value for money, capacity, and repurchase intention on customer satisfaction. The findings revealed a significant interaction between the number of alternatives and the main effect of value for money.

As anticipated, the results showed a positive relationship between value for money and customer satisfaction when the number of alternatives was low. This suggests that customers perceive better value for money when there are fewer alternatives in the market. However, contrary to expectations, the relationship weakened as the number of alternatives increased. This indicates a potential decrease in customers' perceived value for money as competition intensifies.

On the other hand, the moderating variable, the number of alternatives, did not significantly impact the main effects of capacity and repurchase intention on customer satisfaction. Additionally, compared to the conceptual model, the product's capacity had a negative association, implying that customer satisfaction tends to increase as the product capacity decreases. This suggests a preference for smaller, more convenient products. This unexpected finding could be attributed to various external factors, such as changing market trends or evolving customer preferences.

These findings highlight the importance of considering the number of alternatives as a crucial factor when examining the relationship between variables and customer satisfaction. The results imply that alternative products can influence customers' perceptions and satisfaction levels, especially concerning value for money. To further understand the underlying mechanisms and dynamics driving these effects, future research could delve deeper into additional factors influencing customer satisfaction in competitive markets.

Apart from that, within the realm of this thesis, an exploratory analysis delved into several additional factors that have the potential to intricately shape the relationship between the aforementioned main effects and customer satisfaction. To this end, an assortment of insightful dummy variables was introduced, such as incorporating the sales channel employed by customers to acquire the product, exemplified by including an Amazon dummy variable. Furthermore, the profound impact of the pervasive Covid-19 pandemic on customer satisfaction levels was thoughtfully incorporated into the investigation. Lastly, regional variations in customer satisfaction levels for Airfryers were methodically examined, unveiling intriguing insights into diverse customer sentiments across different parts of the globe.

The findings of the thesis lend credence to the concept of 'the natural decay of delight' as mentioned in the Kano analysis (2023) and as originally proposed by Kano in his model (Kano, 1984). Specifically, the thesis corroborates the time aspect in the Kano model. Although Kano mentioned that product-related attributes tend to lose popularity over time, diminishing their impact on customer satisfaction, this thesis builds upon this body of work by shedding light on the critical dimension of time about the number of alternatives. It reveals that as the number of alternatives for a popular product increases over time, customer satisfaction associated with a given attribute is also likely to diminish due to increased demand elasticity for the products (Labandeira et al., 2017). Furthermore, it is important to recognize the non-linear relation between customer satisfaction and the product's attributes, and the results of this thesis have contributed to achieving this understanding.

Furthermore, by leveraging advanced techniques such as sentiment analysis and text mining, this study has showcased the effectiveness of these methods in measuring customer satisfaction. Unlike traditional approaches like customer surveys, which can be time-consuming and costly, utilizing web scraping techniques provides a more efficient and cost-effective means of gauging customer satisfaction.

The application of sentiment analysis and text mining enables the extraction and analysis of valuable insights from a vast amount of online reviews. This research demonstrates that firms can harness these analytical tools to comprehensively understand customer sentiment and satisfaction regarding their products. By collecting and analyzing online reviews, businesses can gather real-time feedback from a large customer base, allowing them to identify strengths, weaknesses, and areas for improvement.

One of the notable advantages of employing web scraping techniques is the reduced constraints on financial and time resources. Traditional customer surveys often require significant financial investment and considerable time to design, administer, and analyze. In contrast, web scraping allows for automated data collection and analysis, enabling researchers to process many reviews without extensive manual efforts efficiently.

Furthermore, this study integrated sentiment analysis and text mining with a multiple linear regression model. By incorporating these techniques into the regression analysis, the study examined the impact of various product attributes on customer satisfaction. This integrated approach provided a deeper understanding of the relationships between product attributes and customer satisfaction, offering valuable insights for businesses in enhancing their products and customer experiences.

## 5.2 Limitations and Future Recommendations

The contributions made in this thesis should be considered alongside certain limitations that may provide insights for future research recommendations. The study has identified several limitations and corresponding recommendations, which are discussed below:

1. First, collecting data sets through the Wonderflow website may have a selection bias. The reviews collected from Wonderflow consist only of online reviews from D2C websites such as Amazon, Bol.com, and Aliexpress. These reviews are posted exclusively by customers who have purchased air fryers from these websites. However, there are other sources of online reviews, such as Reddit, Facebook, and Twitter, which also have many fan pages and other channels where customers post online reviews. These sources of online reviews have yet to be considered. Future research should expand the range of online reviews from other web sources to make the research more comprehensive. Future research can collect data through external sources like Subreddit, Twitter, and Facebook, where customers who purchase products from sources other than online D2C websites also discuss and post their reviews about the product. These sources are also rich sources of data collection and are easily accessible. These reviews are also posted by product experts who provide precious insights into the product. Potential customers generally use these insights before making their purchase decisions. Moreover, researchers can combine and compare the results from online D2C websites and other data sources for better generalizability. This can also lead to data triangulation, thus making the results more substantial. Apart from that, during the development of the dictionaries for

the text mining process for each of the attributes, although the necessary words were taken through the Merriam-Webster dictionary (Merriam-Webster, 2023) and through thoroughly reading through at least 100 reviews from each stratum of the star ratings to make the dictionary more refined for value and repurchase variables, there could still be some words missing related to the attributes of value for money, and the repurchase intention.

2. Second, this thesis focused only on Airfryer's portfolio of Philips Domestic Appliances. Although Philips is the market leader in the Airfryer industry, there are a lot of other strong players in the market. Therefore, it is hard to tell if the sample size for the analysis can be generalized to the larger population (consumers purchasing Airfryer ). Future research can also compare the given attributes between competitor products and analyze how the given attribute of the product performs as compared to the competitor's attribute. By doing so, researchers can determine how their product performs more comprehensively. Finally, only some of the attributes taken for the research were related to the product. Although the capacity of the air fryer and its value for money are key performance features, the repurchase intention is for the customers, not the air fryers. In addition, many technological attributes, such as touch screen features and design (aesthetics), were not considered during the thesis. These are, again, some crucial KPIs that could have been added to the research. Future research can also expand the range of performance features studied. In my thesis, only three attributes were taken into consideration. However, for the piratical implications for research purposes, the number of attributes can also vary based on the type of product under study.

## 5.3 Practical implications

Notwithstanding the limitations mentioned earlier and research recommendations, this thesis provides several practical implications for project managers and product managers interested in assessing their products' performance and understanding the attributes that influence customer satisfaction.

Firstly, the study's findings underscore the significant impact of competition on customer satisfaction. Acknowledging this influence enables managers to understand market dynamics and refine product strategies. To improve customer satisfaction, managers can identify areas where their product falls short compared to competitors and take proactive measures. This involves analyzing customer feedback and competitor products to pinpoint valued features that may be missing. Prioritizing the development of such features and addressing customer pain points can enhance satisfaction levels and foster loyalty. Additionally, leveraging brand identity and unique selling propositions helps differentiate the product meaningfully. Exceptional customer service further contributes to customer satisfaction, leaving a positive impression and building lasting connections. Embracing a customer-centric approach and continuously seeking opportunities to enhance satisfaction will be instrumental in thriving in the competitive business landscape.

Secondly, the thesis highlights the feasibility of measuring customer satisfaction concerning specific product attributes. By dissecting customer reviews and employing techniques like sentiment analysis and text mining, managers can gain insights into how customers perceive different aspects of the product. This enables them to identify how particular attributes can impact customer satisfaction. Therefore, this thesis provides a more comprehensive understanding of all the attributes. It also fosters incremental innovation at the attribute level rather than the product level. This approach also saves a significant amount of money and resources for companies. By enhancing the attributes that impact customer satisfaction, managers can ensure that their product aligns with customer expectations and remains competitive in the market.

Furthermore, for proactive management of customer satisfaction and tackling the challenge of "natural decay of delight," actionable strategies can be implemented. Engaging in consistent efforts to gather customer feedback via surveys, reviews, and direct communication enables pinpointing areas where satisfaction might be waning. Employing advanced techniques such as sentiment analysis and text mining on customer reviews yields deeper insights into evolving preferences. Customer journey mapping aids in comprehending touch points that might witness a dip in satisfaction, presenting opportunities for enhancement. Tracking product metrics like repurchase intention and customer retention rates facilitates tracking long-term satisfaction trends.

Executing competitor analysis and benchmarking satisfaction levels aids in identifying zones necessitating adaptation. Engaging customers through user testing and beta programs cultivates a sense of product ownership. Regular updates and innovations guided by customer feedback and market trends sustain the relevance of the product. Additionally, orchestrating customer surveys and focus groups can further assess satisfaction levels and spot pain points. By embracing these measures, managers can consistently amaze customers and maintain a competitive edge in the market.

Lastly, the thesis acknowledges regional differences in customer satisfaction regarding the purchase of the Philips Airfryer. This underscores the importance of a localized approach to product management and marketing. Managers must recognize that customer preferences and expectations can vary across regions and adapt their strategies accordingly. By conducting market research, understanding cultural nuances, and customizing their offerings to align with regional preferences, managers can effectively cater to diverse customer segments and enhance satisfaction levels.

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## .1 Appendix: Thesis Code

--- editor_options: markdown: wrap: 72 ---

library(readxl) Airfryer <- read_excel("~/Desktop/Airfryer.xlsx") View(Airfryer)

#Create a reproducible results set.seed(123)

# Define the number of samples to take from each stratum

n <- 10000/4

# Load the data

reviews<-read_excel("~/Desktop/Airfryer.xlsx")

sampled_reviews <-read_excel("~/Desktop/Airfryer.xlsx") sampled_reviews <- sampled_reviews[!grepl("^HD99\d{2}", sampled_reviews$sku), ] # Split the data into strata based on star ratings strata_1_2 <- subset(reviews, rating >= 1 & rating < 2) strata_2_3 <- subset(reviews, rating >= 2 & rating < 3) strata_3_4 <- subset(reviews, rating >= 3 & rating < 4) strata_4_5 <- subset(reviews, rating >= 4 & rating <= 5)

# Perform stratified random sampling

sample_1_2 <- strata_1_2[sample(nrow(strata_1_2), n, replace = TRUE), ] sample_2_3 <- strata_2_3[sample(nrow(strata_2_3), n, replace = TRUE), ] sample_3_4 <- strata_3_4[sample(nrow(strata_3_4), n, replace = TRUE), ] sample_4_5 <- strata_4_5[sample(nrow(strata_4_5), n, replace = TRUE), ]

# Combine the samples into one data frame

sampled_reviews <- rbind(sample_1_2, sample_2_3, sample_3_4, sample_4_5)

#removing the SKUs for the accessories, with SKUs HD99xx #sampled_reviews <- sampled_reviews[!grepl("^HD99\d{2}", sampled_reviews$sku), ]

view(sampled_reviews)

### Creating a random sample of 10,000 rows from 116.000 reviews taken from the wonderflow

#data <- reviews[sample(nrow(reviews), 10000), ] library(tidyverse) library(tidytext) library(stringr) library(lubridate) library(syuzhet) # this library for sentiment analysis has 4 sentiment dictionaries.

#Making dummy variables now.

#categorizing the countries based on the continents####

#install.packages("countrycode") library(countrycode)

countires <- sampled_reviews$country # Categorize countries by region regions <- countrycode(sampled_reviews$country, "country.name", "region")

# Load the required libraries. # code from bing for categorizing the countries into continents.

library(dplyr) library(countrycode)

### Assume you have a data frame named 'df' with a column named 'country'

### Convert the country column to ISO2C country codes

sampled_reviews$country_code <- countrycode(sampled_reviews$country, "country.name", "iso2c")

# Create a new column for continent

sampled_reviews$continent <- countrycode(sampled_reviews$country_code, "iso2c", "continent") # Create dummy variables for each continent sampled_reviews <- mutate(sampled_reviews, Africa = ifelse(continent == "Africa", 1, 0), Americas = ifelse(continent == "Americas", 1, 0), Asia = ifelse(continent == "Asia", 1, 0), Europe = ifelse(continent == "Europe", 1, 0), Oceania = ifelse(continent == "Oceania", 1, 0) )

# Print the categorized countries

for (i in 1:length(sampled_reviews$country)) { cat(sampled_reviews$country[i], "is in", regions[i], "\n") }

#### dummy variable for the date based on pre and post covid era.

library(dplyr) library(lubridate)

sampled_reviews$publishedByUserAt <- as.Date(sampled_reviews$publishedByUserAt)

sampled_reviews$pre_post_covid <- ifelse(sampled_reviews$publishedByUserAt < as.Date("2020-03-01"), "pre_covid", "post_covid")

## creating the dummy variable for the amazon and other e-commerce websites.

### Create a new column called 'amazon_dummy' with the value 0

sampled_reviews$amazon_dummy <- 0

### Set the value of 'amazon_dummy' to 1 for rows where the 'product' column contains the word 'amazon' before the dot

sampled_reviews$amazon_dummy[grepl("amazon\\.", sampled_reviews$channel, ignore.case = TRUE)] <- 1

view(sampled_reviews)

#taking required sampled_reviews <- sampled_reviews %>% select(translatedText, sku, publishedByUserAt, country, channel, pre_post_covid, amazon_dummy, continent, rating, Africa, Americas, Asia, Europe, Oceania, capacity ) %>% mutate(publishedByUserAt = as.Date(publishedByUserAt)) #making a new column for date.

view(sampled_reviews)

# remove the last digits after "/" in SKU code

sampled_reviews$sku <-sub("/.*", "", sampled_reviews$sku)

view(sampled_reviews)

#####need to assign volumes associated to the SKUs. # Here I am assigning the capacity in terms of Kgs, the baking capacities #of each SKUs. # Create a vector with the capacity for each SKU capacity <- c( "HD9861" = 1.4, "HD9216" = 0.8, "HD9257" = 1, "HD9742" = 0.8, "HD9100" = 0.8, "HD9247" = 1.2 , "HD9641" = 0.8, "HD9215" = 0.8, "HD9630" = 1.4, "RI9280" = 1.2, "RI9217" = 0.8, "HD9220" = 0.8, "HD9230" = 0.8, "HD9200" = 0.8, "HD9218" = 0.8, "HD9240" = 1.2, "HD9260" = 1.2, "HD9270" = 1.2, "HD9280" = 1.2, "HD9621" = 0.8, "HD9651" = 1.4, "HD9654" = 1.4, "HD9650" = 1.4, "HD9860" = 1.4, "HD9830" = 1.4, "HD9653" = 1.3, "HD9252" = 0.8, "HD9255" = 0.8, "HD9880" = 2, "HD9762" = 1.4, "HD9867" = 1.4, "HD9876" = 1.4, "HD9870" = 1.4, "HD9741" = 0.8, "HD9241"= 1.2, "HD9721" = 0.8, "HD9252" = 0.8, "HD9261" = 1.2, "HD9248" = 1.2, "HD9745" = 0.8, "HD9861" = 1.4, "HD9652" = 1.4)

## Add the new column to the data set

sampled_reviews$capacity <- capacity[sampled_reviews$sku]

view(sampled_reviews)

#taking required coulmns from the data set only sampled_reviews <- sampled_reviews %>% select(translatedText, sku, publishedByUserAt, country, channel, pre_post_covid, amazon_dummy, continent, rating, Africa, Americas, Asia, Europe, Oceania, capacity ) %>% mutate(publishedByUserAt = as.Date(publishedByUserAt)) #making a new column for date.

### looking for the NA terms

na_rows <- is.na(sampled_reviews$capacity)

# View the rows with NA values in the specified column

sampled_reviews[na_rows, ]

#creating dictionaries for the attributes value and the repurchase intention.

library(tidytext)

#dummy variable for the capacity, as of big, medium, and small

sampled_reviews$size <- ifelse(sampled_reviews$capacity >= 0 & sampled_reviews$capacity <= 0.8, "small", ifelse(sampled_reviews$capacity >= 0.9 & sampled_reviews$capacity <= 1.2, "medium", "big"))

view(sampled_reviews)

library(tidytext) library(dplyr)

## Tokenization of the text

## Add an 'index' column with row numbers

sampled_reviews <- sampled_reviews %>% mutate(index = row_number())

# Tokenize the reviews

tokenized_reviews <- sampled_reviews %>% unnest_tokens(word, translatedText)

## # Convert to lower case

tokenized_reviews$word <- tolower(tokenized_reviews$word)

## Left join with sentiment lexicon # sentiment library(afinn )

sentiment_scores <- left_join(tokenized_reviews, get_sentiments("afinn"))

# Sum all sentiments for each index (review)

fin_review_sentiment <- tapply(sentiment_scores$value, sentiment_scores$index, FUN=function(x) sum(x, na.rm = TRUE))

resu <- list()

## For loop to check equality with index and find out the non-matching indices (missing reviews after tokenization)

for (i in 1:10000) { resu[i] <- any(tokenized_reviews$index == i) }

missing_elements <- resu[which(is.na(tokenized_reviews$index[match(resu, tokenized_reviews$index)]))]

# Print the list of missing elements

print(missing_elements)

# get a list of missing indices/reviews after tokenization

false_i <- which(missing_elements == FALSE)

# remove missing indices from original dataframe

sampled_filtered <- sampled_reviews[!(sampled_reviews$index %in% false_i), ]

#CheckPoint: 11:00 AM July 07 # combine subset of original dataframe and sentiment scores review_sentiments <- cbind(sampled_filtered, fin_review_sentiment) #view(review_sentiments)

#Data points removed as outliers such as 72 were causing problems. review_sentiments <- subset(review_sentiments, fin_review_sentiment<30)

# Define the original range

original_min <- min(review_sentiments$fin_review_sentiment) original_max <- max(review_sentiments$fin_review_sentiment)

# Define the desired normalized range

new_min <- -5 new_max <- 5

## Normalize the "values" column while centering at 0, with upto two decimal points.

review_sentiments$fin_review_sentiment <- ((review_sentiments$fin_review_sentiment - original_min) / (original_max - original_min)) * (new_max - new_min) + new_min

view(review_sentiments) # count_positive<- sum(review_sentiments$fin_review_sentiment>0) # count_negative<- sum(review_sentiments$fin_review_sentiment<0) # # print(count_negative) # print(count_positive)

## Now I will conduct the analysis based on the terms like value and repurhcase

#for the sentiment analysis based on the libraries I made.

library(tidytext)

get_sentiments("afinn")

get_sentiment("charm")

#dictionary for the term value; including both synonyms, and antonyms # scores are based on the sentiment score from afinn

value_dictionary <- c ("practical" = 1.0, "advantage" = 0.75, "deal" = 0.25, "advantageous" = 0.5, "worth" = 0.75, "satisfied" = 1, "great" = 0.5, "bargain" = 0.75, "worhty" = 0.75, "gain" = 0.75, "utlity" = 0.4, "prize" = 0.8, "appraisal" = 0.25, "merit" = 0.75, "fault" = -0.5, "deficiency" = -0.5, "insufficient" = -0.5, "treasure" = 0.75, "enjoy" = 0.75, "cherish" = 0.75, "like" = 0.5, "relish" = 0.8, "love" = 0.75, "respect" = 0.5, "admire" = 1, "fancy" = 0.5, "esteem" = 0.6, "appreciate" = 0.5, "delight" = 1, "despise" = -0.75, "detest" = -0.5, "snub" = -0.5, "hate" = -0.75, "loath" = -0.75, "scorn" = -0.75, "forget" = -0.5, "deprecate" = -1, "depreciate" = -0.8, "charm" = 0.75, "advantage" = 0.75, "fine" = 0.25, "amount" = 0.1, "cost" = 0.1, "price" = 0.1, "profit" = 0.25, "good" = 0.75, "well" = 0.8, "save" = 0.5, "happy" = 0.75, "amazing" = 0.5, "impressive" = 0.75, "performance" = 0.4, "quality" = 0.1, "easy" = 0.8, "trust" = 0.5, "fabulous" = 0.5, "perfect" = 0.75, "cool" = 0.75, "generous" = 0.75, "convenient" = 0.8, "enough" = -0.25, "useful" = 0.5, "simple" = 0.1, "chic" = 0.5, "expensive" = -0.25, "high quality" = 0.5, "absolute" = -0.25, "high end" = 0.25, "awesome" = 0.6, "nice" = 0.5, "super" = 0.75, "effective" = 0.8, "workmanship" = 0.1, "better" = 0.8, "proud" = 0.75, "ideal" = 1, "right" = 0.8, "cheap" = -0.5, "away" = -0.1, "enough" = -0.25, "disappoint" = -1, "problem" = -0.75, "miserable" = -1, "average" = -0.1, "refund" = -0.8, "unhappy" = -0.75, "efficient" = 0.75, "handy" = 0.5, "useless" = -0.75, "worhtless" = -1, "return" = -0.5, "compensate" = 0.6, "trashy" = -0.5, "pathetic" = -0.75, "lousy" = -1, "superior" = 0.75, "strong" = 0.5, "well" = 0.8, "fit" = 0.4, "sturdy" = 0.5, "powerful" = 0.75, "sad" = -0.5, "unfortunate" = -0.75, "flawless" = 0.6, "reasonable" = 0.5, "overcharge" = -0.5, "ripoff" = -0.25, "downhill" = 1, "fee" = -0.25, "ingenuity" = 1, "thrill" = 0.5,

)

### Define the value dictionary

value_dictionary_2 <- c("amount", "cost", "expense", "price", "profit", "rate", "appraisal", "assessment", "charge", "equivalent", "market price", "monetary worth", "benefit", "content", "important", "importance", "meaning", "power", "purposeful", "quality", "sense", "significance", "useful", "valuation", "account", "bearing", "caliber", "condition", "connotation", "consequence", "denotation", "desirability", "distinction", "drift", "eminence", "esteem", "excellence", "finish", "force", "goodness", "grade","help","implication","interpretation","practical", "advantage")

## Calculate the value for each word

value_2 <- 1 / length(value_dictionary_2)

## Assign the value to each word

value_2 <- setNames(rep(value_2, length(value_dictionary_2)), value_dictionary_2)

### #dictionary for the term repurchase including synonym, and anotonyms

get_sentiment("boycott")

repurchase_dictionary <- c("recommend" = 0.5, "recommendation" = 0.8, "rebuy"= 1, "offer" = 0.1, "pay" = -0.1, "acquire" = 0.8, "win" = 0.5, "reacquire" = 1, "redeem" = 1, "hold" = -0.25, "refrain" = -0.25, "restrain" = -0.5, "limit" = -0.25, "forfit" = -0.5, "buyback" = 1, "recoup" = 0.1, "repay" = 0.5, "repurchase" = 1, "repossess" = 0.5, "confine" = -0.25, "boycott" = -0.75, "upgrade" = 0.5, "purchased before" = 0.5, "entrust" = 0.6, "relinquish" = -0.5, "keep" = 0.1, "retain" = 0.1, "withhold" = -0.1, "receive" = 0.1, "possess" = 0.1, "accept" = 1, "own" = 0.1, "take" = 0.1, "reserve" = 0.4, "suggest" = 0.75, "counsel" = 0.4, "back" = -0.1, "advise" = 0.8, "propose" = 0.25, "offer" = 0.1, "support" = 0.5, "condemn" = -0.75, "deny" = -0.75, "discourage" = -0.1, "oppose" = -0.5, "reject" = -0.75, "dislike" = -1, "debase" = -0.8, "disapprove" = -0.75, "disregard" = -1, "hate" = -0.75, "recover" = 1, "forfeit" = -0.75, "limit" = -0.25, "purchase" = 0.5, "exchange" = 0.25, "advise" = 1, "warn" = -0.75, "alert" = -0.25, "inform" = -0.1, "caution" = -0.25, "notify" =0.25, "risk" = -0.75, "neglect" = -0.75, "deceive" = -0.75, "lie" = -0.5, "trick" = -0.5, "stop" = -0.4, "fool" = -0.75, "let-know" =0.25, "promote" = 0.8, "defend" = 0.25, "support" = 0.5, "opted" = 0.8, "another" = 0.25) repurchase_dictionary_2 <- c("recommend", "recommendation", "rebuy", "offer", "pay", "acquire", "win", "reacquire", "redeem", "hold", "refrain", "restrain", "limit", "forfit", "buyback", "recoup", "repay", "repurchase", "repossess", "confine", "boycott")

repurchase_2 <- 1 / length(repurchase_dictionary_2)

## Assign the value to each word

repurchase_2 <- setNames(rep(repurchase_2, length(repurchase_dictionary_2)), repurchase_dictionary_2)

view(repurchase_2)

view(value_2)

## Tokenize the text column and store tokens separately for each string (the index is based on each review. So basically I know which review that elemt belong to)

tokens_ag <- copy_check %>% group_by(index) %>% unnest_tokens(token, translatedText)

# Print the resulting tokens

view(tokens_ag)

sum_sav_value_2 <- vector() index_save_temp_var <- vector()

rotatingsum<-0

#tTrow is the iterator, it will take the values from the row number from the data frame for (tTrow in seq_along(tokens_ag$token)){

if (tTrow == 1){ index_save_temp_var<-c(index_save_temp_var, tokens_ag$index[tTrow]) # print(tokens_ag$index[tTrow] %in% index_save_temp_var) }

if (tokens_ag$index[tTrow] %in% index_save_temp_var){

```
# change value_2 with name of dict
rotatingsum<-rotatingsum + ifelse(tokens_ag$token[tTrow] %in%
names(value_2), value_2[[tokens_ag$token[tTrow]]], 0)
```

} else {

```
sum_sav_value_2<-c(sum_sav_value_2, rotatingsum)
# sum_sav_value_2[tokens_ag$index[tTrow]] <- rotatingsum
rotatingsum<-0

index_save_temp_var<-c(index_save_temp_var, tokens_ag$index[tTrow])
```

```
}

}

print(rotatingsum)

sum_sav_value_2<-c(sum_sav_value_2, rotatingsum)

nonNULLcounter <- 0

for (eletemptemp in sum_sav_value_2){ if (eletemptemp!=0.0){ nonNULLcounter<-
nonNULLcounter+1 } }

view(sum_sav_value_2)

nonNULLcounter1 <- 0

for (eletemptemp1 in sum_sav_value_2){ if (is.null(eletemptemp1) | is.na(eletemptemp1)){
nonNULLcounter1<-nonNULLcounter1+1 } }

print(nonNULLcounter1)

updated_tok<-cbind(copy_check, sum_sav_value_2) view(updated_tok) # this one contains
the data set from the value_2 dictionary

print(nonNULLcounter)

view(sum_sav_value_2)
```

### Now adding the seconding dictionary using the same steps, with value_dictionary (the one with values from afinn)

```
#2nd tokens_ag <- copy_check %>% group_by(index) %>% unnest_tokens(token,
translatedText)
```

## Print the resulting tokens

```
view(tokens_ag)

sum_sav_value <- vector() index_save_temp_var <- vector()

rotatingsum<-0

#tTrow is the iterator, it will take the values from the row number from the data frame for
(tTrow in seq_along(tokens_ag$token)){

if (tTrow == 1){ index_save_temp_var<-c(index_save_temp_var, tokens_ag$index[tTrow]) #
print(tokens_ag$index[tTrow] %in% index_save_temp_var) }
```

if (tokens_ag$index[tTrow] %in% index_save_temp_var){

```
# change value_2 with name of dict
rotatingsum<-rotatingsum + ifelse(tokens_ag$token[tTrow] %in%
names(value_dictionary), value_dictionary[[tokens_ag$token[tTrow]]], 0)
```

} else {

```
sum_sav_value<-c(sum_sav_value, rotatingsum)
# sum_sav_value[tokens_ag$index[tTrow]] <- rotatingsum
rotatingsum<-0

index_save_temp_var<-c(index_save_temp_var, tokens_ag$index[tTrow])
```

}

}

view(updated_tok_2) print(rotatingsum)

sum_sav_value<-c(sum_sav_value, rotatingsum)

nonNULLcounter <- 0

for (eletemptemp in sum_sav_value){ if (eletemptemp!=0.0){ nonNULLcounter<-nonNULLcounter+1 } }

view(sum_sav_value)

nonNULLcounter1 <- 0

for (eletemptemp1 in sum_sav_value){ if (is.null(eletemptemp1) | is.na(eletemptemp1)){ nonNULLcounter1<-nonNULLcounter1+1 } }

print(nonNULLcounter1)

updated_tok_2<-cbind(copy_check, sum_sav_value) view(updated_tok_2) # this one contains the data set from the value_dictionary

print(nonNULLcounter)

#now adding the third dictionary based on the repurchase_dictionary #3rd tokens_ag <- copy_check %>% group_by(index) %>% unnest_tokens(token, translatedText)

# Print the resulting tokens

view(tokens_ag)

sum_sav_Repurchase <- vector() index_save_temp_var <- vector()

rotatingsum<-0

#tTrow is the iterator, it will take the values from the row number from the data frame for (tTrow in seq_along(tokens_ag$token)){

if (tTrow == 1){ index_save_temp_var<-c(index_save_temp_var, tokens_ag$index[tTrow]) # print(tokens_ag$index[tTrow] %in% index_save_temp_var) }

if (tokens_ag$index[tTrow] %in% index_save_temp_var){

```
# change value_2 with name of dict
rotatingsum<-rotatingsum + ifelse(tokens_ag$token[tTrow] %in%
names(repurchase_dictionary),
repurchase_dictionary[[tokens_ag$token[tTrow]]], 0)
```

} else {

```
sum_sav_Repurchase<-c(sum_sav_Repurchase, rotatingsum)
# sum_sav_Repurchase[tokens_ag$index[tTrow]] <- rotatingsum
rotatingsum<-0

index_save_temp_var<-c(index_save_temp_var, tokens_ag$index[tTrow])
```

}

}

print(rotatingsum)

sum_sav_Repurchase<-c(sum_sav_Repurchase, rotatingsum)

nonNULLcounter <- 0

for (eletemptemp in sum_sav_Repurchase){ if (eletemptemp!=0.0){ nonNULLcounter<-nonNULLcounter+1 } }

view(sum_sav_Repurchase)

nonNULLcounter1 <- 0

for (eletemptemp1 in sum_sav_Repurchase){ if (is.null(eletemptemp1) | is.na(eletemptemp1)){ nonNULLcounter1<-nonNULLcounter1+1 } }

print(nonNULLcounter1)

updated_tok_3<-cbind(copy_check, sum_sav_Repurchase) view(updated_tok_3) # this one contains the data set from the repurchase_dictionary

print(nonNULLcounter)

view(sum_sav_Repurchase)

#now adding the fourth dictionary based on the repurchase_2 #4th tokens_ag <- copy_check %>% group_by(index) %>% unnest_tokens(token, translatedText)

# Print the resulting tokens

view(tokens_ag)

sum_sav_Repurchase_2 <- vector() index_save_temp_var <- vector()

rotatingsum<-0

#tTrow is the iterator, it will take the values from the row number from the data frame for (tTrow in seq_along(tokens_ag$token)){

if (tTrow == 1){ index_save_temp_var<-c(index_save_temp_var, tokens_ag$index[tTrow]) # print(tokens_ag$index[tTrow] %in% index_save_temp_var) }

if (tokens_ag$index[tTrow] %in% index_save_temp_var){

```
# change value_2 with name of dict
rotatingsum<-rotatingsum + ifelse(tokens_ag$token[tTrow] %in%
names(repurchase_2), repurchase_2[[tokens_ag$token[tTrow]]], 0)
```

} else {

```
sum_sav_Repurchase_2 <-c(sum_sav_Repurchase_2 , rotatingsum)
# sum_sav_Repurchase_2 [tokens_ag$index[tTrow]] <- rotatingsum
rotatingsum<-0

index_save_temp_var<-c(index_save_temp_var, tokens_ag$index[tTrow])
```

}

}

print(rotatingsum)

sum_sav_Repurchase_2 <-c(sum_sav_Repurchase_2 , rotatingsum)

nonNULLcounter <- 0

for (eletemptemp in sum_sav_Repurchase_2 ){ if (eletemptemp!=0.0){ nonNULLcounter<-nonNULLcounter+1 } }

view(sum_sav_Repurchase_2)

nonNULLcounter1 <- 0

for (eletemptemp1 in sum_sav_Repurchase_2 ){ if (is.null(eletemptemp1) | is.na(eletemptemp1)){ nonNULLcounter1<-nonNULLcounter1+1 } }

print(nonNULLcounter1)

updated_tok_4<-cbind(copy_check, sum_sav_Repurchase_2 ) view(updated_tok_4) # this one contains the data set from the repurchase_2 dictionary

print(nonNULLcounter)

view(sum_sav_Repurchase_2 )

#making the final data set with all the sentiment scores from the dictionaries.

library(dplyr)

combined_data <- left_join(updated_tok, updated_tok_2, by = "index") %>% left_join(updated_tok_3, by = "index") %>% left_join(updated_tok_4, by = "index")

view(combined_data)

## Total number of alternatives in the data set.

alternatives <- combined_data %>% group_by(publishedByUserAt.x) %>% summarise(total_alternatives = n_distinct(sku.x))

view(alternatives)

# adding the total number of alternatives to the final combined data set.

combined_data <- left_join(combined_data, alternatives, by = "publishedByUserAt.x")

view(combined_data)

combined_data <- combined_data %>% select(index, translatedText.x, sku.x, publishedByUserAt.x, country.x, channel.x, pre_post_covid.x, amazon_dummy.x, continent.x, rating.x, Africa.x, Americas.x, Asia.x, Europe.x, Oceania.x, capacity.x, size.x, fin_review_sentiment.x, sum_sav_value, sum_sav_Repurchase,total_alternatives)

view(combined_data)

# normalizing the value dictionary

# Define the original range

original_min_value <- min(combined_data$sum_sav_value) original_max_value <- max(combined_data$sum_sav_value)

# Define the desired normalized range

new_min_value <- -5 new_max_value <- 5

# Normalize the "sum_sav_value" column while centering at 0

combined_data$sum_sav_value <- ((combined_data$sum_sav_value - original_min_value) / (original_max_value - original_min_value)) * (new_max_value - new_min_value) + new_min_value

# Format the normalized values with up to two decimal places

combined_data$sum_sav_value <- round(combined_data$sum_sav_value, 2)

View(combined_data)

# normalizing the repurchase dictionary

original_min_repurchase <- min(combined_data$sum_sav_Repurchase) original_max_repurchase <- max(combined_data$sum_sav_Repurchase)

# Define the desired normalized range

new_min_repurchase <- -5 new_max_repurchase <- 5

# Normalize the "sum_sav_value" column while centering at 0

combined_data$sum_sav_Repurchase <- ((combined_data$sum_sav_Repurchase - original_min_repurchase) / (original_max_repurchase - original_min_repurchase)) * (new_max_repurchase - new_min_repurchase) + new_min_repurchase

# Format the normalized values with up to two decimal places

combined_data$sum_sav_Repurchase <- round(combined_data$sum_sav_Repurchase, 2)

# Running multiple linear regression model on the combined_data (dataset)

fit1 <- lm(fin_review_sentiment.x ~ pre_post_covid.x+ continent.x + amazon_dummy.x + size.x + total_alternatives, data = combined_data) #controls

summary(fit1)

fit2 <- update(fit1, .~. + sum_sav_Repurchase + sum_sav_value + capacity.x) #main effects

summary(fit2)

fit3 <- update(fit2, .~. + (sum_sav_Repurchase*total_alternatives) + (sum_sav_value*total_alternatives) + (capacity.x*total_alternatives)) summary(fit3) # moderating effects

summary(combined_data)

#using the stargazer for APA formating install.packages("stargazer") # Load necessary libraries library(stargazer) library(tidyverse)

view(combined_data)

# Fit multiple linear regression model

fit3 <- update(fit2, .~. + (sum_sav_Repurchase*total_alternatives) + (sum_sav_value*total_alternatives) + (capacity.x*total_alternatives))

# Generate LaTeX table in APA format

stargazer(fit1, fit2, fit3, type = "latex", out = "regression_table.tex")

#view(combined_data[8748, ])

summary(combined_data)

##Correlation table for the data set## correlation_data <- combined_data %>% select( amazon_dummy.x, rating.x, Africa.x, Americas.x, Asia.x, Europe.x, Oceania.x, capacity.x, fin_review_sentiment.x, sum_sav_value, sum_sav_Repurchase,total_alternatives) correlation_table <- cor(correlation_data)

view(correlation_table)

install.packages("apa")

install.packages("corrplot") install.packages("xtable") library(tidyverse) library(corrplot) library(xtable)

print(xtable(correlation_matrix), type = "latex")

# Load the necessary libraries

library(tidyverse) library(corrplot) library(xtable) install.packages("papaja") library(papaja)

correlation_matrix <- cor(correlation_data)

view(correlation_matrix)

# Split values and extract everything behind the first comma

countrycounts <- sapply(strsplit(combined_data$country.x, ","), function(x) trimws(x[1]))

# Count the occurrences of each value

fincountry <- table(countrycounts)

# Print the count

print(fincountry)

# Get rows where col1 and col2 have non-zero values

subset_rep_val <- combined_data[combined_data$sum_sav_value != 0.0 & combined_data$sum_sav_Repurchase != 0.0, ]

view(subset_rep_val) # Print the subsetted data frame view(subset_rep_val)

install.packages("Hmisc") # Load the necessary libraries library(Hmisc) library(tidyverse)

# Load the data

correlation_data <- combined_data %>% select( amazon_dummy.x, rating.x, Africa.x, Americas.x, Asia.x, Europe.x, Oceania.x, capacity.x, fin_review_sentiment.x, sum_sav_value, sum_sav_Repurchase,total_alternatives)

# Create the correlation matrix

cor_matrix <- rcorr(as.matrix(correlation_data), type = "pearson")

# Extract the correlation coefficients and p-values

cor_coef <- cor_matrix$r cor_pval <- cor_matrix$P

# Create a function to add stars based on significance levels

add_stars <- function(pval) { ifelse(pval < .001, "***", ifelse(pval < .01,* "*", *ifelse(pval < .05, "", ""))) }*

# Apply the function to the p-values

stars <- apply(cor_pval, 2, add_stars)

# Combine the correlation coefficients and stars into one table

cor_table <- cor_coef %>% as.data.frame() %>% mutate_all(list(~ paste0(round(., 2), stars[rownames(.)]))) %>% as.matrix()

# Print the correlation table with stars

cor_table

view(cor_table)

## .2 Appendix: Result Tables

Table 6: Add caption

| S.no | Capacity | SKUs |
|---|---|---|
| 1 | 0.8Kg | HD9216, HD9724, HD9100, HD9641, HD9215, RI9217, HD9220, HD9239, HD9200, HD9218, HD9621, HD9252, HD9255, HD9741, HD9721, HD9745, |
| 2 | 1.0Kg | HD9257 |
| 3 | 1.2Kg | HD9247, RI9280, HD9240, HD9260, HD9270,HD9280, HDHD9241, HD9261, HD9248 |
| 4 | 1.3Kg | HD9653 |
| 5 | 1.4Kg | HD9861, HD9630, HD9651, HD9654, HD9650, HD9860, HD9830, HD9762, HD9867, HD9876, HD9870, HD9861, HD9652 |
| 6 | 2Kg | HD9880 |

## .3 Syuzhet package sentiment analysis visuals

```
library(syuzhet)

text <- "I have recently started using advance xxl airfryer and I love it. I am mostly using it for
          traditionally deep fried food, and it gives great results. The food fired in it (fries, nuggest, etx) is
          crispy from the outside and juicy from inside. In fact the fried chicken tastes better when
          made using airfryer. The size of this model is big and you can fry for the whole family at once.
          A slight downside is my opinion would be that it doesn't brown the food as much as deep fired one but
          the texture and zero oil more than makes up for it."


sentences <- get_sentiment(sentences, method = "syuzhet")
print(sentences)
sum(sentences)
```

Figure 17: Syzuhet process

Table 7: Distribution of reviews

| S. no | Country | Number of Reviews |
|---|---|---|
| 1 | Argentina | 27 |
| 2 | Australia | 151 |
| 3 | Austria | 38 |
| 4 | Belgium | 2 |
| 5 | Brazil | 63 |
| 6 | Canada | 98 |
| 7 | Chile | 6 |
| 8 | China | 3056 |
| 9 | Colombia | 4 |
| 10 | France | 250 |
| 11 | Germany | 1258 |
| 12 | India | 403 |
| 13 | Indonesia | 2 |
| 14 | Italy | 382 |
| 15 | Malaysia | 11 |
| 16 | Mexico | 5 |
| 17 | Netherlands | 1512 |
| 18 | Panama | 7 |
| 19 | Poland | 23 |
| 20 | Saudi Arabia | 81 |
| 21 | Singapore | 17 |
| 22 | South Africa | 16 |
| 23 | South Korea | 40 |
| 24 | Spain | 178 |
| 25 | Sweden | 52 |
| 26 | Switzerland | 7 |
| 27 | Turkey | 1295 |
| 28 | United Kingdom | 151 |
| 29 | United States of America | 796 |

```
> library(syuzhet)
> text <- "I have recently started using advance xxl airfryer and I love it. I am mostly using it for
+          traditionally deep fried food, and it gives great results. The food fired in it (fries, nuggest, etx) is
+          crispy from the outside and juicy from inside. In fact the fried chicken tastes better when
+          made using airfryer. The size of this model is big and you can fry for the whole family at once.
+          A slight downside is my opinion would be that it doesn't brown the food as much as deep fired one but
+          the texture and zero oil more than makes up for it."
> sentences <- get_sentiment(sentences, method = "syuzhet")
> print(sentences)
  [1]  0.60 -0.60  1.35  0.00  0.00 -0.25  0.00 -1.15  0.85 -0.25  0.85  0.00  0.50  0.35
 [15]  0.00  0.80 -0.75  0.20  0.10  0.00  0.00 -0.65  0.00  0.75  0.90  0.00 -1.25  0.00
 [29]  0.50  0.25  0.00  0.00  0.00 -0.75  0.00 -2.00  0.10  0.90  0.00  0.75  0.10 -0.50
 [43] -0.75  0.35  0.00  0.00  0.00 -0.40 -0.15  0.00  0.00 -1.75 -0.35  0.00  0.00  0.55
 [57]  0.00  0.75  0.00 -1.50  0.10  0.00  0.00 -0.50 -0.25 -0.40 -1.00  0.50  0.00 -0.25
 [71]  0.00  0.00 -0.50 -1.10  0.00  0.50  0.00  0.60 -0.10 -0.50 -1.60 -1.30  0.00 -0.60
 [85] -0.50  0.00 -0.25  0.50  0.00  0.00 -0.40 -0.25  0.00  0.25 -1.75 -0.65 -0.25  0.30
 [99]  0.00  0.00  0.50 -0.75  0.55 -0.25  0.00 -1.55  1.00  0.50 -0.50 -0.50  0.00 -0.25
[113]  0.00 -0.90 -0.40  0.40  0.80  0.35 -0.50  1.15  0.00  0.00  0.60 -0.50  0.05 -0.25
[127] -0.75  0.00 -1.00  0.00 -1.50  0.00  0.50  0.00  1.00  0.00  2.05  1.30 -1.25  0.50
[141]  0.15  0.00  0.25  0.80  0.00  1.00  0.75  0.00  0.15 -0.60 -0.25  0.50  0.05  0.00
[155]  0.00  0.00 -1.35 -0.50  0.00  0.60  0.00  1.40  0.00 -0.25  1.05 -0.10 -1.25  1.70
[169]  0.00 -1.50 -1.25 -0.15  0.00  1.00 -0.50  0.50  0.00  0.30  0.00  0.00 -0.80  0.75
[183] -1.35 -1.50 -0.50  0.00  2.50  0.00 -0.40  0.50  0.00 -0.25  0.00  0.00  2.00  0.00
[197] -0.25  0.50  0.00 -0.40 -0.25 -1.00  0.40  0.00  0.75  0.00  1.20  1.40  0.10 -0.50
[211]  0.00 -1.00  0.00  0.00  0.00 -0.25 -0.75 -0.50  1.25 -0.35  0.50  0.40  1.15  0.60
[225] -0.40 -0.60 -2.50  1.70 -1.15  0.35  0.00 -0.75 -0.75  1.00  0.00  0.00 -0.75 -1.50
[239]  0.35  0.50  0.70  0.00 -0.25  0.00  0.00 -0.85  0.50  0.60 -0.25  0.00  0.00  0.00
[253]  0.00  0.75  0.35  0.00 -0.75  0.00  0.75 -0.75 -0.60  0.00  1.00 -0.75  0.00 -0.25
[267]  1.10  1.00 -1.00  0.40  0.50 -0.55 -0.25  0.15  0.00 -0.90 -0.50 -0.75  0.00 -0.50
[281]  0.00  1.35 -0.25 -1.00  0.75 -0.40  0.10 -0.50  0.35 -0.75  0.00  0.50 -0.25  0.00
[295] -0.80 -0.75  0.00  0.75  0.00 -0.60 -0.25  0.00  0.00  0.10  1.25 -0.75 -0.25  1.10
[309]  0.00 -0.50  0.00  1.00  1.50  0.50  0.00  0.25  0.00  0.00  0.00  0.00 -0.25  0.50
[323]  0.75  0.80  0.00  0.00 -0.25  0.50 -0.50  0.75  0.00  0.00  0.60  0.10 -0.25  0.25
[337]  0.00  0.00  0.50  0.00  0.80  0.00  0.00  0.00 -0.75  0.85 -0.25  1.40 -0.10  0.00
[351]  0.00  1.30  0.00 -0.75 -0.50  0.00  1.30  0.40  0.00 -0.35  0.40  0.80  0.25  0.40
[365] -1.00  0.55  0.00  0.35  1.00  0.00  0.00  0.00  0.85  0.00 -0.80  0.00  0.00  1.10
[379] -0.75  0.00  0.00 -0.35  0.80 -0.25 -0.25  1.00 -0.75 -0.20  0.75  0.60  0.00 -0.25
[393]  0.00 -0.60 -1.15 -1.00  0.00  0.00  0.00  0.00  0.80 -0.50 -0.25  0.80  0.00  0.40
```

Figure 18: sentiment values