A COMPARATIVE ANALYSIS OF CUSTOMER SENTIMENT IN E-COMMERCE: EXPLORING REVIEW ATTRIBUTES AS INDICATORS OF SENTIMENT POLARITY ON AMAZON AND A MANUFACTURER'S WEBSITE

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Jason Raphael, MBA

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by

Jason Raphael

Supervised by

Dr. Anna Provodnikova

APPROVED BY

Apostolos Dasilas

Dissertation chair

RECEIVED/APPROVED BY:

Admissions Director

Dedication

This thesis is dedicated to my wife, Shoshana Mitzman Raphael, whose steadfast support and encouragement have been the foundation of this academic endeavor. Shoshana, you are genuinely my inspiration in every possible way. Isaac Newton said in 1675: “If I have seen further, it is by standing on the shoulders of giants.” You, my dear wife, are my giant.

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ABSTRACT

A COMPARATIVE ANALYSIS OF CUSTOMER SENTIMENT IN E-COMMERCE: EXPLORING REVIEW ATTRIBUTES AS INDICATORS OF SENTIMENT POLARITY ON AMAZON AND A MANUFACTURER'S WEBSITE

Jason Raphael
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Dissertation Chair: Dr. Anna Provodnikova

E-commerce has been evolving rapidly, greatly influencing consumption patterns and business processes on platforms such as Amazon and manufacturers' websites. This thesis investigates consumer review sentiment for a specific skincare product across two distinct e-commerce platforms: Amazon and the Manufacturer's online retail store. Employing both qualitative and quantitative analyses, the study examines review attribute features indicating sentiment polarity in customer reviews. It evaluates indicators of consumer sentiments, including review length, and assesses the influence of factors such as incentivized or Vine-free products, product or brand perception, and overall sentiment polarity. The research utilizes NVivo 14 for sentiment analysis as well as STATA for logistic regression to identify elements defining consumer sentiment across platforms. Findings reveal noteworthy differences between the two platforms relating to consumer attitudes, with important implications for e-commerce companies aiming to improve customer experience and improve market strategies. By analyzing sentiment polarity in customer reviews, this study postulates guidelines for harnessing customer feedback to boost brand image and increase sales in the competitive e-commerce environment.

TABLE OF CONTENTS

LIST OF TABLES

List of Figures

Chapter I

INTRODUCTION

1.1 Background of the Study

The advent of the digital era and its swift progress have resulted in substantial changes in the digital economy. The widespread expansion of online e-commerce platforms has led to significant changes in both customer behavior and business operations. The evolutionary shift in technology adoption has resulted in the increasing importance of e-commerce in transactional business, transforming traditional retail dynamics and requiring substantial online consumer engagement. Analyzing consumer emotions portrayed in online feedback is a fundamental theme, emerging as an important tool for the complex interaction between customers and businesses (Ruiz-Mafe, Chatzipanagiotou, and Curras-Perez, 2018, pp. 336-344). This study attempts to examine the sentiment analysis of reviews collected from Amazon and a manufacturer's website for the same cosmetic skin care product. This research seeks to assess the varied consumer attitudes towards the same product on two distinct online platforms by collecting customer evaluations from both platforms and analyzing several aspects that indicate consumer sentiment valence.

E-commerce has sparked a revolution in the fast-growing retail landscape. The enhanced accessibility and practicality of online buying have compelled companies to prioritize their online e-commerce capabilities (Lumpkin, Droege, and Dess, 2002, pp. 325-340). Sentiment analysis can be used to quantify the emotions of customers, which helps determine the likelihood of their behavior (Mäntylä, Graziotin and Kuutila, 2018, pp. 16-32). Online reviews can provide valuable insights for managerial teams to improve their brand management strategies, resulting in enhanced customer experiences and better outcomes. This study aims to offer advice for companies to enhance their performance by gaining a deeper understanding of review variables in the rapidly evolving digital landscape.

Sentiment analysis, also known as opinion mining, involves the process of carrying out text analysis with natural language processing (NLP) to classify data as positive or negative in its emotional valence. Sentiment analysis has attracted the interest of researchers and business persons in reviewing customers' feedback regarding products and services. The information gathered from sentiment analysis may be valuable for organizations that aim to improve the quality of their product offerings, services, or customer experience. This can aid organizations in monitoring the progress of their marketing efforts across multiple media channels and platforms, including the Internet. Sentiment analysis is utilized in the field of e-commerce to determine the emotions expressed in consumer feedback which helps organizations discern whether the reviews are positive, negative, or neutral (Ruiz-Mafe, Chatzipanagiotou, and Curras-Perez, 2018, pp. 336-344).

This study compares consumer evaluations by analyzing variables that may indicate sentiment polarities, such as the length of customer reviews, the inclusion of image attachments in reviews, and the presence of free product giveaways on both the Manufacturer's retail website and Amazon for the same product. This study aims to compare the results of customer review sentiment analysis on two platforms, namely Amazon and the Brand-owned website. The study also seeks to examine how specific review attributes on each platform can be used as indicators of consumer emotions toward the same product.

1.2 Problem Statement

The proliferation of Internet retailers has resulted in a substantial influx of customer comments and reviews, which significantly influence shoppers' perceptions and buying choices. Nevertheless, the sentiments conveyed in these reviews fluctuate greatly between various e-commerce platforms, particularly on marketplaces like Amazon and a manufacturer's online retail store. This diversity in the sentiment of customers across different platforms raises concerns about the dependability and integrity of consumer feedback from two distinct platforms which may reflect different attitudes and opinions for the same product. There is a prominent gap in research on the comparative analysis of review sentiments on a manufacturer's e-commerce platform and Amazon for the same product, even more so regarding a singular product from the cosmetic niche.

Prior studies have focused on sentiment analysis across a wide variety of scenarios. Li, Wu, and Mai (2019, pp. 172-184) conducted a study where they analyzed the polarity of feelings through opinion mining and customer reviews to assess their influence on product sales. Nevertheless, this research study seeks to compare the levels of customer satisfaction with a certain product when it is sold on Amazon, a vast and diverse e-commerce platform, versus when it is bought straight from the Manufacturer's official retail website.

Moreover, the characteristics contained in the reviews also influence the feelings of potential consumers browsing the platforms and reading the reviews. Previous research has focused on the assessment of attributes from reviews and the impact that it has on shoppers' emotions and subsequent buying decisions. For example, in the study examining the relationship among variables, Aggarwal and Aakash (2020, pp. 361-376), analyzed the relationship between the review length, review count, product price, and customer sentiment. The researchers found these factors influence sales on Amazon. In the same manner, Boumhidi, Benlahbib and Nfaoui (2022, pp. 2515-2531) explored review attributes such as review time, review rating, and review usefulness. The researchers then estimated the effect by analyzing the reviewers' sentiments found in the reviews. However, the existing literature lacks the comparative analysis and correlation of the review attributes collected from Amazon and the Manufacturer for the same singular product, and their indication of the valence of reviews for each platform.

This research study seeks to analyze particular review elements and their correlation with sentiment polarity. The attributes under investigation include review length, image attachment, and the presence of Vine-free/incentivized products. The study will compare these attributes across reviews of the same item on both Amazon and the Manufacturer's website. The findings will help e-commerce businesses make informed decisions by using sentiment analysis results in marketing efforts. Additionally, e-commerce platforms will be able to optimize their platforms, ultimately leading to more positive sentiment.

1.3 Purpose of the Study

This study aims to investigate the impact of review characteristics as indicators of sentiment across two different e-commerce platforms for the same product. Understanding this correlation is essential for the success of businesses operating in the rapidly expanding e-commerce market. This research compares customers' sentiments extracted from reviews for a particular skincare product sold directly by the Manufacturer on Amazon and the Manufacturer's platform. The analysis highlights the factors that are indicators of the customer's perception of a particular product. Exploring the degree of interrelation between the length of a review, the addition of images in reviews, whether the reviews are in return for receiving a free product, and its correlation to customer sentiment polarity within these specific stores. By assessing this interaction, the analysis envisions identifying factors indicating customers' sentiment valence in responses to the same product in different e-commerce contexts.

The outcome of this research has significant implications for companies seeking to influence customer reviews of their products and services in the e-commerce landscape. This study promotes business development and innovation in the realm of online platforms (Li, Wu and Mai, 2019, pp. 172-184).

1.4 Research Questions and Hypotheses

The research questions and hypotheses in this study aim to investigate specific factors that indicate customer sentiment in reviews. By examining customer reviews from different platforms, this research also seeks to understand the nuances of consumer behavior and sentiment for a specific skincare product on two distinct platforms, providing valuable insights into the dynamics of e-commerce.

Research Question 1

How do the sentiments of the customer for a particular skincare product differ between Amazon and the Manufacturer's platform?

Hypothesis 1

Customer opinions on Amazon differ significantly from those on the Manufacturer's online store in terms of sentiment for the same product.

In a highly competitive e-commerce market, the platform where the consumer purchases the product can significantly impact customer behavior and perception. This hypothesis suggests that customers' sentiments and feelings vary from platform to platform for the same product, thus, customers who visit the Manufacturer's retail platform may express their sentiments differently than customers on Amazon.

Research Question 2

Is there a relationship between prior familiarity with a product and sentiments expressed in customer reviews?

Hypothesis 2

There is a significant relationship between shoppers' previous knowledge of the product or brand and the sentiment valence of customer reviews for the product on the Amazon platform and the Manufacturer's online retail store.

This hypothesis postulates that customer perceptions are interlinked with product familiarity in a complex manner. The study underlines the fundamental role of product perception and customer sentiment for the same product on two different platforms, namely Amazon and the Manufacturer's store. Therefore, pre-perception of the product significantly impacts purchasing decisions and customer sentiment in reviews. Customers may have predetermined ideas about the quality or credibility of a brand or product based on previous experiences that influence their opinion of the product.

Research Question 3

Do giveaways, incentivized products, or Vine-free programs influence customer sentiment in reviews?

Hypothesis 3

The provision of Vine-free or incentivized products increases the probability of positive valence in the reviews either on Amazon or the Manufacturer's website.

The presence of incentivized reviews and the vine-free program underlines the tactical importance of gathering positive customer sentiment in an extremely competitive e-commerce market. By taking advantage of incentivized reviews and free products, businesses can increase positive customer perceptions and buying decisions. This hypothesis demonstrates that customers are more likely to leave positive feedback when incentivized by complementary products or giveaways. Furthermore, the strategic propagation of such feedback can further enhance the credibility, trust, and visibility of a product.

Research Question 4

Is the length of reviews an indicator of the sentiment valence of customer reviews on Amazon and the Manufacturer's platform?

Hypothesis 4

The total character count, also referred to as the duration of reviews is not an indication of sentiment polarity on Amazon and the Manufacturer's platform.

The length and depth of customer reviews are important aspects of customer sentiment analysis. Customers who devote time to creating more in-depth reviews are inclined to express deeper sentiments and share more details about their experiences with a product. However, this hypothesis proposes that longer reviews are not indicative of overall review sentiment direction. Longer reviews with higher character counts can be indicative of both positive and negative sentiment polarity.

To test these hypotheses, this research implements a mixed-method approach, combining qualitative sentiment analysis techniques with quantitative methods including logistic regression to thoroughly analyze the review content along with their attributes. Using Natural Language Processing (NLP), the categorization of sentiment classifies reviews as positive, negative, or neutral. Simultaneously, the qualitative analysis includes manual coding to analyze polarity, patterns, key themes, and their comparative analysis. However, the specific attributes of consumer reviews indicating sentiments were analyzed by logistic regression models separately for both the platforms, before their comparison. By applying these methodologies, this research develops a thorough understanding of customer sentiment on both Amazon and the Manufacturer's retail website for the same product.

1.5 Significance of Study

The fast-moving field of e-commerce requires a more detailed examination of customer behavior and sentiment analysis across multiple digital platforms for the same product. By performing a comparative analysis of consumer sentiment on Amazon and the Manufacturer's e-commerce platform, this analysis aims to bridge this gap. This study aims to provide a practical understanding of the sentiments conveyed in customer reviews and the role of chosen variables in indicating sentiment polarity, which ultimately influences the purchasing decisions of future shoppers. The findings from this work can practically assist businesses and digital marketplaces to improve their marketing and sales strategies while also substantially impacting the e-commerce industry.

This study offers a deeper understanding of customers' sentiment and their behavior across two different platforms for the same beauty product, which contributes to the body of knowledge regarding the relationship between review attributes and sentiment polarity. This information can be used to guide real-world strategies in marketing and customer relations, resulting in benefits for a wide range of businesses. While previous studies have primarily examined sentiment analysis in the context of numerous e-commerce platforms and items, or a single platform with either one or multiple products, this study is unique in that it analyzes the sentiment of a singular product across two distinct websites. To offer a more comprehensive understanding of digital customer behavior, this study explores the review attributes that indicate customer sentiment valence and the overall user experience.

The analysis of the correlation between review features and buyers' sentiment is a remarkable improvement in the race to garner positive reviews. By examining the relationships among various review characteristics such as incentivized reviews on customer sentiments across two platforms, this research contributes to the emerging field of e-commerce and makes a substantial practical contribution to companies and customers. This field of research aims to analyze the correlation of different characteristics of online reviews on the overall sentiment, to gain a more in-depth understanding of the mechanisms of consumer feedback.

The contribution of this research is evident in its capacity to provide direction to businesses regarding review parameters and sentiment analysis, improve the current understanding of consumer habits, and extend the existing knowledge on the issue. The variation in the sentiments across platforms and their review features are also addressed in this study. The research outcomes can help maintain or improve brand reputation, product quality, and marketing promotion tactics.

1.6 Definition of Terms

To avoid ambiguity and enhance the levels of standardization within the paper, the following terms were defined.

Sentiment Analysis

Sentiment analysis is a term that identifies sentiments or emotions expressed in a textual dataset. It can be positive or negative, depending on the feelings conveyed. Sentiment analysis is a useful tool performed by data analysts, businesses, or brands (Taboada, 2016, pp. 325-347).

User-Generated Content (UGC)

User-generated content includes views, opinions, judgments, personal experiences, recommendations, and comments about a product or brand and services. It is solely created by the user and includes individual experiences about any particular product or service (Krishnamurthy and Dou, 2008, pp. 1-4).

E-commerce

E-commerce involves products or services exchanged through an online platform via the Internet. E-commerce includes selling products or services to buyers directly through an e-commerce website or similar platform (Bhat, Kansana, and Khan, 2016, pp. 16-21).

Natural Language Processing (NLP)

Natural language processing (NLP) is a domain of artificial intelligence that has the capability of a computer database to read, understand, and interpret human language (Khurana, 2023, pp. 3713-3744).

Vine-free Products

Vine-free products or incentivized products are free or complementary products offered by a company or marketplace to garner reviews or feedback. In exchange for supposedly unbiased reviews of a customer, a brand offers free products to the reviewers. However, “Vine program” is the name of this opportunity exclusively on the Amazon platform. (Deng, Khern-am-nuai, and Qiao, 2024). Reviews, where the customer received free or incentivized products in exchange for a review, are required to be labeled as such across all e-commerce websites and platforms.

Logistic Regression

Logistic regression is a statistical tool that can be used to determine an odds proportion in the presence of more than one independent variable. It establishes the probability of the dependent binary variable and independent variables by using a logistic function that yields a value ranging from 0 to 1. This method is employed in the classification type analysis when it is necessary to estimate the probability of the occurrence of an event.

Marginal Effects Estimation

Marginal effects estimation is a technique used to measure the level of change in dependent variables when a rate of change is made in a specific independent variable while keeping all other variables constant (Mize, Doan and Long, 2019, pp. 152-189).

1.7 Assumptions, Limitations, and Delimitations

This section of the study outlines aspects that were considered during the analysis, as well as the restrictions and delimitations that provide the necessary bounds of the study to ensure the credibility of the research. The study’s assumptions, limits, and delimitations are emphasized based on the focus of customer sentiment analysis on digital platforms.

1.7.1 Assumptions

- During the study, the technique of sentiment analysis is assumed to be accurate and precise in recognizing the valence of customer reviews.
- Examining customer trends of the selected skincare product could reveal insight into customers' experiences or feelings about other skincare products on the two different platforms: Amazon and the Manufacturer's online store. Both offer insights into customer sentiment of the selected product and may also be reflective of other customers' experiences with other skincare products. Reviewers sometimes review the consistency or effects of a product as a comparison based on their experiences with other products.
- It is recognized that the reviews collected from both Amazon and the Manufacturer are assumed to be genuine and represent the actual perception of customers.

1.7.2 Limitations

- This research is most relevant to a specific type of product, specifically a skincare product, and therefore it is not a given that the results can be generalized to other products.
- This research neglects the demographic differences among the reviewers of both platforms, which can impact the behavior and sentiment of customers.
- The study depends on automated sentiment analysis, which may ignore the background nuances of reviewers, possibly leading to less optimal interpretations of sentiment in some cases.
- The impact of external factors, such as variations in demand and the variable price of the product on different platforms exemplify the additional complexity in variable selection. The researcher limited independent variable selection to chosen review attributes.

1.7.3 Delimitations

- The research particularly focused on the comparative sentiment analysis of Amazon and the Manufacturer's website for the product, eliminating other digital websites, products, and platforms from the analysis.
- The analysis includes sentiment, length of reviews, vine-free products, and image attachments while delimiting other potential influencing factors on customer sentiment.
- The methodology encompasses a mixture of statistical tools and sentiment analysis to discover the correlation between review sentiment valence and the chosen variables.
- The study neglects the qualitative examination of factors such as review validity or reviewer location, concentrating on quantitative factors such as review length and sentiment polarity.

CHAPTER II

LITERATURE REVIEW

This literature review chapter highlights the importance of the current research by examining previous works in the field of sentiment analysis and identifying a gap between theoretical knowledge and the practical application of sentiment analysis. This is achieved by evaluating customer reviews for the same product sold directly by the Manufacturer through their retail e-commerce shop, as well as by the Manufacturer via the Amazon platform. The literature review examines the study's methodology and relevant theories on customer behavior, purchasing intention, and marketing. This essential analysis clarifies the basic theoretical foundation directing the research and evaluates the theoretical framework's limitations and scope. This chapter examines the influence of multiple e-commerce platforms on customer attitudes, specifically focusing on customer reviews and their characteristics. These factors are crucial in shaping individuals' decisions to make purchases through digital e-commerce platforms. It defines the formation of sentiment analysis as an effective method to gain insights from text, specifically in digital marketing and e-commerce. Within this context, various approaches and tools of sentiment analysis are discussed, with specific reference to how these can be useful in identifying multiple perspectives, opinions, and feelings of the customer. Further, this research seeks to explore different variables that possibly indicate the sentiment polarity of customers including Vine-free or incentivized product reviews, length of reviews, and image attachments within reviews. In this study, these stated variables will be used to capture the complex interaction of different review aspects and their use as indicators of customers' perceptions and feelings towards a product. Further, the assessment of the customer viewpoints on two different platforms, namely Amazon and the Manufacturer's website will be helpful in capturing the impact of platforms on customers' preferences and emotions. This literature review identifies and admits research gaps in prior studies and investigates how this current study addresses these gaps to offer specific insights into customer behavior in relation to e-commerce.

2.1 Theoretical Framework

The trend of Internet shopping is advancing rapidly. The main factors driving the expansion of online shopping over traditional in-store shopping include enhanced Internet accessibility, the convenience and popularity of smartphones, and increased awareness of e-commerce platforms (Almarashdeh, 2019, p. 10). Online retail systems like Amazon facilitate efficient product selection for consumers, saving them time and ensuring prompt delivery through services like Amazon Prime. Many firms choose to engage in e-commerce rather than operate physical stores to potentially expand their consumer base across a larger geographical area. Digital platforms also assist organizations in minimizing overhead costs and avoiding substantial expenditures. Contemporary online retail platforms also enable firms to collect client feedback for their products, typically in the form of online reviews. Consumers frequently choose products that satisfy their requirements and preferences while also consulting online reviews for the product. Favorable evaluations can aid in both establishing a larger consumer base and boosting sales. Conversely, unfavorable evaluations can result in decreased sales. Therefore, companies must recognize customer sentiments and uncover consumer feelings and demand regarding a product (Hamdallah, 2021).

Meire (2019, pp. 21-42) highlighted the mechanism of managing the customer engagement activities and the feedback of the experienced emotion. Increased consumer engagement puts in place closer and longer-term relations between a company and its buyers. Customers' reviews are another way by which they communicate with the business and the businesses can use the feedback to learn customers' impressions of the items they produce. Also, the customers' reviews may affect the decisions of future consumers when making purchasing decisions. Because the contemporary market environment demands attention to review input, organizations have to focus on its collection and processing (Schoenmueller, Netzer and Stahl, 2020, pp. 853-877). Business entities will use sentiment analysis with the main aim of improving their operations within the market.

As stated by Karamitsos, Albarhami and Apostolopoulos (2019, pp. 276-294), when it comes to using sentiment analysis, a company will be able to get useful information about customers' experiences and perceptions of what the company is offering. Therefore, where applied suitably, the client feedback enhances the creation of better marketing strategies and sometimes marketing campaigns in organizations. Sentiment analysis can assist companies with limited existence after their formation to increase the coverage of positive evaluative remarks in word-of-mouth product promotion. Opinion mining can be used by a company or competitor to find out more about the consumers and the kind of interactions that they indulge in within the industry or perhaps in a given segment of the industry. It does this in a way that allows businesses to gain highly utilitarian, real competitor product data from a wide array of online channels. Mehraliyev, Chan, and Kirilenko (2022, pp. 46-77) also focused on approaches, such as text mining, sentiment analysis, and others which form the basis of understanding and using user feedback. Businesses can gain insights from data generated from the reviews and comments on social media platforms can be of benefit to firms, and may even help repair damaged reputations. Product reviews have a dual purpose: they help the producers and manufacturers in improving the quality of the product they offer and on the other hand the prospective buyers in choosing the right product. The analysis of a product shifts the purchasing decision of a consumer (Jain, Malviya and Arya, 2021, pp. 665-670). Lim (2019, pp. 124-150) stated that the most prominent retail stores in the USA embrace customer reviews on the Internet to enhance clients' satisfaction and the reputation of the stores online. For instance, if a given product or a service is complained about, some businesses rush to assess such areas to look for damages and sort them out. A review that has quality issues or a pricing problem can be handled by a firm and rectified. Schoenmueller, Netzer and Stahl (2020, pp. 853-877) collected a massive dataset of 280 million reviews to analyze their distribution from 25 online platforms including Yelp and Amazon. These reviews concerned different products and services, and using the material for analysis, it was found that a large number of reviews had a shortage of positive-negative polarity. The variation in reviews could be attributed to the rating scale, the structure and the model of the online website, and the periodicity of the reviews done. Such determinants as above are beneficial to sites like Amazon in terms of seeking positive product reviews. Reddy and Jaidev (2016, pp. 216-224) carried out a literature review of sentiment analysis in the e-commerce business sector. The reviews that the two researchers sought to analyze were those that had a bearing on the customers' buying decisions. They said that consumer-polarized opinions can be captured and interpreted by the e-commerce firms to decode the latent emotional message of the customers. Thus, the sentiment analysis of product reviews enables businesses to better understand consumer experiences. A buyer can provide a review to show either satisfaction or dissatisfaction with the product. However, some customer reviews may not demonstrate the degree of sentiment regarding the buyers' experience. To categorize the degree of consumer satisfaction, it can be classified as positive, negative, or neutral valence depending on linguistic characteristics (Govindaraj and Gopalakrishnan, 2016, pp. 494-501). Sharma, Chakraborti and Jha (2019, pp. 261-284) performed an investigation to examine the influence of online reviews on book sales, focusing primarily on the widely used e-commerce platform, Amazon. Before reaching the purchasing decision, the consumer emphasized prior reviews of the product. The decision to purchase was correlated to the valence of online reviews for the product, which had a considerable impact on purchases.

This study is directly linked to the existing literature on consumer sentiment analysis related to e-commerce platforms, concentrating on factors indicating the sentiment of customers including review features, and platform-specific factors. Prior research has proven that these determinants substantially affect consumer opinions and purchase intentions. This study was expanded by analyzing the influence of multiple review characteristics that contribute to understanding customer sentiment polarity and behavior in online shopping across two e-commerce platforms for identical products. The comparative analysis in this study permits a nuanced investigation of how various platforms shape consumer sentiments and experiences. This study attempts to clarify the intricate relationship between customer perception in reviews of the same product from two different platforms; review attributes and their indicative nature of customer sentiment in e-commerce.

The novel theoretical framework used in this study offers a comprehensive analysis of the factors that may indicate and ultimately affect consumer attitudes and perceptions found in online reviews of products. Such factors include the length of the review, product incentivization, and if the review includes user-generated content in the form of images. Taking into consideration the information presented in this context, a better understanding of customers' activity in the sphere of electronic commerce can be learned. Furthermore, this research examines the differences in the expression of sentiments on two different platforms to understand how different digital platforms affect sentiment in reviews. The study also reveals how review attributes influence the behavior patterns of the customers across the two platforms. Starting from the review length, which proposes that lengthy reviews do not indicate the polarity of customer sentiment. This study will help e-commerce platforms grow and craft their marketing strategies based on deconstructing real-world user feedback. Thus, the data depicting consumer sentiment analysis, often affecting buying intention, can help businesses maximize consumer satisfaction and preserve their reputation within the e-commerce marketplace (Meire*,* 2019, pp. 21-42).

Notably, several factors should be considered on account of the limitations of this study that might affect the feasibility and generalizability of this work. One possible disadvantage is the notion that this framework can be applied out-of-the-box to other products or niches in its entirety, without additional research enforcing its viability for those other business areas. These findings cannot necessarily be generalized across different organizations and are specific to this product and the platforms in this study. Other factors, including market dynamics, culture, and technology, can affect the application of this study on other markets or products and raise a flag for caution when contextualizing the findings across different products or platforms. A limitation of the analysis is the lack of research into the topic of causality. This study focused solely on correlational analysis to examine the relationship between review variables as indicators of review sentiment.

Thus, the analysis explores the relationships among variables and does not create causal relationships. This limitation prevents the research from producing absolute claims about the directions of the effects or causal mechanisms related to customer behavior. In the future, researchers should employ longitudinal design studies to provide more exact proof of causal relationships in this field over time. Other factors, such as product characteristics, pricing, and brand reputation are essential determinants of customer behavior in online shopping environments. This research is vulnerable to the impact of complex variables related to marketplace features and optimizations. Ignored variables or confounding factors that were not the focus of this analysis might influence the associations perceived between review sentiments and the indication of review attributes and characteristics. The limitations likely require additional methodological techniques to reduce the influence of confounding variables which are well beyond the scope of this study.

2.2 E-commerce and Online Reviews

E-commerce, or electronic commerce, refers to the use of an Internet platform for the exchange of goods and services. E-commerce requires firms to harness the Internet and employ web technologies to sell products online through marketplaces as sellers and engage with customers. Consequently, online platforms, whether they are the Manufacturer’s retail store or third-party platforms like Amazon, offer the opportunity to sustain the business (Jain, Malvia, and Arya, 2021, pp. 665-670). This enables customers to purchase goods or services directly from a website without physically visiting the store. The proliferation of the Internet and the integration of information technology into everyday life have led to the rapid growth of e-commerce, fundamentally altering consumers’ purchasing behavior. The rapid development and widespread adoption of modern technologies have greatly expedited the progress and utilization of e-commerce platforms. As a result, buyers now exhibit a preference for online purchases over traditional brick-and-mortar retail establishments (Faccia, Le Roux, and Pandey, 2023, p. 3419). Due to the growing prevalence of Internet access, online shopping has experienced a substantial surge in this era of electronic commerce. Presently, customers engage in the process of seeking out products on multiple e-commerce platforms, gathering information, evaluating products based on their quality and price, frequently consulting reviews, and ultimately making their selections (Tang, 2021, pp. 1-15). In their study, Jain, Malvia, and Arya (2021, pp. 665-670) analyzed different categories of e-business activities; business-to-business (B2B), business-to-customer (B2C), business-to-administration (B2A), and customer-to-administration (C2A). This research targets the business-to-consumer segments where firms sell their products through e-commerce platforms.

In the field of e-commerce online shopping trends have also increased. Online shopping has improved its efficacy by giving access to online product reviews to buyers with the modern technologies of computers, tablets, and smartphones (Tang, 2021, pp. 1-15). According to Anitha (2015, pp. 74-80) online shopping is a process where buyers can accessible to a huge range of products or services on the platform without the need for a distributor. According to the Global Online Consumer Report conducted by KPMG (2017), the advancement of technology such as mobile phones and tablets has led to a rise in online shopping. Users now can access a wide range of e-commerce platforms at any time, allowing them to browse and review product details without being limited by the operating hours of physical stores. Both customers and enterprises have the potential to greatly reduce the amount of time and effort in the purchasing cycle. Online shopping enables consumers to access a wide range of product choices within their budget, frequently surpassing the limited selection available at small local stores or other brick-and-mortar retailers. Another crucial aspect of online shopping for consumers is the comprehensive product information and online reviews contributed by fellow customers, which can serve as a source of motivation for consumers to make purchases online. (Taher, 2021, pp. 153-165). Customers utilize the Internet to express their thoughts through online product reviews (Purnawirawan, De Pelsmacker and Dens, 2012, pp. 244-255). Customer product reviews can vary in sentiment, either being positive, negative, or neutral, based on the individual's experience with a certain product. Customers who previously purchased and used the product are often prepared to share their ideas with others, and discuss the merits or shortcomings of the product (Hennig-Thurau, 2004, pp. 38-52).

The digital experience of browsing and interacting with online reviews helps consumers to generate opinions about products before buying them. The advent of digitalization and the transition from traditional brick-and-mortar purchasing to online shopping via e-commerce platforms empowers customers to easily and openly communicate their product experiences with others. Radujkovic (2023, pp. 1-20) observed the impact of online reviews from the customer's point of view in the beauty and personal care business, and marked online reviews as a powerful source of information for consumers.

2.2.1 The Importance of Branding in E-commerce

Branding is essential in the field of e-commerce. It serves as the business's primary selling point and sets it apart from other businesses while building people's trust and an emotional connection. Attempting to introduce a new concept of branding for businesses functioning in the sphere of digital technology, it is possible to define the formation of brand identity as one of the most significant branding components meeting the necessity of industry development and promoting its members' success within the specified environment. For example, Amazon's brand identity can be perceived as both convenience and consumer satisfaction, characteristics that are seen as potential drivers for its recognition in the market. Customer preferences and buying decisions based on the concept of brand equity are influenced by branding. Brand equity is the perception and importance of the brand, including factors such as brand reputation, awareness, and brand quality (Cobb-Walgren, Ruble, and Donthu, 1995, pp. 25-40). Well-known brands enjoy brand equity, which allows them to attract loyal consumers. Customers are willing to pay a premium price for brands with higher brand equity because of their credibility and consistency. This highlights the significance of brand-building struggles in e-commerce, as the marketplace is highly competitive, often with a flood of comparable brands and choices. A positive brand experience leads to consumer satisfaction and in turn, positive customer feedback (Bougenvile and Ruswanti, 2017, pp. 12-18).

2.2.2 Role of Online Reviews in Customer Purchasing Decisions

Advancements in technology have brought about significant changes in customer behavior and product purchases. For millennia, individuals have been physically visiting marketplaces or stores to purchase goods and items. With the rapid expansion of the Internet, it has become second nature for customers to buy products on e-commerce platforms effortlessly without the need to leave home, thereby further increasing online shopping popularity. Customer behavior changes in conjunction with the process of digitalization (Singh and Sailo, 2013, pp. 45-49). Customer reviews have a significant and intricate impact on purchasing decisions in e-commerce and are necessary for solidifying the credibility and assurance of goods sold online (Sajid, Rashid and Haider, 2022). Customer product reviews give shoppers confidence about their purchases by favoring the reliability, trustworthiness, and quality of the products. On the other hand, unfavorable reviews may cause shoppers to hesitate and become unfavorable towards a product, thereby discouraging them from purchasing. The existence of user reviews significantly influences consumer perceptions and confidence in products showcased on digital e-commerce platforms.

Consumer reviews also have a substantial social impact on buying behavior, especially in conditions involving high-value purchases online. Customers are motivated by the opinions and experiences of other users, particularly when navigating the substantial and often dizzying range of product and service opportunities available online. Positive product reviews help prove the authenticity of a product and act as a type of social evidence (Christopher and Rahulnath, 2016, pp. 1-7). In addition to simplifying decision-making, this social authentication encourages a feeling of community and shared public experiences among customers, which strengthens the influence of customer feedback on buying decisions (Radujkovic, 2023, pp. 1-20). For businesses, customer reviews provide valuable understanding related to product characteristics, customer experience, and areas for development and improvement. Positive online reviews improve the credibility of a brand and build trust for consumers. However, consumers are now gradually becoming dependent on peer reviews and customer-generated content to finalize their buying decisions. Sellers must identify the importance of user reviews to continue thriving in the e-commerce channel. By efficiently collecting and evaluating customer opinions, a brand may achieve greater success in e-commerce.

A study performed by O'Reilly (2018, pp. 375-400) highlights multiple factors that influence consumers to focus on online product reviews when buying a product. The factors that influence decision-making and product outcomes are motivation and decision-making ability. By analyzing online evaluations and forecasting a product's success rate, shoppers can make informed decisions when selecting superior products. Jepsen (2007, pp. 21-34) explains the fact that consumers are eager to search the web to find product information, arming themselves with the benefits of the product before purchasing. Thus, online product reviews play a vital role in shaping a consumer's perspective about a product, and influencing them to purchase the product with the highest ratings and maximum positive reviews.

2.2.3 Electronic Word of Mouth (eWOM)

The concept of eWOM was established in parallel to the development of e-commerce websites. eWOM is known as any review statement, whether optimistic or negative that was written or said by a buyer about a particular product experience, and was provided on an Internet website (Hennig-Thurau, 2004, pp. 38-52). eWOM is identified as a top source of information used to extend information globally (Jalilvand, Esfahani and Samiei, 2011, pp. 21-34). The high competence, extensive use, and accessibility of the Internet allows customers to easily and anonymously share their opinions and experiences about various topics and diverse products or services (Wang, Cunningham and Eastin, 2015, pp. 151-159). The eWOM concept may be more competent and effective than paid digital media and advertising (Verma and Yadav, 2021, pp. 111-

128). eWOMs for a particular product are often found on e-commerce platforms. Wang, Cunningham and Eastin (2015, pp. 151-159) found that reviews play a pivotal role in influencing buyers. Indeed, the main goal of eWOM is to get the overall evaluation and attitude of the customers toward a specific product.

Jalilvand, Esfahani and Samiei (2011, pp. 21-34) also discussed various identifiable dimensions of eWOM. The most critical aspect is the individual's requirement for expressing satisfaction or dissatisfaction with the product. The expressed experience of products has the potential to be positive or negative regarding the actual product experience. Positive reviews are achieved when the customers are happy while using a product while negative reviews come as a result of unhappy customers.

2.3 Sentiment Analysis

Opinion mining or sentiment analysis classifies and gains data and information from the textual data sets. The aim of sentiment categorization in the context of the e-commerce industry is to identify the sides of a particular customer for a given product or service. Based on how the reviews are expressed, sentiments can be classified as positive, negative, or neutral (Liu, 2015). Sentiment analysis is the process of determining the polarity or the nature of sentiment (positive or negative) of each of the reviews which can be collected from a database or the website. This phenomenon has become increasingly prevalent, as demonstrated by contemporary e-commerce platforms that enable purchasers to provide feedback on various products. Customer opinions are sometimes fragmented, time-consuming to gather, and difficult to tabulate on the fly which provides a challenge for organizations attempting to effectively monitor and analyze the interactions. Hence, it becomes crucial to analyze massive volumes of such reviews in systematic ways that can be leveraged by sentiment analysis. Functionality of sentiment analysis has been pointed out by Kumar, Desai and Majumdar (2016, pp. 1-4) and its primary objective lies in the identification and capturing of sentiment from text. Their study was centered on the analysis of specific reviews that were posted on sites such as Amazon where customers can freely write their product experiences. Customers invest their time and resources in formulating thoughts, while businesses likewise allocate considerable effort and expenses to identify these reviews. Therefore, the analysis of sentiments has emerged as a crucial component in online review analysis. Opinion mining provides insights about the feelings of customers, providing a glimpse into the psyche of the customer regarding the product or service under review. The actual text in the review used for this analysis can be obtained from any reputable source, for instance; product reviews on sites such as Amazon, Tweets, blogs, and Facebook comments (Palanisamy, Yadav and Elchuri, 2013, pp. 543-548). It's pertinent to describe sentiment analysis as a method of analyzing texts to identify the valence and feelings associated with the texts. This study agreed with Medhat, Hassan, and Korashy (2014, pp. 1093-1113) who found that sentiment analysis captures the sentiment of a given text and then processes it. Therefore, reflecting from the above analysis sentiment analysis is the most optimum method to express opinion, classify sentiments, and could even rank sentiments as positive, negative, or even neutral as per the manifested emotions. Similarly, Singla, Randhawa, and Jain (2017, pp. 1-6) also performed sentiment analysis on a dataset that includes the review of mobile phones available on e-commerce bigwigs like Amazon. Positive, negative, and neutral emotions were identified with the help of which the overall picture of the products' reviews was given. Their research study was to bring into focus online sentiment analysis in marketing research and to explore the practical, technical, and even ethical issues that come with it from scholars and businesses. Alsehaimi (2021) in his study described the method of training sentiment analysis for a comparative rating approach using digital media reviews. Sentiment Analysis can be conducted using various methods: such as the use of machine learning and lexicon-based approaches, and sentiments are classified as positive, negative, or neutral depending on the existence of emotional valence in the text (Mercha and Benbrahim, 2023, pp. 195-216). When trying to classify the sentiment of a specific text as being positive, neutral, or negative, this is termed as the sentiment polarity. The polarity of sentiment can be classified into different kinds of levels for example document level, sentence level, and aspect level (Nafees, 2018, pp. 1-6). In general, the first level, known as the "document level" is employed in the identification of the polarity of sentiment. The second one is referred to as the ''Sentence level" and aims at determining the sequence of the phrases being used. The aspect level speaks about how customer deals with perceived factors associated with elements like price, quality, and services (Patil and Yalagi, 2016, pp. 523-528).

Luo, Li and Cao (2016, pp. 276-281) highlighted that sentiments can be classified as negative, positive, or neutral. Sentiment analysis clarifies the expressive direction of customer reviews, and examining the sentiment trends of customer reviews not only provides suggestions to other customers, but also helps companies who sell online enhance their product quality and customer satisfaction (Yang, 2019, pp. 173-186). Customer reviews are helpful for businesses to gain an understanding of consumer behavior. Sentiment analysis is also performed to evaluate market trends due to consumer feedback, and address customer concerns as it helps discover customers' intentions (Hamdallah, 2021). The topic of online shopping presents challenges for sentiment analysis, specifically due to the exponential increase and vast amount of data that needs to be collected from online reviews that encompass both positive and negative sentiments. Contemporary technology is necessary for the evaluation and interpretation of data (He, 2019).

E-commerce is a vast ecosystem for online shopping of products and services. With the rapid increase and adoption of Internet access, e-commerce has expanded in recent years. To improve sales consistency and likelihood, some e-commerce brands motivate customers to review their products and services. It's common for customers to provide their feedback, perceptions, emotions, and experiences on digital platforms which are known as customer reviews (Wang, Niu, and Yu, 2019, pp. 2026-2039). With these reviews, customers can readily express their opinions on whatever they experience, positive or negative. A long-term business strategy is to maintain a high level of customer satisfaction and collect more responses in the form of reviews in order evaluate the data and make actionable business decisions. These decisions help improve the customer experience of a product (Jain and Kumar, 2017, pp. 216-224). E-commerce websites often allow for the sharing of reviews and personal experiences. Sentiment analysis appears to be an emerging and evolving tool that boosts e-commerce markets by analyzing opinions gathered from Amazon and other marketplaces, social media, and brand-specific websites. Online product and service reviews are a remarkable and symbolic format for communicating emotions in written text (Mittal, Goel and Jain, 2016, pp. 2300-2305).

2.3.1 Sentiment Analysis Techniques

The necessity for sentiment analysis is paramount because of the increased demand for evaluating and structuring concealed information collected from e-commerce platforms as unstructured data (Haenlein and Kaplan, 2010, pp. 200-228). Thus, businesses require modern sentiment analysis techniques. There are two common practical techniques for sentiment analysis: machine learning (ML) and natural language processing (NLP), based on lexical analysis (Kolchyna, 2015).

Machine learning-based techniques are used for analyzing sentences and aspect levels. Paknejad (2018) described three aspects of machine learning: Support Vector Machine (SVM), Naïve Bayes, and Maximum Entropy. The SVM is a supervised learning technique that can be applied to resolve the classification problem of sentiments. It separates data into groups or classes. However, Naïve Bayes is also considered supervised learning, which is identified for its strength rather than its simplicity. Before applying Naïve Bayes, the primary step is feature extraction. The process of converting written texts into features is called a bag of words, which is a frequently used process for feature extraction. This feature extraction approach generates various bags of words that appear in the training dataset, where the individual word is linked with a distinctive number (Luo, 2016, pp. 276-281). This number highlights the occurrence of each word in a text. This technique can handle a larger quantity of data. There are three categories of machine learning techniques: i) supervised learning ii) unsupervised learning; and iii) semi-supervised learning (He, 2019, pp. 504-515). The process by which the procedure or steps are learned from the training data is considered supervised learning. Supervised learning works smoothly as labeled data is provided (Brownlee, 2016). Unsupervised learning is instructed on unlabeled data with inconsistent results. Regarding unsupervised learning, one of the most vital issues is clustering. It identifies the same clusters of data in a dataset (Rodriguez *et al.,* 2019, pp. 1-34). Semi-supervised learning is a combination of both supervised and unsupervised learning, in which a lesser amount of data is labeled, and the remaining training dataset is unlabeled (Zhu, 2008, pp. 7-44).

Paknejad (2018) also discussed a lexicon-based method, which is an unsupervised approach that depends on words and phrases. This is the simplest method for evaluating the sentiment of a review text. The positive and negative sentiments in the texts indicate the sentiment polarity of a review. If the number of positive words is greater than the number of negative words, then it is considered to have positive polarity. A lexicon can be generated either manually or by automatic expansion (Taboada, 2011, pp. 267-307). This approach involves the use of semantic orientation analysis to define the sentiment as a whole for the entire document or set of sentences. Many researchers have used the WorldNet dictionary in a manual approach. Initially, after reading the whole document, lexicons are removed, and WorldNet or any other electronic dictionary may be employed to find the antonyms as well as synonyms for the further extension of the lexicon (Gupta, and Agrawal, 2020, pp. 1-23). Khoo and Johnkhan (2018, pp. 491-511) also showed that sentiment lexicons have high efficiency in the activity of sentiment level at the document and at the sentence levels by utilizing the datasets of Amazon product reviews and news headlines. Sentiment analysis involves using a sentiment lexicon in which sentiment polarity, positive, negative, or neutral, in a text is identified. For identification of the contextually dependent reviews, the study proposed by Ding, Liu and Yu (2008, pp. 231-240) describes the use of a lexicon-based approach that was dependent on the framework of Aung and Myo (2017, pp. 149-154). In their research, they used a lexicon-based approach to predict teaching performance. The lexicon polarity of the English sentiments was from a lexical database to form a lexical source. In this thesis, a lexicon-based method was adopted to analyze the sentiment of the reviews in Amazon and in the Manufacturer's retail e-commerce store for the product.

2.4 Factors of Customer Sentiment

Customer perception about a particular purchased product is a function of tangible and non-tangible attributes accompanying the purchasing process. It can be for instance the quality of a product or a service, on which the satisfaction and value of the consumer depends. Others include features that attract the customers, the relations held between customers and the manufacturers or sellers, and other factors that are reflected and if the interaction is negative, then the attitudes portrayed are negative. On the other hand, efficient and helpful customer service is likely to have a positive effect on customers' attitudes and feelings towards the product. Reputation and reliability are also related to customers' emotions since the customer is most likely to develop positive emotions about a certain brand if it's considered reputable. According to Liang (2015, pp. 236-260), advertising and engagement can enhance the emotional appeal of clients, thereby fostering beliefs and increasing their affinity towards products. Consequently, components of reviews that could be obtained from the product incentivization programs and image feedback that some consumers utilize may be beneficial as sentiments about a specific product. These and other measurement parameters may also influence the buyers' attitudes towards the organization and the associated products or service offering, as well as the buying behavior. In this sentiment analysis of reviews of Amazon and the Manufacturer's website for the same product, the factors include the length of the review, images, the sponsored products, and these factors' implications on customer sentiment.

In the context of factors that affect sentiment analysis of consumer reviews, the study conducted by Li, Goh and Jin (2020, pp. 4387-4415) compared the effect of review text readability on sentiment classification using deep learning models of Simple Recurrent Network (SRN), Long Short-Term Memory (LSTM), and convolutional neural network (CNN) with an attached movie reviews data set, and subsequently applies multiple regression models on the gathered data. The researchers believed that among all the tests, sentiment classification works best when applied to easily readable review summaries. Oueslati, Khalil and Ounelli (2018, pp. 34-40) identified the total character count as another feature highlighted as having an impact on customers' attitudes. It also represents the customer participation and intensity of customer sentiments.

Liao, Chen and Jin (2023, pp. 1626-1644) argued that there is a direct relationship between review ratings of products given by customers and customer engagement level. The review rating identifies the polarity of sentiment as strongly positive, strongly negative, or neutral (De Albornoz, 2011, pp. 55-66). A framework designed by Qiu (2018, pp. 295-309) incorporated sentiment analysis techniques to determine review ratings based on the positive and negative aspects highlighted in online reviews. Another common technique used by e-commerce marketplaces is the offering of free products in exchange for reviews. Companies that use these tactics expect to increase positive reviews and obtain higher review ratings. Brands offer incentivized campaigns on online marketplaces to gain more positive customer sentiments (Petrescu, 2018, pp. 288-295). Digital platforms sometimes offer free products to collect incentivized reviews because they affect review quality. Qiao and Rui (2023, pp. 676-697) investigated the use of incentivized reviews on Amazon's platform, which resulted in more positive reviews. Utilizing incentive products leads to a greater prevalence of favorable review text compared to unfavorable review text (Woolley and Sharif, 2021).

Online reviews can sometimes include customer-uploaded images that facilitate customers' understanding of the product. The images often show the intensity of customer sentiment. Wu, Wu, and Wang (2021, pp. 364-378) found in their study that online businesses should encourage customers to add images to reviews when rating a product with a satisfactory experience. Therefore, images in a customer review can provide a more complete transference of information that assists other shoppers in buying the product. Previous literature has shown that when an image is attached to a review, the shopper's consideration shifts to image review (Bigne, Chatzipanagiotou and Ruiz, 2020, pp. 403-416). The image captures the customer's focus irrespective of image size. These images contain the customer sentiment of a product and help in buying decisions (Pieters and Wedel, 2004, pp. 36-50). Review images can effectively convey sentiments regarding review content, which increases the informational significance of a review. The study by Zinko (2020, pp. 525-541) also found that when a reviewer adds an image, the quality of information increases, reducing information unevenness, and consequently leading to an increase in the effectiveness of a review. The pictorial addition in reviews not only increases the effectiveness but also allows shoppers to benefit from actual results of the product. In addition, customers tend to attach photographs to reviews that are emotionally charged. This allows them to convey their genuine experiences, whether positive or negative, along with detailed written reviews (Oueslati, Khalil and Ounelli, 2018, pp. 34-40).

2.4.1 Other Factors Impacting Customer Sentiments

Customers are increasingly directed to digital platforms to purchase goods and services. However, e-commerce platforms push additional goods or services through product recommendations to consumers. Some platforms feature these products based on the number of positive customer reviews. Online reviews have significantly altered customer buying behaviors by providing peer-generated evaluations of purchased items. These viewpoints are regarded as customer sentiment, and sentiment analysis, also known as text orientation analysis, which is a method employed to examine consumer sentiment (Alsaeedi and Khan, 2019, pp. 361-374). Customers' opinions in reviews contain attributes and behaviors that are helpful in the purchasing decision-making process, and their opinions are affected by both tangible and intangible factors. These factors include product pricing, quality, user experience, brand value, and discounts or giveaways (Malik and Hussain, 2017, pp. 290-302).

Wang (2020, pp. 463-485) investigated how perceived product quality positively influences customer reviews, which consequently impacts purchase decisions. Maulana and Novie

(2024, pp. 2921-2928) pointed out some of the factors that affect customer sentiments about the quality of a product. The results revealed that brand image has a positive impact on online reviews, and customer sentiment is affected by product quality, product pricing, and delivery of services provided by the platform. The research performed by Yao (2022) developed a research framework on customer trends, specifically about buying decisions. Customer sentiment tendencies played an important role in Yao's study. Various factors, including product quality, product feedback, brand credibility, price, and promotional schemes affect customer trends. Xie and Lou (2020, pp. 209-224) also proposed that product information, product price, brand loyalty, quality of the product, and reviews of the product influence the customer's perception. Customers' sentiment trends can help e-commerce businesses enhance product quality and consumer satisfaction (Yang, 2020, 23522-23530). Thus, previous research has revealed multiple attributes and influencing factors that shape the intention of consumers to purchase and leave favorable feedback in response.

A study conducted by Rane, Achari and Choudhary (2023, pp. 427-452) revealed that customer satisfaction is influenced by technology and the role of technology in improving the consumer experience of online shopping. Valuable customer feedback and issue management are important for creating a positive customer experience. The quality of the services and products provided reflects the level of consumer satisfaction. The reliability, credibility, and responsiveness of a service or product play a fundamental role in shaping customers' positive perceptions of the experience and loyalty to the brand when buying goods. Buyers retain trust in brands that provide them with high-quality service. Enhancing service quality results in greater consumer loyalty (Luarn and Lin, 2003, pp. 156-167). Brand image and reputation influence customer sentiment. Brand image affects how consumers perceive a brand, comprising its identity, value, and behavior. It also influences consumer satisfaction with the brand. The positive reputation and image of the brand can further increase consumer satisfaction, and ultimately, create more positivity in future consumer feedback (McColl-Kennedy and Schneider, 2000, pp. 883-896). Customers who have higher expectations of a brand's quality, credibility, and services often lead to increased customer satisfaction with buying decisions (Rane, Achari and Choudhary, 2023, pp. 427-452). However, there are numerous factors indicating or possibly affecting the polarity of the sentiment of customer reviews, including those that have a direct impact on the sentiment of consumers and managing their purchasing decisions.

2.5 Platform Comparison - Amazon Versus Manufacturers' Retail E-commerce Websites

The comparison of e-commerce platforms, particularly Amazon and manufacturers' retail e-commerce websites, shows notable differences in terms of product variety, availability, cost, trustworthiness, ease of purchasing, implied product authenticity, customer support, and delivery. Amazon provides a platform for numerous merchants, both third-party and Amazon itself, who offer a diverse range of products across multiple categories, including home appliances, fashion, furniture, books, and food (Edwards, 2023, pp. 691-747). By contrast, manufacturer-owned e-commerce websites primarily concentrate on particular categories of products/services or the offerings of a single brand, with the manufacturer having direct control over the stock being sold (Modi and Singh, 2023, pp. 721-742).

2.5.1 Key Differences - Amazon and Manufacturer Websites

There are several key differences often noted between Amazon and brand-owned platforms. Starting from the pricing strategies of Amazon and a brand's e-commerce website which vary considerably. As at least several vendors commonly compete for consumer interest via Amazon's marketplace, it leads to competitive pricing, which frequently results in discounts and other incentives (Edwards, 2023, pp. 691-747). Buyers can conveniently compare prices in this highly competitive setting. However, direct brand sellers on independent platforms typically set their prices higher with occasional discounts or promotions offered. Although these costs may be substantially higher than those on Amazon, brands may provide unique discounts that cannot be found anywhere else (Nambiar, 2023). Ellison and Synder (2014) examined the competition between businesses selling via online e-commerce platforms and identified the factors that cause companies to change their prices. The focus of their study displayed companies' pricing strategies for selling different commodities. The analysis results prove that different companies employ varied pricing strategies. Warrier (2021, pp. 7-17) evaluated the factors that caused Amazon to become one of the top online shopping platforms. The findings included the following reasons for Amazon's success: customer perception, consumer satisfaction, competitive advantage in multiple areas, and consumer awareness. The study concludes that there is a positive correlation between these factors and Amazon's success. Dinerstein (2018, pp. 1820-1859) claimed that platform design impacts buyers' and sellers' behavior. This is particularly relevant in circumstances in which commodities change only in terms of price.

Authenticity and integrity are also important variables that affect customer decision-making. The inclusion of independent sellers increases the risk of counterfeit items, even when Amazon attempts to prevent imitation of goods through a variety of procedures. On the flip side, products bought directly from a manufacturer's website are presumed to be genuine, considerably minimizing worries about fake goods (Nambiar, 2023). Consumers who place higher value on product authenticity shape their decisions accordingly.

A marketplace's return policies, support policies, and standards can set them apart from the competition even further. Returns and refund rules are lenient in the Amazon marketplace because they have buyer-friendly return policies and outstanding customer support (Monestier, 2021, pp. 705-780). In contrast, return processes and customer assistance on brand-specific websites can be more stringent (Yao, 2022). Subsequently, there are substantial differences in the shipping and delivery alternatives available on various platforms. Jung and Kim (2017, pp. 253-266) noted that Amazon provides a range of options, such as overnight and two-day shipping with Amazon Prime, which often comes free of extra charges per order. However, e-commerce stores dedicated to a particular brand may have different delivery policies; some may charge for shipping, while others may provide free delivery for purchases exceeding a specified threshold. Shipping options on these manufacturer websites are often longer than Amazon Prime or charge a fee per order for faster shipping.

2.5.2 Influence of Platforms on Customer Sentiment

Customer sentiments vary from platform to platform, and brands are seeking to understand customer behavior in the digital realm of e-commerce, concentrating on identifying sentiment attributes and trends on prominent websites (Wassan, 2021, pp. 695-703). Amazon, the well-known e-commerce platform, offers a meaningful collection of verified customer reviews across various products and genres, making it an excellent focus for examination due to the important consumer reviews it delivers. Sentiment research based on Amazon reviews provides a rich and valuable understanding of customer behavior, trends, and preferences, which are necessary for forming specific market forecasts and creating successful business strategies. The platform's significant global shipping coverage and diverse customer base offer ample sentiment data, which covers an exhaustive range of customer inputs. This data is important for performing comprehensive market sentiment analysis. Businesses can efficiently reveal market opportunities and decrease possible risks through comprehensive sentiment analysis (Nandal, Tanwar, and Pruthi, 2020, pp. 601-607).

Platform differences have an enormous effect on customer attitudes and behaviors. Customers who desire convenience and extensive choices are drawn to Amazon because of its one-stop shopping functionality and wide product categories, which improves the overall buying experience (Monestier, 2021, pp. 705-780). However, to guarantee product authenticity and gain access to exclusive promotions, brand loyalty frequently prompts customers to make direct purchases from a manufacturer's online store (Wassan, 2021, pp. 695-703). While brand-specific e-commerce sites establish confidence through assured validity and dedicated customer support for the brand, Amazon's policy on returns and customer service can help relieve concerns about the quality of goods. Price-conscious customers are drawn to Amazon because of its competitive pricing environment, which give the impression of superior value (Nambiar, 2023). Conversely, brand-specific websites can potentially be seen as providing high-end goods with unique advantages, drawing customers who are less concerned with cost and more interested in the value of the brand (Barlow and Stewart, 2004).

The dynamics of Amazon's market plays a key role in affecting sentiment results. Customers can voice their opinions thereby providing significant data on their experiences and product uses as well as their needs, wants, and requirements of the products. To build trust between the buyers and the companies, the platform applied a review process that also served to boost self-assurance (Huang, 2019, pp. 689-706). AlQahtani (2021, pp. 15-30) found that Amazon endeavors to arrange the order of reviews based on the review's significance and helpfulness, and this impacts consumers' emotions and buying attitudes.

Academic literature has provided assessments on how consumers on platforms make decisions to either purchase or abandon a product. Manufacturers who sell direct to consumers online have the important advantage of tailoring the buying experience on their sites to express their unique corporate values, brand values, and consumer service focus. These targeted website experiences are significant factors that affect the attitudes that customers ultimately portray in the online review feedback. For instance, a well formulated exchange or return policy allows customers to return purchased products or services and get a refund or a replacement in a simple manner (Pu, 2022, pp. 159-186). Stevens (2018, pp. 375-384) acknowledged that quality customer service could work towards positive sentiments about a product or conversely have a negative impact and create unpleasant sentiments against the product. The association between platform-specific factors and customer experience is essential because it can influence customer sentiment, apparent value, and perceived quality of the product. Rocklage and Luttrell (2021, pp. 364-380) performed a comparative analysis of sentiment analysis data for a particular product and determined that overall sentiments could change with time due to changes in consumer expectations, market trends, or brand development. Sentiment analysis of various products in the same niche might provide a different understanding of the particular aspects of a product or service that cause positive or negative customer reviews. Brands must conduct a comparative analysis to understand the various ranges of customer sentiment within a market segment and adapt their strategies to increase customer satisfaction and devotion.

2.5.3 User Experience and Review Features Across Two Platforms

Limited research exists on customer reviews and comparative user experience that specifically identifies the feelings expressed by customers on various e-commerce platforms for the same product. The lack of research in this area highlights the need for a detailed understanding of how customers experience the same product purchased from various e-commerce stores, mainly regarding product opinion and quality. Xiao (2016, pp. 142-162) constructed an inclusive digital quality evaluation of e-commerce websites as mediators, studying both the performance and functionality of the platform itself as a self-regulating supplier. The study elaborated on the synergistic impact of e-commerce website attributes and merchants' performance on customers' online purchasing experiences and satisfaction levels. Xiao's research investigated the effects of e-service quality on these factors across two main digital platforms, Amazon and eBay. The results assist with understanding the various impacts of diverse quality factors on the online shopping experience across different online market platforms. The study conducted by Mu and Zhang (2021, pp. 994-1020) examined the impact of marketing competence and brand reputation on consumer journeys within e-commerce platforms. The researchers determined that marketing capability has a substantial impact on consumer engagement and purchase results, whereas brand reputation has a complex U-shaped effect on consumer behavior. The research performed by Al-Qudah (2023, pp. 1237-1246) compared two websites: Amazon and eBay. They discovered that a website's design can affect the purchasing pattern of customers within a given e-commercial environment. Over time, as the application of technology in producing newer methods of conveying such information is developed, there is increasing demand for the marketing of all product-related information on any particular product type within a single outlet of the Internet.

In Amazon's feedback section, customer insights are accessible in a variety of ways regarding their feedback and experience about a certain product. Amazon has a vast number of search options and filters that are straightforward and show suggestions depending on previous selections (Jiang and Zou, 2020, pp. 900-916). On the other hand, websites fully focused on a single brand offer a search interface for products that is simpler and more homogenous even if it imposes more filters compared to Amazon, and it may still be appreciated by dedicated brand users (Lei, 2020, pp. 41-44). There are Billions of consumer reviews and ratings by actual Amazon product buyers which hugely assist the consumer when deciding what product to buy (Wassan, 2021, pp. 695-703). Whereas, the feedback systems at manufacturer-specific websites are fairly restricted to the website technology applied, so there are comparatively fewer comments for the products under consideration (Huang, 2019, pp. 689-706). Amazon is also frequented more often than any particular brand due to its extensive ranking on search engines and popularity, a factor often leading to a greater number of reviews for a given product. Furthermore, Amazon uses sophisticated algorithms because they depend on the initial customer activity to improve consumer purchasing conditions by providing recommendations for the needed product (Huynh, Miller, and Karger, 2006, pp. 125-134). Manufacturers who sell products through a retail website allow for a highly differentiated and constrained experience (Jiang and Zou, 2020, pp. 900-916).

Fan and Gordon (2014, pp. 74-81) analyzed and assessed in their study the role of different platforms concerning consumer behavior. The customer cultural differences were identified by the researchers to exist in some geographical locations. It was established from the analysis findings that buyers make a quick decision if they will purchase a particular product from the identified platform. The analysis also pointed out two other influences on purchasing behavior, namely the user experience on an individual platform and the presence of a review function. Notably, the customers who perform the interaction during non-working time and those who are more concentrated in a residence area rather than a commercial one demonstrate considerable purchase behavior differences. Kim (2021) investigated the quality factors of platforms as influences on customer's loyalty context to online shopping. An empirical analysis was performed and the results portrayed the fact that there was a tangible relation between customer loyalty and the quality of the platform in question. The aspects that can characterize the quality of a site are the usability interface, reliability, security, and customer support. Quality is one of the aspects that can be used to influence the probability of customers' loyalty to a particular website and brand. Handarkho (2020, pp. 369-386) examined the determinants of consumers' loyalty towards e-commerce websites. Some of the identified factors included customer purchasing behavior, consumer drive, and the shift in consumer attitude across the different websites they use.

The total user experience for products on Amazon and the Manufacturer's e-commerce store contain characteristics that meet and cater to the diverse customer demands and tastes. Amazon provides suggestions via search, price friendly products, and thorough detailed descriptions of products, leading many clients choose the Amazon platform. However, the official sites of brand merchants are aimed at those consumers who buy original goods, seeking an exclusive product with brand identification that guarantees its original nature and the availability of various offers and discounts. Such differences put consumers in a privileged position to choose the platform that suits them and that attracts them most when it comes to buying. These attributes, which are unique to platforms, not only influence the consumers' purchasing decisions but also their attitude and overall impressions towards the products purchased.

2.6 Review Valence

Customers' experiences with a specific product are revealed by analyzing the valence of reviews. Gallagher, Furey and Curran (2019, pp. 21-47) pointed out that valence is a critical component of sentiment analysis as a reference point for the attitude and expression displayed in customers' reviews. Review valence depicts the broad measure of positive or negative opinions that customers have regarding a product. This highlights the importance of the emotional component of reviews, specifically concerning the intensity or magnitude of the indicated emotional value. Thus, the valence of a review for a commodity or product can either be positive or negative. Haque, Saber and Shah (2018, pp.1-6) emphasize the extensive variety of reviews that can be found on e-commerce platforms, and they assert that the overall assessment of a product frequently dictates its level of success. Nonetheless, negative review valence may substantially dissuade the potential consumer, while helpful reviews enhance the appeal and believability of a product (Reimer and Benkenstein, 2016, pp. 5993-6001). Based on the literature analysis, it is recognized that feedback valence influence is feasible and impactful for users considering the purchase of a product or service. According to Ullah (2016, pp. 41-53), the polarity of evaluations has a significant impact on how the product and its offerings are seen.

2.6.1 Impact of Review Valence on Consumer Perception

Although review valence assists with understanding of how a specific customer feels, it’s one of the key components to affect the other consumers’ decisions. To this effect, valence helps to categorize the customer based on their tone, as to whether they are positive or negative. This helps in securing a better picture of the levels of satisfaction among the customers and identifying the potential concerns. Furthermore, the consumers’ perception of a specific product or brand might be influenced by the positivity or negativity of the reviews they read. Receiving positive feedback from users is likely to enhance the perceived value of the product, leading to more sales and greater consumer loyalty to the brand. Platforms such as Amazon utilize algorithms that incorporate feedback, enhanced rankings, and recommenders to increase the appeal and attraction of products (Hariguna, Baihaqi and Nurwanti, 2019, pp. 48-55). On the other hand, unfavorable evaluations have the potential to harm by informing consumers about shortcomings and discouraging them from purchasing. The review valence also impacts perceived reliability and brand excellence. According to a study by Nambiar (2023), positive reviews are more prevalent than negative feedback within specific product brands. However, negative feedback can disproportionately influence customer perception and trust models.

There is a direct correlation between a highly positive emotional response and a well-established perception of a product, which leads to improved consumer trust, more sales, and greater awareness of the business. On the other hand, a powerful negative perception can greatly damage a company's reputation, potentially discouraging potential purchasers and forcing existing customers to question their allegiance to the brand (Hong and Pittman, 2020, pp. 892-920). Ketelaar (2015, pp. 649-666) determined in their research that the level of product knowledge and expertise of the shopper influences their buying intention for a product after reading reviews on an e-commerce platform. Based on their research hypothesis, the depth of a consumer's product knowledge can have two effects: a) it can determine how positive or negative reviews influence their desire to make a purchase, and b) it can lead to an unequal impact of negative and positive reviews. A random sample of 470 reviews was collected, and the sentiment of the reviews ranged from favorable, negative, or neutral. The explained variable was buying intention. The findings demonstrated that the knowledge level of the recipient regarding the product has an impact on how the review's emotional tone is interpreted. Purnawirawan, De Pelsmacker and Dens (2012, pp. 244-255) reviewed the positivity and the necessity of online reviews for both customers and companies. In their study, the authors paid special attention to the review tone, which is positive or negative. Park and Kim (2008, pp. 399-410) in their study found new online buyers were less influenced by online reviews while experienced online buyers were more influenced by the attribute-based online reviews.

Hajli (2020, pp. 774-791) investigated the impact of brand trust and electronic word of mouth (eWOM), specifically customer reviews on consumer buying behavior with online websites. Data was collected from the urban Iranian market to recognize customer behavior. Regression analysis demonstrated that brand trust has a significant impact on customer reviews, influencing consumer purchasing behavior. Customers often rely on the polarity or valence of the reviews as well as the insights of other customers to build up their standpoints and form purchase decisions (Nian, 2018, pp. 580-584). The valence of reviews plays a significant role in influencing individuals' decisions to purchase. Consumers are often influenced by product reviews while making a purchase, whether they are positive or negative. This is particularly true when businesses offer products in densely saturated e-commerce environments with similarly abundant products.

It is possible to determine valence using several techniques that can range from fairly simple to highly complex. The first approaches of deriving the valence values were even more straightforward in which the keywords were increased with two values; positive and negative (Pudaruth, 2018, pp. 41-48). This, however, is not the most ideal way in the sense that there are more advanced machine-learning algorithms that encompass contextual understanding, sarcasm, or even the degree of intensity of the words used (Hariguna, Baihaqi and Nurwanti, 2019, pp. 48-55). To better understand the role and objective importance of valence in the framework of the concept of product sentiment, it can only be stated that valence must be viewed as an element in a larger system. It is important to ascertain the meaning of valence and in what context it needs to be studied in the domain of product sentiment analysis and this is why testing of valence is vital. However, to study the consumer's attitude to a particular company or product in detail, it is advisable to compare the data regarding valence alongside other aspects of the reviews. Also embedded in this large strategy is the capacity either to provide or to assess opinions in terms of positive or negative. It offers some important strategic steps which any organization requires for maintaining and creating brands' profitably in the long run.

2.7 Review Length

Certain researchers have established that the length of the review period is instrumental in determining the consumers' perception of a product in e-commerce and equally crucial in the buying process. Reimer and Benkenstein (2016, pp. 5993-6001) highlighted that posting detailed reviews enhances the perceived quality and functionality of products among consumers. According to Ghasemaghaei (2018, pp. 544-563), comprehensive evaluations are helpful to its target consumers because they provide extensive analyses that offer support to the buying decisions. Again, time-consuming reviews can help reduce prejudice since the review contains a product assessment. In total, the effects of numerous short and brief reviews may sometimes overwhelm the effects accomplished by longer and elaborate feedback.

In the case of sentiment analysis further assessment of the relationship between the length of the reviews and the level of sentiment expressed is vital (Aggarwal and Aakash, 2020, pp. 361-376). It is useful to have longer reviews since this can provide a better understanding of the feelings that are being encountered and thus provide good qualitative results rather than getting quicker and biased results based on the consumer's perspective (Pambudi and Suprapto, 2021, pp. 21-30). Research reveals that longer reviews are of great worth to companies as they can isolate attributes that customers find important or on the other hand can indicate areas that the firm is weak in and requires enhancement.

2.7.1 Relationship between Review Length and Customer Sentiment

This implies that the relation between emotions and the length of the customer reviews is multifaceted, and thus shapes how evaluations exert and bring about changes in purchasing decisions. Consumers can be affected by extended reviews because they provide details on a particular product or service. Extended reviews contain additional elements in addition to extensive product reviews (Kim, Maslowska, and Malthouse, 2020, pp. 29-53). Customers can read many detailed and motivated comments or opinions of previous buyers, for instance, on Amazon when they decide to make purchases of a particular product. This goes a long way in easing concerns customers may have concerning fake paid reviews or fake products. Negative reviews can illuminate problems and offer an extensive insight into customer attitudes (Cao, Dewan and Lin, 2023). Lee, Park, and Han (2011, pp. 187-206) found that longer customer reviews on e-commerce sites are generally perceived as more credible and insightful. The sense of credibility and insightfulness can result in heightened optimism and greater influence over purchasing decisions. A comprehensive evaluation that includes both positive and negative input should be considered, as both types of statements have significance. Oftentimes, unfavorable comments and reviews include thorough reasons for the shortcomings of a particular product, and these insights can be helpful to a shopper. Therefore, evaluating a complete review as opposed to a section of it can reveal the overarching sentiment polarity.

Some of the previous studies have pointed out that the length has a direct influence on the degree of trust consumers have in the review as well as the level of helpfulness (Aggarwal and Aakash, 2020, pp. 361-376). An overall conclusion of this method of analysis therefore is that reviews that are larger count more than others and are perceived as more reliable and valuable for their ability to give as much information as possible. Therefore, the study by Li, Goh and Jin (2020, pp. 4387-4415) aimed to investigate the rating and the relative impact of brief and concise reviews and matched it against the readability theory. Therefore, different approaches have been proposed and used to determine the relationship between the word count and the intensity of the review sentiments (Nian, 2018, pp. 580-584). Such methods can be regression analysis, text analysis, or text mining. Analysts can make assumptions and find informative patterns on the aspect of the relative intensity of customers' feelings, given the length and detail of the reviews.

2.8 Product Focus in Sentiment Analysis

Sentiment analysis has turned out to be one of the most effective tools and is beneficial in understanding the feelings of consumers and the attitudes of customers regarding purchases in the field of e-commerce. This is one of the analytical tools which involves the identification of emotions and disposition towards something in this case the customers' perception of a given good or service (Liu, 2015). Thus, directing attention to a specific product and its reviews to get more relevant and accurate data is feasible, which can contribute to the enhancement of the marketing strategies and promotion techniques of the given product (Al-Natour and Turetken, 2020).

The following section of this literature review is to explain the product sentiment analysis, advantages and disadvantages of product contrast, and how characteristics of one particular product may affect the outcome of such a type of study. This is to enable researchers or companies to avoid potentially incorrect outcomes with distortionary data when performing comparisons of various research terms or products. One strength of the current study is that it investigates positive and negative feedback solely for a particular good, thus increasing the richness of the study's outcomes (Shafin, 2020, pp. 1-5). This makes it possible to examine variations with far greater granularity on the relationship between customers' feelings and a particular product, which is available in multiple online stores. This makes it possible to have a more enhanced awareness of the consumers' behaviors that may be associated with specific qualities and features of a product; and touches on experiences likely to be seen with a product (Aung and Myo, 2017, pp. 149-154). The information generated through sentiment analyses can thus be used as part of a competitive analysis by organizations to obtain detailed and current information on the status of a specific product.

2.8.1 Importance of Product-Focused Sentiment Analysis

Sentiment analysis research mainly aims at identifying accurate and comprehensive data on customer sentiments. One advantage of this strategy is that comments from buyers may be filtered and the filter may be scanned for specific elements of the product which can provide much-valued feedback on positive customer emotions or discontent. Marketers using sentiment analysis can provide more detailed and constructive feedback concerning product innovation or advertising since they can focus directly on the sentiments concerning a particular product offered in the market (Mukherjee and Bhattacharyya, 2012, pp. 475-487). Concentration on a single product will help to identify certain weaknesses that can be difficult to identify in the case of a group of goods or categories. Further, it is pointed out that the focus on a single product offers the specific direction to grasp the nature of the tangible consequences of the given product attributes, aesthetics, and performance in addition to the general satisfaction level concerning the consumers who are interested in purchasing the given product type. Some key advantages or disadvantages of customers may be overlooked when the scholars focus on multiple products or the different product categories compared to focusing on just one product (Yang, Zheng and Mookerjee, 2019, pp. 351-374). For instance, a detailed analysis of feedback on a certain model or brand of cell phone may reveal problems with that specific cell phone, including hardware failures, or software glitches, which can be helpful information for the manufacturer.

2.8.2 Benefits and Challenges of Product-Focused Sentiment Analysis

There are advantages in carrying out product-focused sentiment analysis including the benefits of relevancy and accuracy. Companies can employ it to focus on some particular characteristics of their products, or to appreciate what buyers may like or dislike about such products. According to Liu (2015), this enables companies to make changes that would be of value to the consumers. Besides, analyzing sentiment on an individual product can be significant in the sense of revealing several features of a particular product, and therefore, deepening the understanding of the competitive position of the product (Aung and Myo, 2017, pp. 149-154). This analysis can then be compared to other similar products in the market and; it will suit manufacturers or sellers who need to determine their shop standing or special features to distinguish themselves in the market.

Product developers and marketers can obtain a vast amount of competitive information out of focusing on a single product. However, a further assessment of customer emotions concerning a specific product enables marketers to communicate with and touch the hearts of the consumers. By carrying out specific marketing activities, the differences in aspects of a product that are particularly liked can be highlighted and the issues that may be raised in the course of reviews can be adequately addressed (Kauffmann, 2019). The practice of sentiment analysis gives direct and strategic guidelines to the developers of products so that the products can be tailored in a manner that would satisfactorily meet the needs of the consumers. Sentiment analysis defines the features of the product that exceed customer-perceived expectations or gross disappointment. Through the analysis of feedback from customer reviews, virtually any business that sells online can readily change its strategies, improve its capacity to satisfy customers, and thus design products that will better fit market demand.

There are also potential difficulties associated with analyzing customer sentiment for a single product. Since the outcomes are framed specifically within the context of a single product, the revealed insights might not apply to similar commodities in the specified product class (Yang, Zheng and Mookerjee, 2019, pp. 351-374). Moreover, focusing on a single product across multiple platforms can be time-consuming and require meaningful resource utilization. This is particularly relevant when the product is one of the most popular in its class and has many comments. Mainly due to lacking diversification in products, the emphasis is often put on deeper and all-encompassing analysis as opposed to the brief comparison of multiple products. The more detailed analysis can take a relatively longer time and requires knowledge about the product under scrutiny as well as specific methods and approaches for data analysis.

2.8.3 Impact of Product Characteristics on Sentiment Analysis Outcome

An aspect that needs to be mentioned is the fact that the results of the sentimental analysis may be impacted by the nature of the product being assessed. Multiple factors influence customer feedback in reviews which affects the outcomes sentiment analysis including: the characteristic of the good or service, the price of the product, the usage frequency of the product, and the type of reviews selected for a particular analysis. For instance, consumers may write detailed, long and technical review of complex and costly products and covered more aspects of the product than for simple, cheap, and brief usage product (Kauffmann *et al.,* 2019, pp. 1-19).

These are the general sentiments that customers have about a given product or service, especially with regard to the value and drawbacks of the product. In addition, these attitudes depend on the kind of industry or the market segment within which the product is targeted to operate. Some categories have an affinity to cause a higher order of emotional response from the customer because of the nature of a certain category. According to Rathore and Ilavarasan (2020, pp. 111-127), products that consumers come across in their daily lives will create broader and more intense testimonials than products that are complex and used minimally. Besides, the degree of variation and distinction between the products can dictate the number of customer reviews and the ways the customers express their demands. Thus, for the process of sentiment analysis, and consequently, decision making, the peculiarities of the certain product and its influence upon the given feedback should be taken into consideration.

2.9 Research Gap

Researchers and businesses have shown considerable interest in examining customer sentiment in reviews from e-commerce sites and analyzing the polarity of their evaluations. Comparative research, which analyzes customer reviews across numerous products on Amazon or across multiple e-commerce platforms, is a well-established practice. A number of studies have examined the sentiment analysis of a particular product on a single platform. However, there has been very limited, if any research conducted on the comparison of sentiment and review attributes for a specific cosmetic product sold by the Manufacturer on the Amazon platform, and by the Manufacturer on its own e-commerce website. This study focuses on evaluating the sentiment of reviews collected from a manufacturer's e-commerce website and the Amazon marketplace, specifically for a single product. This study also evaluates different review attributes and investigates their capacity to indicate or disclose the sentiment valence of customer opinions. These attributes include the overall length of reviews, incentivized reviews or vine-free product, and the presence of user uploaded picture attachment in reviews. This research study aims to provide a comprehensive understanding of how customers perceive and evaluate the same cosmetic product on two distinct e-commerce platforms. It also investigates the specific qualities of the product according to customers' reviews and their implications for customer sentiment.

2.9.1 Identified Gaps in the Existing Literature

Despite the broad research on customer reviews and sentiment analysis, there is a considerable lack of research that examines and compares buyer opinions on various e-commerce websites for the same product. In the context of a particular product, the current literature mostly focuses on single platform studies, even though there might be differences in the customers' behavior and opinion depending on the online platform on which the identical product is being sold. This limitation makes evident the need to investigate the value differences that customers have toward the same product in multiple online retailing platforms.

Currently, there is no study done to identify and compare the positive or negative sentiment of a product review hosted in two different e-commerce sites along with the review attributes indicating this sentiment polarity. This means there is a lack of awareness of how customers' perceptions may vary across the platform. Previous studies have suggested that valence be used in categorizing the review as positive or negative; the polarity and textual feature had to be given significant attention when assessing the quantity of consumer sentiment (Tata, Prashar, and Gupta, 2020). These studies have not provided adequate insight into review attribute characteristics like review length, free products offered to buyers, and the presence of images that depict polarity.

There is limited literature on the positive or negative sentiment analysis of the reviews for the same product on two different e-commerce websites. This also implies that there is still a lack of knowledge regarding how customers' perceptions would be cross-platform. The previous studies suggest that valence is highly effective in sorting the reviews into two categories of sentiments (positive and negative) and customer satisfaction are the two other important factors in measuring the sentiment of the consumers (Tata, Prashar, and Gupta, 2020). These studies have not adequately taken into consideration other aspects of review attributes including length of the reviews, the use of free product offers, and the presence or absence of images as a measure of sentiment polarity. This gap is particularly concerning as different websites and platforms may have dissimilar review cultures and consumer engagement behaviors, and may attract different buyer types for the identical product. It's plausible that these nuances lead to different sentiments amongst customers of the same product cross-platform.

Regarding incentivized product distribution in exchange for reviews, insufficient comparative research exists on the sentiment polarity of sponsored reviews on different e-commerce sites for an identical product. However, research reveals that if a consumer pays for a product, the feedback reviews are generally deemed genuine by shoppers, and potentially hold leverage in shifting the overall consumer sentiment (Qiao and Rui, 2023, pp. 676-697). Conducting a comprehensive analysis of the overall effects of incentivized reviews, such as Amazon Vine reviews, compared to regular user reviews on Amazon and other platforms is essential for comprehending their impact on customer perceptions and product evaluations.

Image attachments in reviews shows another subject that has been discovered in prior research. The presence of images in reviews has a measurable positive impact on the levels of credibility of the review, which in turn influences the perception and buying behavior of the customer (Zinko, 2020, pp. 525-541). However, there is an absence of comparative analysis on how the addition of images in reviews is an indicator of customer sentiment variance on two platforms for the same product. This gap is particularly relevant in product categories such as beauty and personal care, where visual proof can greatly impact buying choices.

Existing research does not compare the various customer sentiments across multiple e-commerce platforms for one cosmetic product, along with the effectiveness of other review attribute features as indicators of the sentiment valence of those same reviews. This understanding is necessary for creating strategies to improve consumer engagement and increase sales on various e-commerce websites.

2.9.2 Bridging of Gaps by This Research

This research aims to fill the recognized gaps by conducting a thorough comparative sentiment analysis of reviews collected from Amazon and a manufacturer's retail e-commerce platform for the same single skincare product. By investigating review length, Vine-free and giveaway products, and image attachments in reviews by users, this study explores and reveals sentiment patterns on both platforms. It shifts from usual calculations and simple rating scales to the narratives and actual experiences that resulted in these estimations, using a mixed-methods approach.

This literature review unlocks the lack of knowledge regarding review valence variations for the same skincare product on multiple e-commerce platforms, as well as the usage of review attributes as indicators of sentiment direction. These factors are relevant in the research's goal of identifying and analyzing the sentiment of reviews for the product on both Amazon and the Manufacturer's website for significant differences in the overall tone and valence of the reviews. This research provides an understanding of how customers convey their satisfaction or dissatisfaction in social feedback, and how businesses can learn from customer attitudes to better their brands, resulting in potentially more revenue for the business.

Furthermore, this study aims to present specific review features as indicators of review valence. By utilizing the findings of this study, it will be more convenient for businesses to identify approaches to enhancing customer satisfaction, hence resulting in increased sales and improving the effectiveness of the product review application across different online retailers.

Therefore, the study proposes the need to develop a comprehensive comparative understanding of customer feelings on both Amazon and the Manufacturer site to fill the literature gaps. The study attempts to identify other important aspects of reviews such as the length of a review, Vine-free and giveaway products, and images attached to the reviews that indicate customer behavior in a nuanced manner. The findings contribute to the literature by suggesting how e-commerce websites can potentially transform their practices in ways that might enhance satisfaction, contentment, and trust, all of which are significant for long-term success in online shopping.

CHAPTER III

METHODOLOGY

The chapter will include methodology regarding the presented work and will contain the aspects related to the research process including research design, data collection, data pre-processing, sentiment analysis technique, model specification, variables and correlation, data analysis plan, and ethical issues that may trigger while conducting the research work. Therefore, this chapter elucidates the general framework for the study and presents the path to comprehend the research development and implementation processes.

The initial stage of research design leads to the subsequent phases inclusive of data collecting, preprocessing of the data, and the techniques used to perform the sentiment analysis of data as depicted in Figure 1. The model specification which is part of the study entails the determination of the regression equations. Therefore, the clarification of how several variables might work and how they are interconnected and related is also presented in this chapter given the significance of the concept in the scope of the research. However, the viable approaches for the analysis of the collected data, and the tools and procedures that facilitate the achievement of the best results for the generation of comprehensive insights are outlined. Most importantly, the concepts of ethical considerations are incorporated into each stage of the study preventing the non-observance of accountability and ethical values in the course of the research. This chapter consists of a detailed description of the methodological framework that underlies the stated study. Consequently, the chapter is overall comprehensive of the research design, as well as ethics to make it easier for the readers to grasp the mechanisms of the methodical strategy and provides a guideline on how to perform the study properly.

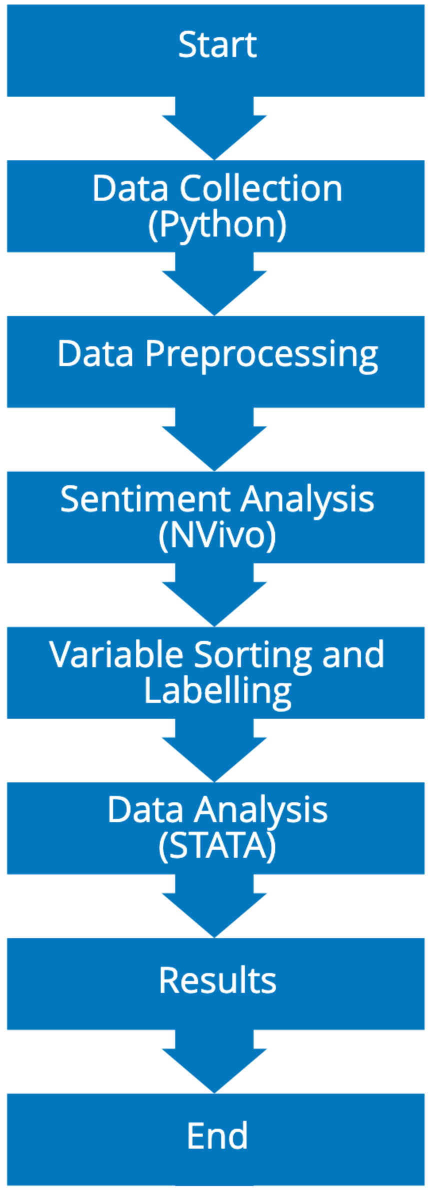

Figure 1. Workflow Diagram
(Jason Raphael, 2024)

3.1 Research Design

The structure of this study was purposely designed to effectively plan and execute the research and in particular the assessment and analysis of online evaluations from users of a skincare product that is offered for sale on two different e-commerce platforms by the

Manufacturer. Consequently, in this study, a mixed method of data collection techniques has been adopted whereby an analysis of the reviews given by customers concerning the given product on both platforms has been done. This technique is useful because it can provide a better understanding of consumer feedback including feelings that are impacted by the platform, as well as the relations between different sentiment-indicating variables.

This study aimed to employ secondary data sources for data collection and analysis which has been advantageous in many ways. Firstly, it allows the study to carry out sentiment analysis for a particular range of customers in a specified timeframe, offering a targeted view of consumer sentiments during a given period for the particular product. Further, by evaluating present sentiment patterns, the cross-sectional nature of the research enables direct contrast between the data extracted from Amazon and the Manufacturer’s e-commerce platform. This comparative approach of the research design is especially advantageous because it opts to reveal any notable difference in customer sentiment across different online platforms, and this is beneficial for business decisions while developing marketing plans and managing brand value. The rationale for using secondary data sources is to accurately present and analyze real-world data as it is, from openly available sources.

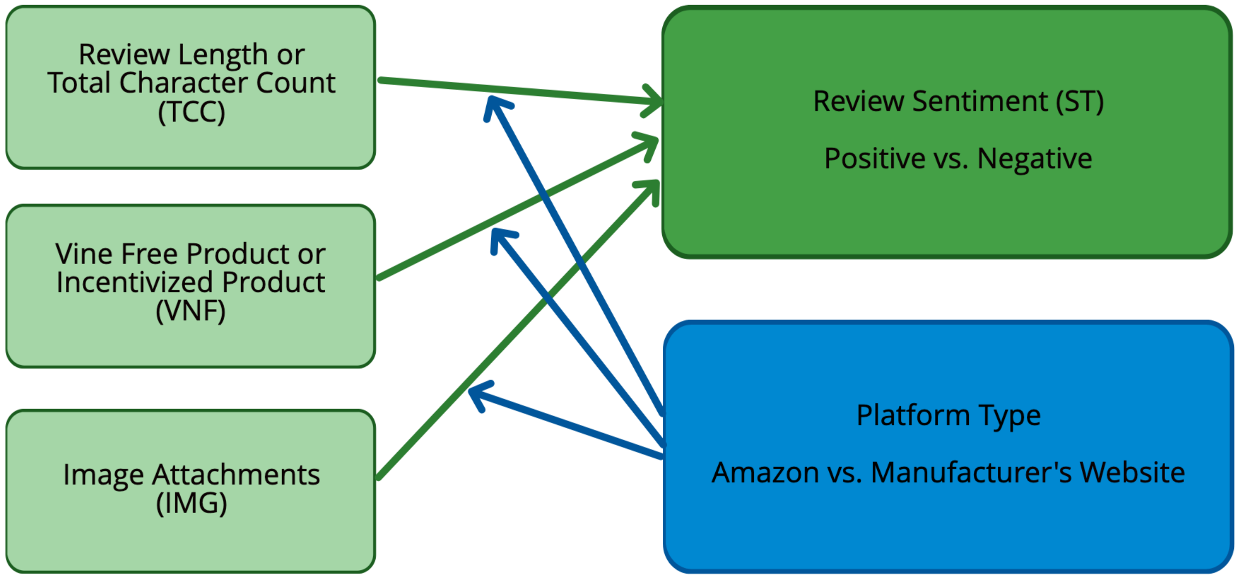

Figure 2. Theoretical Framework

(Jason Raphael, 2024)

In outlining the conceptual framework, this study aims to identify the emotional valence (either positive or negative) in the feedback including the intensiveness of emotions expressed by the degree of detail and lexicon in the customer reviews. By this approach, the study is directed to identify the inclinations and connections in the review data set, particularly focused on review duration, incentivized reviews (Vine programs for Amazon), and user-uploaded picture attachments in reviews. The research intends to meticulously evaluate the association between these review factors and the valence of sentiment expressed to gain a precise grasp of the review factors that indicate client attitudes.

While delineating the research design, the identification of whom and what to consider for the study was a crucial part of the structure (Punch, 2013), in this case, the study purposefully considered the customers of a skin-care product who provided feedback on two different e-commerce platforms. Moreover, the study investigates the precise elements of consumer sentiment to analyze the content and characteristics of reviews to identify underlying attitudes and behavior. Systematic customer feedback extraction from both online platforms is the foremost step in the data-acquiring part of the research, thus, the web collection strategy was implemented for the gathering of data. Subsequently, the data was prudently coded and analyzed to find underlying sentiments, themes, and tendencies presented in the reviews of customers on Amazon and the Manufacturer's e-commerce platform for the skincare product.

Conclusively, the research design employs a mixed approach of both qualitative and quantitative methods to the data obtained from secondary sources to explore the online customer reviews of the same skincare product on two different platforms; Amazon and the Manufacturer's e-commerce store. The study aims to provide deep insights into customer attitudes by inspecting different aspects of customer reviews including the valence and depth of consumer thoughts. Further, the factors indicating the sentiment valence of reviews are also considered an important part of the research structure. According to Yang, Zheng, and Mookerjee (2019, pp. 351-374), the direct evaluation of sentiment trends across various e-commerce websites allows the research to simplify buyer perception. This comparative nature of the research further enhances its effectiveness and helps to offer a pathway for decision-making associated with brand management and strategic marketing.

3.2 Data Collection

Data collection was the next major feature in the methodological framework of this study following the research design. Before assessing the customers' review behavior, it was essential to obtain information concerning their perception of this specific product on two platforms and therefore the data collection is a crucial step in the present research study. The collection of the data was done through a systematic approach to data gathering over the World Wide Web. This was done using Python, a general-purpose high-level programming language that is well-known for the versatility it offers while conducting web data extraction tasks (Thomas and Mathur, 2019). Consequently, Python proves very useful in gathering secondary data sources from the Internet.

The features available in Python had their utility extended by the use of available modules, among them being the BeautifulSoup module for handling HTML and the Requests module for the handling of requests. The employment of these modules enabled it to be possible to create two comparatively alike scripts or programs that were expected to retrieve the required data by moving through the pages that contained the product reviews of the given e-commerce platforms. The data collection procedure was performed in a sequential manner where the first step involved, using the Request module of Python to extract the information from the e-commerce site of the product on Amazon and the next step was to extract the information from the Manufacturer's website. This made it possible to initiate the main process, that of data collection. Subsequently, with the help of the BeautifulSoup module of Python, the extraction of the HTML structure of the given web pages was possible and the reviews were obtained. The collection of data involved all the necessary information for this research study which included, the collection of title, text body, review date, image attached, indicators of incentivized product, and other meta info of each of the reviews mentioned in both sites.

The scripts used were designed to read only the review pages to gather the relevant datasets from January 2022 to January 2024 to ensure that all the reviews were obtained. Due to the scripts' construction, during the data retrieving process, the scripts gathered only specified data while omitting others. This particular approach of data collection helped in getting a relevant and valuable data set, and the data gathered were full of the feelings and attitudes of customers in the reviews section.

Ethical concerns were also considered while collecting data and to ensure that there was no violation of the web scraping ethics, ethical standards for web collection were followed to obtain data that was both valid and reliable (Gupta, 2017, article D1). For instance, special care was taken to ensure that all the gathered data was easily accessible to the public sphere and not spurned behind login accounts, icons, and other barriers. In addition, none of the Python scripts attempted to decrypt the screen names of the reviewers and match them with people's identities which guided the privacy provision and PII to its highest level. Other precautions were also put in place to minimize any possibility of the data collected being harmful or leaking the confidentiality part of the data. To achieve honest and trustworthy results and analysis, it was imperative to match the ethical principal standards of the study while conducting the research.

Data collection was not only restricted to obtaining the reviews with written text on both e-commerce sites, but also the other components of the reviews such as the presence of signs of sponsored reviews and the use of customer-uploaded pictures in the reviews. These elements were integrated into the dataset to assess the extent of consumer interest coverage for the two different websites, and the effects of these review characteristics as the measures of the valence of consumer sentiment.

The last procedure involved data storage and management of collected data where the data was maintained in a structured format, and it was preferable to create a CSV file format so that the data could be easily imported as and when needed into the analysis software. The format of storage chosen was CSV on the basis that this file format is common and because the data can be easily transferred to other software for future analyses. This data management approach offered a solid foundation to ensure the accuracy and reliability of the data collected to analyze sentiments regarding each of the platforms.

In terms of the study's methodological approach, this paper identifies the systematic and ethical collection of the data. With the support of Python's web-collecting modules, the data-collecting process was more concentrated on the collection of a large amount of data, which can be useful in providing a detailed picture of consumer perceptions and attitudes. Adherence to high ethical standards ensured the best way of collecting the review data. Contextual factors enhanced the analytical intensity and enabled the Research to consider the factors occurring on Amazon and affecting the Manufacturer’s website in terms of the customers’ attitude. While capturing and categorizing the outlined data in this study, the methods followed allowed for the sophisticated analysis and study conclusions. The findings of this research are useful for digital marketing management because it provides useful information for the company to plan its strategies at the tactical level of the digital marketing environment. Thus, the findings of this research enrich the understanding of consumer sentiment about aspects of contemporary customer behavior in the e-commerce field.

3.3 Data Preprocessing

The data collected from Amazon and the Manufacturer’s website for this study was cleaned through the process of data preprocessing to perform sentiment analysis. The preprocessing stage is very important when analyzing a textual dataset, particularly when the data involved have aspects such as recurrence, inconsistency, and duplication (Shoukry and Rafea, 2012, pp. 47-56). This step is further supported by the inclusion of several refining sub-stages to improve and expand the data for further use. One of the most important aims of this approach was to standardize the data and ensure its stability. Therefore, the data collected from the e-commerce platforms to understand the attitude of the customers in the reviews of a particular skincare product for further analysis was standardized. This was done to achieve high reliability of the results of the study undertaken. The importance of the preprocessing stage is well explained because the accuracy of the dataset can have an impact on the results. When it comes to the steps of preprocessing, data cleaning, removing punctuations, converting text to tokens, deleting stop words or blank spaces or unwanted special characters, the general process of eradicating unwanted attributes was done as well (Pyle, 1999, pp. 11-52; 107-131).

The first step of preprocessing was done manually where the dataset was cleaned by removing false values, and error values from the text along with the unwanted characters and spaces. The objective of this step was to check the homogeneity of the data and to correct any mistakes that were present in the data set, which was also useful in making the data more accurate for further data analysis and assessment. Likewise, punctuation marks without relevance in the text were removed by hand to ensure that only critical data were extracted from the text and then words were tokenized to split the text into phrases and sentences into parts or tokens. As tokenization is a standard procedure for closer investigation of written material at the level of semantic blocks (Wongkar and Angdresey, 2019, pp. 1-5), this is vital and mandatory when the patterns and conclusions in the text are important for further NLP for sentiment analysis.

To enhance the quality of the text further, all the stop words whose importance for text analysis is marginal at best (and, actually, maybe completely unimportant) were removed from the list (including 'the', 'is', 'am', 'on', etc.). In the textual dataset for this study, common words that make up the stop words list generate unwanted and irrelevant additional terms of information. This also made it less difficult to reduce focus on other irrelevant features of the review process as the main parameters of the reviews became the viable path to the draft of the cleansed and enriched set. Also, during data cleaning other peculiarities that might affect the evaluation were removed including the use of short forms and other characters such as abbreviations, contractions, as well as misspelled words. As part of the data pre-processing process, extra spaces were eliminated to make the structure of the data more normalized and standardized. Additional tags such as '%', '$', '&', and '#' were removed from the extracted data as they also boost the context value and minimize the detailed textual analysis as they are not able to hold sentiment (Iqbal, 2022, Article 10844). Every extraneous feature identified in the acquired dataset was removed; the only data required to perform sentiment analysis are those that remained in the source and target fields. This process fine-tuned the dataset and made clear what aspects of are relevant.

Data cleaning was the first and primary step of the further analysis, and, in this case, it was specifically manual data cleaning. This involved pre-processing of the data set where all the necessary procedures for data cleaning and removal of the irrelevant information were done as suggested by Shoukry and Rafea (2012, pp. pp. 47-56). The data was then analyzed using NVivo

14 which is a commonly used analysis tools in academic research especially those with qualitative datasets. The identified sentiments and the insights coming from the reviews were analyzed with the use of the sentiment analysis feature in NVivo about the dataset. The sentiment analysis conducted in NVivo helped to identify the chances to define the positive, negative, and intermediate sentiments that consumers expressed about the product under review on both platforms. The result of sentiment analysis was gathered and a new feature containing the original dataset was appended, a flag of valence of positive or negative sentiments was imputed against each review. The addition of review valence, positive or negative, before each review was meant to help simplify the subsequent data analysis steps. In addition, the review valence and other review variables in wordy forms were coded into simple digital forms, 0 or 1, which enabled sentiments to be compared with the different qualities of the reviews and to show the nature of the different attributes of the review as the indices of customer review polarity.

To conduct further in-depth quantitative analysis, logistic regression using STATA software was employed. The relevant variables selected for this study's analysis were appropriately labeled with abbreviations to streamline the logistic regression analysis. The selected specific variables in the present research were; sentiment valence, the length of a review, Vine-free products or other incentivized giveaways, and image attachments by customers in reviews. These variables were then abbreviated as 'ST' for sentiment valence, 'TCC' for total character count or the length of the reviews, 'VNF' for Vine-free products/incentivized reviews, and 'IMG' for image attachment with the review. The concern of the logistic regression analysis was to identify potential facets of customer sentiment and analyze the basic review characteristic features illustrating satisfactory or dissatisfactory observations concerning the product by using relatability. Hence the correlation analysis between the sentiment valence of the reviews and other sentiment polarity-suggesting factors was determined.

In conclusion, it should be mentioned that the data preparation comprises the set of micro text preprocessing activities that were all intended to prepare the data for modeling and analysis by removing any noise, errors, or any other damaged entries from the data set as well as find out which data are irrelevant or devoid of any meaning. These micro processes were employed to establish reliability and standardization of data that were collected as excessive information and noise were omitted to extract only inclusive data. This cross-sectional survey used an itemized approach to evaluate the Firm's collected feedback on a skincare product purchased at the Manufacturer's online store and Amazon. The study seeks to identify and summarize the customers' perceptions of the selected product using sentiment analysis of the reviews by NVivo 14 and estimation of logistic regression using STATA. The step-by-step approach to dealing with the data ensures the credibility of this study and the correlation between sentiments and various review characteristics provides a clear and practical way of improving customer engagement and optimizing the customer experience.

3.4 Sentiment Analysis Techniques

Interpreting customer attitudes has emerged as one of possibly the most crucial tasks for companies and brands that seek to enhance customer satisfaction in the dynamic environment of the digital business space and e-commerce (Prananda and Thalib, 2020, pp. 1-8). The research in this study was carried out with a view of assisting businesses especially those that have faced significant challenges in courting customers online to make purchases. After research structuring, data acquisition, and preprocessing of data, the data was geared towards the main goal of the research, which was to establish the polarity of sentiment. This important phase of the study focused on evaluating the attitudes concerning their purchases that customers said in the body of the review gathered from Amazon and the Manufacturer's online store. This section of the study gives a detailed outline of the different approaches that can be employed when performing sentiment analysis on textual data, a brief overview of the cardinal principles of each of the methods, and how the adopted approach was used in the context of the study methodology.

3.4.1 Lexicon-based Approach

Lexicon-based is the fundamental approach of sentiment analysis since it is a method that uses already prepared sentiment lexicons to identify the polarity of words and masked expressions in textual data (Chu, Keikhosrokiani and Asl, 2022, pp. 2535-2561). In this work, the sentiment analysis was done using the auto-coding feature of NVivo software which employs an NLP, lexicon approach. These sentiments extracted from the automated feature of NVivo were used for identification and categorization. Moreover, NVivo has a feature of identifying synonyms for the words as well, which not only helps augment the sentiment analysis process but also helps in identifying similar words more accurately (Chang, 2021, pp. 398-412). For example, the word 'puffiness' is available in the data set, and other related words like 'swelling', 'inflated', 'inflamed', 'distant', and 'enlarged' were also counted under the mentioned category. Finally, the auto-coding characteristic of the NVivo also helped in the labeling in as much as the sentiments were tagged as negative sentiment, positive sentiment, and neutral sentiments. The sentiments are then divided into two general extremes which are the extremely positive and highly negative sentiments along with moderately positive and moderately negative sentiments based on lexicon-based sentiment analysis. The automated tagging of sentiments ensured exactness and reliability in the sentiment analysis of the review of the dataset.

3.4.2 Natural Language Processing (NLP) and Machine Learning (ML)

For sentiment analysis, NLP is an influential technique that includes lexicon-based methods. Artificial intelligence and computational linguistics emphasize enhancing communication between human language and computers, and a significant range of approaches in sentiment analysis are covered by NLP techniques to collect insights from text data (Tunca, Sezen and Balcioglu, 2023, pp. 1-16). These approaches include subject demonstrating, frequency examination, and part-of-speech category. NVivo 14 has strong support for natural language processing techniques, allowing for the identification of sentiments in customer reviews. NLP methods are adaptable, and researchers can reveal important perceptions veiled in data text by examining the intricacies of customer feedback. In addition, NLP enhances the process of sentiment analysis and the result's efficiency, reliability, and accuracy. Machine Learning (ML) is another commonly utilized technique for sentiment analysis, but its general complexity was beyond the scope of this study. Hence, the auto coding feature of NVivo based on NLP and lexicon methodology was chosen for its straightforward, effective, and low technical barrier to competent sentiment analysis.

3.4.3 Comparative Approach in Sentiment Analysis

The dataset which was cleared of irrelevant data and then sentiment analysis was processed using the methods discussed earlier. For autonomous sentiment analysis of customer feedback, NVivo 14 was used. This process allowed for a clear analysis of the reviews articulated on each e-commerce website, providing a more complex understanding of the customer's reviews in different online settings. Afterward, to compare the reviews of customers extracted from both websites, a comparative study revealed possible variances or resemblances in the sentiments of the customers of both platforms. NVivo 14 was used for this comparison. Synonym identification, automated sentiment labeling, and the conservation of distinct lexicons for categorized sentiment were techniques utilized via the advanced functionality of NVivo 14. Sentiment analysis is the foundation of this thesis and utilized auto-coded NLP with lexicon-based method principles. Businesses can utilize sentiment analysis to uncover relevant consumer insights regarding a product, hence aiding the success of e-commerce ventures.

3.5 Model Specification – Amazon and the Manufacturer

The study used cross-sectional data of reviews from Amazon and the Manufacturer's platform to estimate the effects of Vine-free product, total character count, and image attachment as indicators of the positive or negative sentiment classification of customer reviews. Equation 1 below represents the Amazon review data, while Equation 2 represents the Manufacturer's review data.

$$ST_{Ai} = \alpha + \beta_1 VNF_{Ai} + \beta_2 TCC_{Ai} + \beta_3 IMG_{Ai} \ + \varepsilon_i \qquad \textbf{....(1)}$$

Where ST represents the sentiments of the Amazon reviews which are positive or negative. The positive and negative sentiments are categorized by the binary digits 1 and 0 respectively. VNF represents the categorical variable which is a Vine-free product/incentivized product and the customers who received VNF are classified with '1'. Those who did not receive VNF are classified with '0'. TCC represents the total character count or review length, and IMG represents the image attached by customers in their reviews, which is a categorical variable. The customers who attached an image are delineated by '1', and those who did not attached an image are delineated by '0'. The population size of the Amazon data set is 126 reviews, thus, *i* represents the cross-sectional data set from 1-126 reviews collected from the Amazon platform for the product. The inclusion of ε_i in the equation accounts for the variability in sentiment that is not explained by the independent variables. The above equation displays the model used for the analysis of Amazon reviews. The sentiment analysis polarity is the dependent variable and vine-free product, total character count, and image attachment are independent variables.

$$ST_{Mi} = \alpha + \ \beta_1 VNF_{Mi} + \beta_2 TCC_{Mi} + \beta_3 IMG_{Mi} + \varepsilon_i \qquad \textbf{....(2)}$$

For the Manufacturer's review data, where ST represents the sentiments of the Manufacturer reviews which are positive or negative sentiments. The '1', and '0' represent the positive and negative sentiments respectively. VNF represents a categorical variable, which is a Vine-free product/incentivized product. The customers who received VNF are '1', and the customers who did not receive VNF are '0'. TCC represents the total character count. IMG represents the categorical variable for image attachment in reviews. The customers who attached an image are '1', and those who did not attach images are '0'. The population size is 708 reviews, and *i* represents the cross-sectional data from 1-708 reviews collected from the Manufacturer's e-commerce platform for the product. The inclusion of ε_i in the equation accounts for the variability in sentiment that is not explained by the independent variables. The above equation shows the model used for the analysis of the Manufacturer's reviews. Sentiment analysis polarity is the dependent variable and Vine-free product/incentivized product, total character count, and image attachment are independent variables.

3.6 Variables and Measures

The equations used in this study focus on dependent (explained) and independent (explanatory) variables. While the dependent variable is the Sentiment (ST) valence of the reviews, the independent review attribute variables encompass Vine-free product/incentivized (VNF), total character count (TCC), and image attachment (IMG). The selection of these variables and their usage were essential for the further research of the specific interactions in the sentiment analysis of the reviews and the indicators of the polarity of customer sentiment in the field of e-commerce analysis.

3.6.1 Data Collection and Initial Sentiment Analysis

The first part of the sentiment analysis was conducted with the help of NVivo software which classifies the identified reviews into positive, negative, and neutral groups based on the NLP and lexicon analysis.

3.6.2 Data Preprocessing for Logistic Regression

To conduct logistic regression analysis in STATA, it was essential to perform a binary sentiment classification, distinguishing between positive and negative sentiments. Thus, a manual classifying procedure was executed.

1. Criteria for Reclassification

- Positive reviews included those that brought out a star rating of 3 or more out of 5 as arrived at through hand coding.
- Negative reviews included all the reviews that had a star rating of 3 or below through hand coding.

2. Inclusion of All Reviews

Unlike the auto-coded qualitative analysis done in NVivo where neutral sentiments where recognized, this manual binary classification was used when conducting the quantitative logistic regression done in STATA.

The reclassification process made it possible in such a way that all the reviews were incorporated in the quantitative analysis in a way that the data set that was used in logistic regression was consistent. However, it is possible that this lead to different sentiment categorizations than that found through the NVivo auto-coding. The dataset used for STATA was binary sentiment, and so the analysis could be undertaken separately under positive and negative categories in logistic regression.

3.6.3 Logistic Regression Analysis

The review data was subjected to logistic regression analysis, which utilized independent (explanatory) variables. In addition, this study used marginal effect estimation to examine the impact of sentiment as the dependent variable. The software STATA was employed to determine the overall outcome of the variable. Additionally, it emphasized the effect on the likelihood of receiving positive or negative sentiment when there is a one-unit change in a predictor variable. The phrase "one-unit change" refers to a modification of a predictor (independent) variable while keeping all other variables constant. This study conducted an estimation to determine the direction and magnitude of the influence of certain review variables on consumer sentiments.

This research methodology enabled the analysis of the correlation between consumer sentiment and the review valence indicators obtained from both Amazon and the Manufacturer's e-commerce shop, utilizing variables and measurements. The study incorporated marginal effect and logistic regression analysis to investigate the intricate relationship between sentiment and independent factors. Its main objective was to uncover markers of sentiment valence in reviews for two different e-commerce platforms.

3.6.4 Dependent Variable

Sentiment valence is the dependent variable in this research, extracted from the sentiment analysis performed on the consumer reviews of both platforms. The classification of each sentiment as negative, positive, or neutral based on emotions and language written by customers in their text-based reviews was included in the process of sentiment analysis. With the use of sentiment analysis on reviews, the research was able to gather insights into the prevalent behavior and consumer perceptions, as well as determine the polarity of the review.

3.6.5 Independent Variables

These specific independent variables were selected because they carry the likelihood of forecasting the valence of customer's feelings and sentiments. In addition, to analyze the relationship between each of the chosen variable and sentiment polarity, the method of logistic regression was used to avoid errors. Some of the variables are categorical which came useful in determining the efficiency of the logistic regression model. Logistic regression therefore can be described as a statistical approach for developing the model of a relationship between a univariate dependent variable and one or more independent variables that are categorical in nature (Boateng and Abaye, 2019, pp. 190-207). In this case, the other utility of logistic regression model is to assess any impact that the categorical independent variables may bear in signaling disposition in the reviews as positive or negative.

The research covers selected explanatory variables that can possibly predict or reflect the sentiment direction of customer reviews. The following are the independent variables included in the analysis:

Total Character Count (TCC) - The total character count of reviews also known as the length of reviews was added as an independent variable. This variable is correlated by the logistic regression technique to determine the role of the length of reviews in indicating the sentiment valence of customers in both scenarios, either in the Amazon reviews or in the Manufacturer's online store reviews.

Incentivized Reviews (VNF) - The provision of incentivized products or giving away goods in return for reviews was selected as an independent variable on both e-commerce platforms. Programs such as Amazon Vine were evaluated as a potential indicator of reviewers' sentiment polarity. Therefore, this factor of giveaways and vine-free products for reviews is categorized as an independent variable in this study to explore the role of incentive schemes in viably predicting the valence of customer feedback of those who received a free product.

Image Attachment (IMG) - The attachment of images in reviews was chosen as an independent variable. On both platforms, pictures were sometimes uploaded to reviews to show the visual examples of the product packaging or the effects after product usage. This independent variable was studied to determine if the reviews of the customers on both Amazon and the Manufacturer's website featuring images are indicative of positive or negative sentiment.

3.6.6 Methodological Approach

This methodological approach included logistic regression analysis and marginal effect estimation. Logistic regression is a commonly used statistical technique for classifying data into several categories. In this study, the categories being evaluated are positive or negative in order to assess the dependent variable. The logistic function used in the logistic regression model is also known as the "sigmoid function," used to assess the likelihood of an opinion relating to a specific class of sentiment, either positive or negative. Logistic regression analysis was used on review data based on independent (explanatory) variables. Moreover, through marginal effect estimation, this study analyzed the marginal effect of sentiment as the dependent (explained) variable with the help of STATA to find out the overall outcome of the variable. It also highlights the instant change or immediate impact on the probability of getting positive or negative sentiment for a one-unit change in a predictor variable. The one-unit change of a predictor (independent) variable by keeping other variables constant. By this estimation, the study identified the direction and the extent of the effects on the dependent variable, consumer sentiments, views that were quite helpful in considering the variables pointing to customer perceptions.

This segment can be summarized as follows: This research technique enabled a way to define and measure the dependent and independent variables so as to explore the correlation between consumer sentiment and the review valence indicators from Amazon and the Manufacturer’s e-commerce store. In applying a marginal effect and logistic regression analysis, the study aimed at investigating the interactions between the sentiment and the independent variables and identifying the overview of the valence of review sentiment for two different platforms of e-commerce.

3.7 Data Analysis Plan

In the context of analyzing customer behavior, a well-thought-out data analysis plan plays the crucial role of extracting meaningful and valuable information from customer reviews (Bilro, Loureiro and Souto, 2023, pp. 122-142). The data analysis plan in this study has two distinct phases: reflecting the application of both the qualitative and quantitative methods. In each step, efforts were made to understand the diverse and complex space of customers’ feedback. Both approaches were used to stake advantage of the statistical accuracy of numbers, as well as the deep insight offered by customer sentiment with descriptive analysis. This was useful in that it created an opportunity to assess the overall perception in sentiment analysis. This analysis focused on the key indicators that can accurately reflect customer sentiment, and the outcome of this dual mixed-methods analysis will furnish the essential information required for strengthening brand strategies.

3.7.1 Sentiment Analysis

The initial phase of the data analysis plan with NVivo entailed conducting a comprehensive sentiment analysis on customer reviews. NVivo is a beneficial tool for discovering the intricacies of the customer reviews collected from the websites of Amazon and the Manufacturer. The sentiment analysis categorized the sentiment into positive, neutral, or negative. NVivo goes beyond basic analysis by enabling the identification of sentiments within qualitative data, including words and phrases that convey emotions (Wong, 2008, pp. 14-20). A primary objective of this analysis was to identify conveyed sentiments in the reviews, and to disclose frequent themes by applying sentiments to visual images such as word clouds and hierarchy charts for evaluation.

Regarding this sentiment analysis, it’s prudent to acknowledge the varied behavior of consumer sentiment and the emotions derived from the textual data. The ideas and the distinctive actions of reviewers depict a broad spectrum of positive to negative sentiments, and it would be plausible to analyze trends and the customer’s perspectives. The Analysis provides a significant understanding of the behavior and the attitude influencing the actions of the consumers by categorizing sentiments.

Furthermore, the quantitative length of the reviews was also measured as it can be related to the understanding of consumers and the intensity of emotions involved. This was done through integration of different activities in NVivo whereby data is managed and sorted (Aggarwal and Aakash, 2020, pp. 361-376). With the help of the division of the described reviews according to the character count, it was possible to gain a significant amount of understanding of the length of the reviews as the potential indicator of the sentiment valence.

3.7.2 Regression Analysis

After the completion of the qualitative data analysis using NVivo software and sentiment analysis of the textual data set, the next step in the data analysis plan was to perform regression analysis. In this analysis, the statistical software STATA was used in data analysis. This is the quantitative analysis type that un-complicate the complex relationship between sentiment variation and review features, that lead to a deeper comprehension of the elements that can predict the consumer's sentiments identified in the reviews. To identify the behavior of the impact of every aspect of the reviews on the sentiment of customers, the method used in this study involves regressing the polarity of sentiment over the explanatory variables (Mertens, Pugliese and Recker, 2017). To increase the comprehension of the complex interconnections between these variables, the research aimed at verifying the connection of options, such as review length, incentivized reviews, image attachment in the review, and sentiment valence. This was done by descriptive and regression analysis by estimation of marginal effects. Notably, incorporating NVivo of qualitative analysis with STATA of quantitative analysis, the Study obtains a general and comprehensive examination of the review sentiment, thereby enabling the Study to pay attention not only to the presence of opinion but also to the valence of opinion.

3.7.3 Integrated Approach

The data analysis plan applied an integrated or mixed method approach to study the relationship between quantitative and qualitative methods. This was achieved through an understanding of sentiment expressed in online evaluations. The combination of integrated approaches assisted in comprehending the emotional tones of consumer reviews while providing statistical and mathematical analysis. This hybrid research approach facilitated the acquisition of valuable insights, which are crucial for developing effective business strategies to enhance the success of products on e-commerce platforms. The outcome of this type of mixed analysis can assist e-commerce sellers with the decision-making process leading to more successful outcomes.

This data analysis exemplifies the methodological approach to understanding the intricacies of consumer sentiment extracted from customer feedback from the selected e-commerce shops. The objective was to analyze the quantitative and qualitative aspects of customer reviews by leveraging STATA and NVivo, which provide a thorough understanding of customer opinions. By applying an integrated framework, the research endeavored to abstract understandings that will assist planned decision-making and lead to the success of organizations in the field of e-commerce.

3.8 Ethical Considerations

Ethical consideration plays a vital role in sustaining the credibility of the study and preserving the rights of participants' confidentiality while conducting qualitative research. This research focuses on conducting sentiment analysis on customer evaluations obtained from publicly available secondary sources, including the Amazon store and the Manufacturer's e-commerce website. The study ensures the dependability, impartiality, and ethical behavior by meticulously incorporating and adhering to ethical principles at every stage, ranging from picking the research topic to collecting and analyzing data, and employing various statistical and qualitative methodologies. The study prioritizes the incorporation of accountability, impartiality, and conformity to standards in each step, and it acknowledges the pivotal role of research integrity (Weinbaum, 2019). Ensuring academic credibility highlights the ethical context of the study and stresses the significance of impartial, truthful, and ethical analysis methods.

3.8.1 Selection of Research Theme

The study was carried out on the selected research theme which is the evaluation of sentiments of customers from two e-commerce stores for the identical product. The ethical dimension was thoroughly examined from the outset of the research. The chosen research topic was clearly defined, aligning with academic and research goals, while also adhering to ethical norms that pertain to society and the persons whose online, publicly available data is being studied.

The study focused on evaluating the sentiment of reviews received through Amazon and the Manufacturer's online shop, with a particular emphasis on its potential impact to individuals. Hence, to reduce the impact of the invasion of the privacy of the consumers, the study focuses on a subject that sources secondary data easily accessible to the public to understand the sentiment of the consumers.

3.8.2 Data Collection

The stage of information collection was conducted strictly in compliance with the requirements of ethical standards and demonstrated constant attention and protection of the rights of the responders. The data was collected from a secondary source and as such, certain ethical issues were observed while seeking and using information that was gained from Amazon, as well as the manufacturer's retail marketplace. Some of the elements of this ethical approach were strict compliance with the usage guidelines or permissions necessary for one's access and evaluation.

Also, the research adopted a practical approach to moral authenticity and used techniques to maintain the customer's privacy and confidentiality. Through observing ethical actions at each stage of the process of data collection, the research indicates observance to ethics and at the same time creates a positive image and confidence from the customers. The follow-up of ethical standards enabled the safeguarding of the research's integrity and the anonymity of the reviewers (Fouka and Mantzorou, 2011, pp. 3-14).

3.8.3 Open Access for Secondary Data

The information employed in this study was easily accessible and the Internet was used as the source of the data for this study since the data is public and intended for educational utilization and research. In this research data were collected from the public domain of both Amazon and the Manufacturer's platform and it shows the standards that exist for ownership of rights of data.

3.8.4 No Potential for Harm

Ethical consideration was embraced to diminish any potential harm to reviewers or participants involved in the overall process of research. Damage can be of different types such as emotional, physical, psychological, and confidentiality-related damage (Fleming and Zegwaard, 2018, pp. 205-213). Various types of damages were considered, and ethical means were applied from the starting position to the end of the research. Subsequently, in this study, to reduce the damage to the reviewers whose feedbacks were collected, consideration was given to confidentiality and privacy. The reviewer screen names and identities were kept anonymous in the data collection stage avoiding the collection of personal identifiable information (PII), and the images attached by reviewers in their feedback were kept confidential even though they were posted on the open Internet, accessible by the masses. Respect of privacy was a top priority throughout this study.

3.8.5 Data Accuracy

Accuracy of the results is important to make sure that a study is done ethically. This is disadvantageous in research because the data collected may have variations which will lead to wrong conclusions of analysis or wrong conclusions and recommendations which are not healthy for the research process. Therefore, various strict actions were taken in the research endeavor to ensure that the gathered data is accurate as well as consistent. To manage the threat of using inaccurate data the criterion of data accuracy, which included the method used to gather the data and the reason as to why the data was collected, was utilized. It is a prerequisite for building data trust within a study as noted above. Among all the factors of data reliability, data accuracy is the most significant one, by which data can declare its value and credibility. In the data preprocessing, a manual examination of the data was done to check for their validity in this study.

3.8.6 Data Analysis Process

This is the process that was followed to extract relevant information from the obtained and preprocessed data set. While analyzing the data there was strict adherence to ethical considerations taken into account. Since the focus is on maintaining rigor and ensuring the reliability and validity of analysis, data analysis must be conducted according to ethical standards (Harriss, MacSween, and Atkinson, 2019, pp. 813-817). In NVivo 14, the process of embedding sentiment was used and for the logistic regression model, STATA was used. While performing the analyses, any possible bias from either of the datasets collected was avoided through manual review. Thus, using such an approach, the study was able to achieve the goal of minimizing biases in the results obtained. From the customers' reviews, sentiment analysis entails the extraction and analysis of feedback, feelings, and other attributes. This makes provision of an overall view of the customers' opinion about a product. The study does not require any identification information about the reviewer and thus makes sure that the reviewer remains anonymous.

Another consideration in the ethical assessment of information is the degree of dependency and access (Vecchio, Tiznado-Aitken and Hurtubia, 2020, pp. 354-381). In addressing the research questions of this study, these methods may be utilized by other scholars in furthering the knowledge base in the future. The sharing of information however should be balanced with the provision of privacy and consent necessary to protect people's rights.

Furthermore, the practice of logistic regressions was employed to establish the interaction between the customers' attitudes and the review characteristics. For such research, it is mandatory to ensure that analysis is completed effectively without rigging the outcome that is needed. In returning the emphasis on an ethical approach leading to the analysis of data, the research does not lose the ethical norms of carrying out the investigation and keeps the faith and relevance of the outcomes.

3.8.7 Conclusion

Ethical consideration is an important aspect of conducting research. It is a crucial part of research planning to ensure ethical implementation in the study. For sentiment analysis of Amazon and the Manufacturer's reviews, the upholding of the ethical considerations was of paramount importance. From the beginning of the research thorough data analysis, principles of ethics have been incorporated to ensure viability of the research and maintain the rights of reviewers. By maintaining ethical standards, endorsing clarity, and reliability during the research, this study provides important insights to customer sentiment and also prioritizes participant privacy. Ethical consideration is a fundamental aspect of this research ensuring the rights and privacy of participants.

CHAPTER IV

RESULTS

Sentiment analysis of customers' reviews from two platforms for a single product was conducted using NVivo 14, a premier software for qualitative data analysis. The purpose of using NVivo was to analyze customers' sentiments and feelings from their reviews of the chosen cosmetic beauty product. The product chosen for examination is purposefully a skincare product, an area where making concessions is usually not an option (Al-Fattal and Aldebe, 2022, 1-58). The aim was to apply sentiment analysis to reviews of the skin care product collected from the two distinct platforms, Amazon and the Manufacturer's e-commerce website. The customers' reviews were gathered, encompassing all pertinent information about the reviews, in order to examine the feelings and sentiments conveyed in them. The aim was to determine how the polarity of the sentiments were related to specific attributes of the reviews.

NVivo's powerful text sentiment coding and other advanced capabilities make it efficient for extracting feelings from customer evaluations (Saura, Palos-Sanchez, and Grilo, 2019, pp. 1-14). The auto-coding feature of NVivo 14 was used to conduct a sentiment analysis of the given survey dataset for qualitative analysis. The sentiments were detected by this function and as a result, the classification of sentiments was provided as highly positive, moderately positive, highly negative, and moderately negative. These sentiments were classified using NVivo based on lexicons and vocabularies. By evaluating the emotions present in the reviews, NVivo provided the optimum result for each category of sentiment.

NVivo's ability to detect sentiments and ascertain emotional valence within a given environment is enhanced by its visualization features, which enhance its efficacy in visually representing detected themes and emotions in a comprehensible manner. NVivo 14 has a built-in feature for transforming data into various forms of charts and graphs, including word clouds, hierarchy charts, frequency tables, bar graphs, and code trees. The charts and other outputs provide for a visual representation, and a full comprehension of the patterns, trends, frequencies, and attitudes found in the provided data. For instance, the word cloud displays the presence of words in context, and the words with greater prominence relate to greater word frequency. Hierarchical charts visually depict the connections between various themes and sentiment-related codes in the data. Word trees are visual representations that depict a chosen word or phrase as the central point, with branches illustrating the different situations in which the word or phrase occurs within the data. Bar graphs were constructed on a simple and comparative basis to represent a clear image of the sentiment distribution.

The sentiment analysis of the survey dataset was processed by the auto-coding feature of NVivo, which identifies repeated ideas and feelings. Sentiments were extracted and then classified. With the help of this categorical distribution, reviews gathered from Amazon customers who came across the product and purchased from the store were considered. Afterward, the same analysis was extended to include the reviews collected the same product on the Manufacturer's e-commerce store. The reviews were collected in the form of open-ended comments, along with the relevant attributes for sentiment correlation. The sentiments from the two different platforms were systematically analyzed to unravel the intricacies of the feelings expressed by customers on each platform.

This comparative approach assisted with highlighting the similarities and variances in the emotions and feelings found in the reviews of both platforms. These open-ended reviews, along with the relevant information for the correlation of attributes with sentiments and emotions, were made possible by the identification of sentiments by NVivo. This systematic strategy, using NVivo's features, provided a nuanced and detailed explanation of the dynamic behavior of sentiments throughout the collected data.

For the qualitative sentiment analysis, the review data was categorized into positive and negative through manual coding, and regression analysis was performed using STATA, a statistical software for data science. Given that the characteristics of the dataset contained categorical variables, the statistical method employed for the regression was multivariable logistic regression analysis (Liang, Zeger and Quaqish, 1992 pp. 3-24). This methodological approach is based on the inclusion of a dependent variable that measures the sentiment of customers. Other variables, such as the provision of Vine-free or incentivized products, the length of reviews, and customer-uploaded images, were used as independent variables.

Managing datasets with STATA is efficient when it comes to logistic regression, and this allowed for the handling of complex-natured categorical variables. In addition, it enabled a correlation of sentiments extracted from the reviews and the other independent variables to be estimated. The study encompasses the characteristics of customers' reviews and the review attributes that indicate the customers' attitude when expressing their opinions through a review.

Customers' biases and preferences for giveaways or free product offers were analyzed through the relationship of Vine-free product utilizing sentiment polarity as the dependent measure. Additionally, the images uploaded by the customer in their reviews (user generated content) are relevant too in the process of developing an understanding of the customer, and their indication on review polarity (Kübler, 2024, pp. 5-23). Likewise, the length of the reviews were also analyzed to evaluate its correlation to the emotional valence of the customers, therefore, it was added as a necessary component in the study.

The use of STATA for performing logistic regression analysis provided deep insights into the multivariable system allowing for the study of the relationships between consumer sentiment polarity and these self-reliant variables. Subsequently, the marginal effect of the output result from the regression was estimated to analyze the influence of the instantaneous unit change of each variable on sentiment, while keeping the other independent variables constant. This approach of taking the partial derivatives of the regression equation by estimating the marginal effect provided a deep analysis of the given dataset.

The remainder of this chapter is organized as follows: Section 4.1. Provides an overview of the dataset using descriptive analysis. Section 4.2. provides a sentiment analysis of Amazon's customer reviews. Section 4.3. comprises a sentiment analysis of reviews gathered from the Manufacturer's online store. Section 4.4. showcases a comparative analysis of the sentiments of both platforms. Section 4.5. provides a regression analysis of the Amazon reviews. Section 4.6. provides a regression analysis of the Manufacturer's online store reviews. Section 4.7. explains the comparative analysis of the regressions of both platforms. Section 4.8. presents the findings and a summary. Section 4.9. summarizes this chapter with the chapter conclusion.

4.1 Descriptive Analysis

The descriptive analysis, as represented in Table 1 below, provides useful insights into the sentiments and other attributes included in the review content for the product on both the Manufacturer's website and Amazon. The sentiment score measures the positive sentiments conveyed by customers in their evaluations, while the other variables associated with review characteristics display notable variations. On Amazon, the standard deviations of sentiment scores and total character counts of reviews indicate a greater degree of variety. The average length of Amazon reviews is greater than that of the Manufacturer's evaluations, with a small percentage, 9.6%, containing picture attachments and 21.6% marked as participating in the Vine-free program. In contrast, the sentiment scores of the Manufacturer reviews are more consistent, and they tend to be shorter compared to the Amazon reviews. In addition, the evaluations also exhibit a significantly higher occurrence of sponsored free products, 96%, and a larger percentage of image attachments, 40%. These findings emphasize the intricate dynamics associated with evaluating the sentiment of evaluations obtained from these two sites.

Table 1. Descriptive Analysis Table

	Amazon's Reviews			Manufacturer's Reviews		
Variables	Mean	Mode	Standard deviation	Mean	Mode	Standard deviation
Sentiments	0.6	1	0.49	0.94	1	0
Total Character Count	303.18	64	989.11	222.85	170	119
Vine-free and sponsored free product	0.216	0	0.41	0.96	1	0.18
Image Attachment	0.096	0	0.30	0.40	0	0.49

(Jason Raphael, 2024)

The table above presents an extensive overview of the descriptive statistics and relevant factors across both Amazon and the Manufacturer's web store for the given cosmetic beauty product. Remarkably, despite reviews on both platforms being typically positive, the mean sentiment value of reviews on Amazon is 0.6, while the mean score of manufacturer reviews is 0.94, indicating a frequently favorable opinion of the product linked to the Manufacturer's e-commerce website. Additionally, the average character count of Amazon reviews was 303.18, which is significantly greater in length than that of the Manufacturer's reviews at 222.85. This finding suggests that Amazon consumers are more likely to provide comprehensive feedback. For the Vine program or incentivized offers, it is noticeable that 96% of the reviews on the

Manufacturer's product page were incentivized with a complimentary product, whereas Amazon reviews have a lower prevalence of 21.6% designated as a Vine-free product.

The modes demonstrate this difference, with the Manufacturer reviews primarily demonstrating VNF having a mode value of '1' and Amazon reviews exhibiting non-VNF more frequently having a mode value of '0.' In addition, although image attachments are not overly common in Amazon reviews at 9.6%, image attachments are more prevalent in the Manufacturer reviews, showing a 40% presence in total reviews.

The various aspects of customer feedback on Amazon and the Manufacturer reviews are illuminated by these descriptive statistics, which reveal unique traits and deviations in the sentiment analysis of customer reviews.

4.2 Sentiment Analysis of Amazon Reviews

Sentiment analysis began with Amazon customer reviews. Essential data was uploaded to the NVivo software following careful data cleaning and preprocessing, which included the eradication of the customer ID, review links, and other identifying details. Subsequently, the data was transformed into a useful format using the auto-coding method. NVivo provides a clear and comprehensive analysis of word clouds, tree-maps, bar charts, and hierarchy charts. The outcomes, including graphical displays, were exported and carefully interpreted to obtain significant insights from the dataset. This methodological approach utilized the NVivo environment's quick data processing and visualization to provide a thorough understanding of customer attitudes.

4.2.1 Overview of Sentiments - Amazon

NVivo evaluated a wide range of attitudes in each Amazon consumer review, and a hierarchy chart was generated to visually represent the results. Using this analytical method, it was identified that distinctions and complex patterns of emotional expressions were found in the dataset.

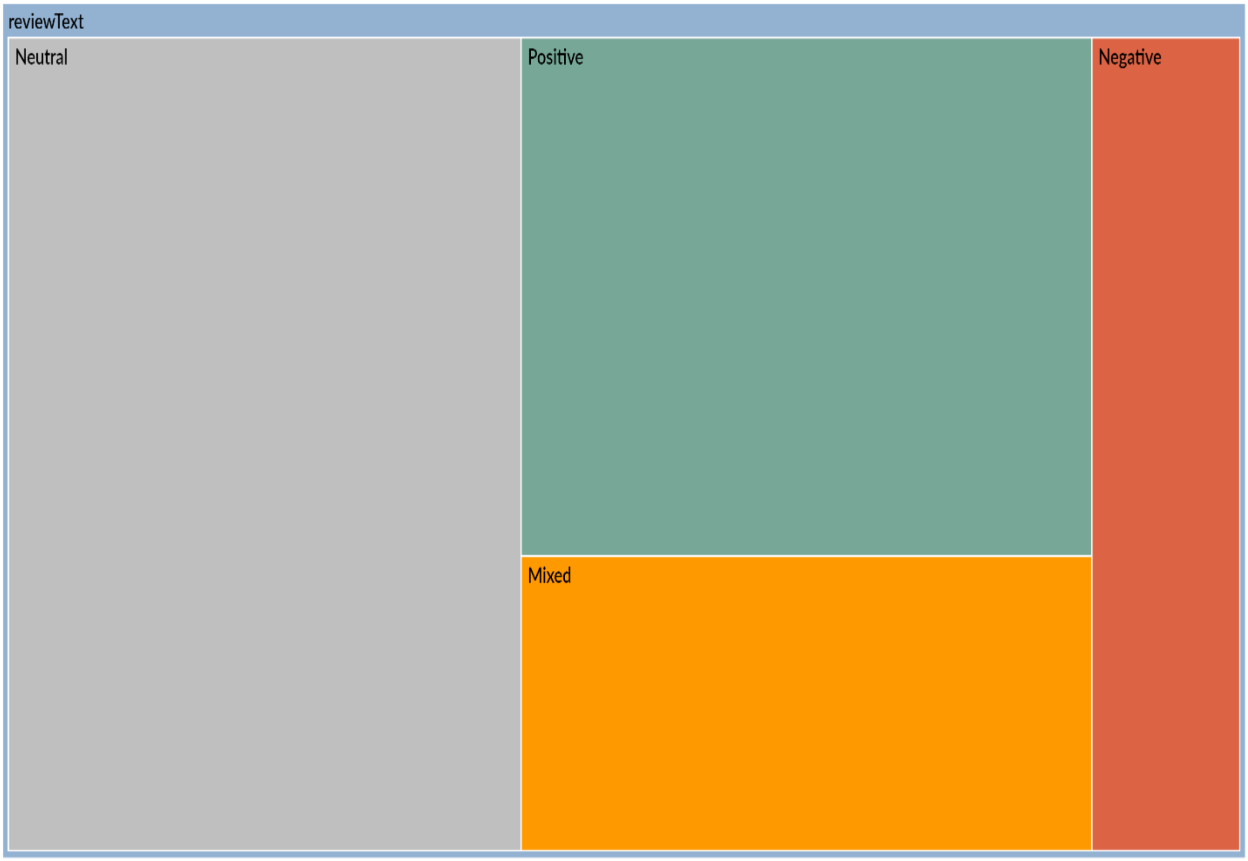

Figure 3. Hierarchy Chart of Sentiments – Amazon Reviews

Chart generated by NVivo (QSR International, Version 14, 2024)

The hierarchy chart of the Amazon reviews in Figure 3 displays the sizable and important sections devoted to 'Neutral,' 'Positive,' 'Negative', and 'Mixed' reviews. However, strong or moderate positive as well as strong or moderate negative sentiments were not observed in this distribution. The large number of neutral evaluations indicates that a significant number of consumers do not overtly support or criticize the product in the review text according to the NVivo analysis.

A lower but significant number of positive evaluations are located next to the neutral category. These evaluations express contentment, endorsement, or favorable experiences with the product. The positive segment shows that some customers are satisfied with specific features of the offering, which adds to the overall positive attitude.

A smaller section is devoted to negative assessments, in contrast to the predominately neutral and positive segments. These reviews provide complaints, critiques, or unfavorable experiences. Reviews that express dissatisfaction with products are scarcer, indicating that most customers are generally content.

Although hierarchical classification primarily defines discrete categories for positive, negative, and neutral emotions, it is essential to recognize the possible interaction and interdependence between these categories. Neutral reviews, even if supposedly objective, might display a subtle convergence of both good and negative aspects, capturing each aspect of customers' complex or divergent viewpoints.

4.2.2 Detailed Analysis and Classification of Sentiments – Amazon

The sentiment analysis of Amazon reviews conducted using NVivo 14 employed lexical analysis to assess reviews with the utilization of language and vocabulary (Wilk, Soutar, and Harrigan, 2019, pp. 94-113). Reviews that included critical or unfavorable language were categorized as negative, whereas evaluations that included phrases expressing admiration, appreciation, or contentment were categorized as positive. Thus, this lexicon is gauged by the auto-coding feature of NVivo, resulting in the identification of positive and negative sentiments and their percentage coverage in the references and frequency of emotional words presented in the reviews. An example representation of the sentiment data produced by NVivo is presented in Table 2 below, which shows the distribution of both positive and negative sentiments for Amazon reviews only. The displayed coverage percentage of the positive sentiments is a percentage of the total positive Amazon reviews. The displayed coverage percentage of the negative sentiments is a percentage of the total negative Amazon reviews.

Table 2. Reviews Classification of Sentiment Analysis – Amazon Reviews

AMAZON REVIEW SURVEY		
Sentiments	**Reviews**	**Coverage**
Positive	I love that its free of alcohol and fragrance and has no scent	0.05%
Positive	I will always need concealer but I feel my under eye area appears brighter	0.05%
Negative	Silicones are hydrophobic so they repel water which makes them really hard to wash off	0.01%
Negative	It was really hard to get off and there was still some left on the bottom part of the jar I just could not get off I always hate that	0.01%
Positive	I do also use a brightening serum at night under this cream	0.04%
Negative	However after regular use of it, it started irritating my skin, which was odd for me because my skin isn't sensitive at all	0.01%
Positive	It's fragrance-free paraben-free phthalate-free and dye-free	0.01%
Positive	It feels nice and refreshing	0.01%
Negative	But the idea that silicones are bad for clogged pores may come from the fact that they are occlusive	0.01%

(Jason Raphael, 2024)

The sentiments were divided into positive and negative categories. The feedback received from customers on Amazon varies in valence, revealing a relatively balanced mix between positive and negative syntax, which demonstrates the randomness of the data and unbiased behavior of customers while providing feedback on the encountered product. This randomness could be due to the variety of customers present in the Amazon store as well as chance encounters with this particular product while browsing. The provision of positive comments relates to product attributes, including the product being free from alcohol, non-irritating, having a pleasant fragrance, no parabens, and no dye. These product characteristics are appreciated by customers, and positive emotions can be observed in the reviews when mentioning these advantages of the product. However, consumers also admired the sensational and refreshing texture of the product, which can be seen in the positive classification of review sentiments.

On the contrary, negative comments were also present in the reviews; and these comments were mainly focused on product efficiency and performance. Reviewers mentioned the product's ineffectiveness in resolving skin problems, and some reviews demonstrated dissatisfaction by mentioning itching, irritation, and a burning sensation on their skin. Nevertheless, Amazon's store features both a portion of negative and positive remarks simultaneously in the same reviews, indicating the impartiality of the reviews on this site.

This sentiment analysis of reviews collected from Amazon's store for this particular product revealed useful insights into the customer experience. The flaws mentioned by the consumers are potential product improvement opportunities (Goldberg and Abrahams, 2022, pp. 1-13). For instance, the perceived ineffectiveness of the product needs to be addressed, and the skin irritation problems needs to be corrected in the formulation. Similarly, the positive comments about the composition and refreshing texture of the product highlight the outstanding physical consistency of the product that consumers appreciate. The analysis of sentiment categorization and emotional patterns can assist businesses with taking more advantageous decisions to improve the quality of their products and raise customers' contentment levels through the effectiveness of this study. The identification of sentiments using NVivo's auto-coded sentiment analysis can lead to companies making better informed decisions about what their customers want and expect from their brands and products.

The distribution of positive and negative sentiments present in the Amazon reviews are further classified into the subgroups of 'Very Positive' and 'Moderately Positive,' similarly, 'Very Negative' and 'Moderately Negative,' as illustrated in Figure 4. This classification expands the understanding of customers' specific attitudes. The Positive section including the 'Very Positive' and 'Moderately Positive' occupies more area than the Negative sentiment sections. This disparity is evidence of a higher number of satisfied customers among the Amazon cohort of purchasers, and suggests that positive customer feedback prevails. This hierarchy chart of the various amplitude of sentiments improves the accuracy of understanding sentiment classification by providing a clear picture of the sub-categories rather than a mere general distribution. With the assistance of this complex classified model, it is simpler to gauge the levels of positivity and negativity in context. This detailed approach not only improves the visualization perspective of sentiments, but also offers a more insightful interpretation of emotions.

Figure 4. Subcategories of Sentiments – Amazon Reviews

Chart generated by NVivo (QSR International, Version 14, 2024)

The reviews garnered from Amazon's store are comprised more of appreciation, admiration, and contentment, which can be seen in the above pictorial analysis labelled Figure 4, in which more areas are possessed by positive domains. The greater area, which is the combined orange region is also an endorsement of the high level of customer satisfaction in comparison to the negative ones reflected the blue region. This favorable opinion not only expresses the contentment of the customers of this particular product on Amazon, but also enhances the brand's reputation among shoppers who find the product on Amazon. However, the category labeled as 'Moderately Positive' occupies a larger portion of the chart compared to the category labeled as 'Very Positive'. This indicates that within the overall 'Positive' area of the hierarchical chart shown in Figure 3, there are more comments classified as ‘Moderately Positive’ in relation to ‘Very Positive’ comments. This finding implies the range of customer reviews classified as ‘Positive’ is distinguished by a significant majority of opinions that fall into the ‘Moderately Positive’ category, highlighting a more complex and graded positivity. This distinction elucidates how positive sentiments are distributed by emphasizing the frequency of ‘Moderately Positive’ statements within the larger positive portion, as seen in the hierarchical representation shown in Figure 3.

The smaller percentage of comments classified as ‘Very Negative’ and ‘Moderately Negative’ implies that complaints or unfavorable remarks are not extremely common. Although there are unfavorable opinions, their lesser frequency suggests that most consumers’ experiences are more aligned with moderate contentment. The product manufacturer may address particular issues revealed in the reviews and improve the overall customer experience by utilizing these sub-categories of sentiment, which helps to identify areas that may need improvement and increase the proportion of ‘Very Positive’ in customer reviews. In conclusion, the hierarchy charts highlight a landscape of largely favorable attitudes on Amazon, highlighting the necessity for the company to build on its strengths while addressing areas where they may be able to improve the product and brand perception.

Utilizing NVivo’s data visualization feature for sentiment analysis, a bar chart was created to improve the accuracy of the sentiment distribution assessment which can be seen in Figure 5. It offers a detailed depiction of the sentiment percentages, carefully distinguishing between positive and negative phrases. The chart provides a thorough summary of the category distribution in reviews and precise information on sentiment fluctuations. Using this chart not only makes sentiment prevalence simpler to grasp, but also ensures a thorough analysis of the clearly distinguished positive and negative sentiments, which adds to a more deliberate and comprehensive examination of the sentiment landscape in the Amazon review dataset.

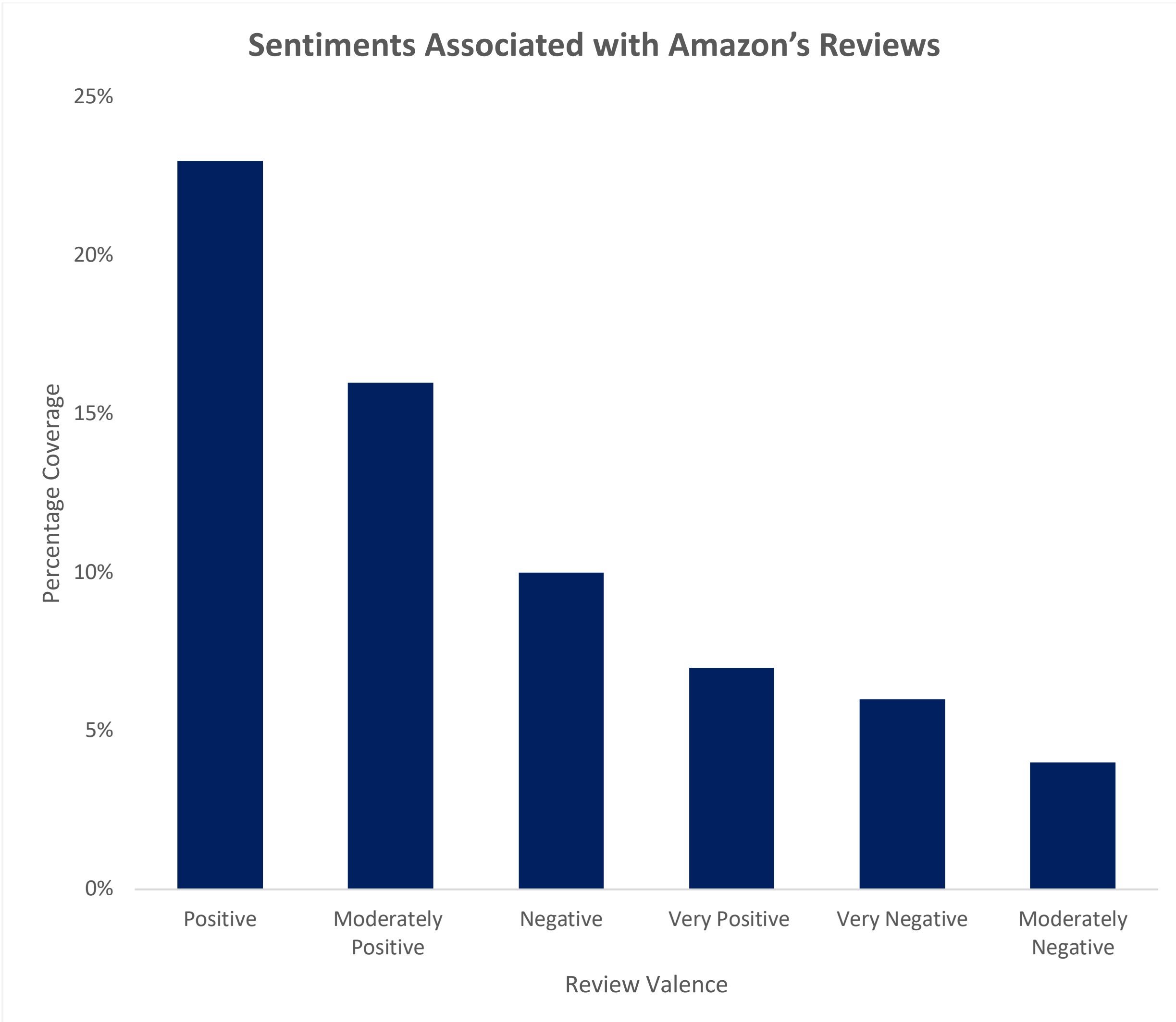

Figure 5. Bar Chart of Sentiment Analysis - Amazon Reviews

Chart generated by NVivo (QSR International, Version 14, 2024)

Based on the results of the Bar Chart of sentiment analysis, the majority of Amazon customers had positive experiences with the product when compared to other sentiment classifications. A significant proportion of customers expressed passionate acceptance of and contentment with the product, as seen by the 23.33% of the total review dataset which contains 'Positive' valence. Of these positive reviews, 15.89% demonstrated 'Moderately Positive' comments, indicating a sizable portion of customers who had a positive but somewhat more cautious viewpoint, and 7.43% of the total positive Amazon reviews which are considered as 'Very Positive'. Remarkably, only 10.16% of the total Amazon evaluations were 'Negative', suggesting that a relatively small percentage of consumers were unsatisfied with their purchases. Among these 10.16% adverse portion of reviews, 5.80% were shared by 'Very Negative' sentiments in the reviews, whereas 4.35% of these were 'Moderately Negative'. The significant disparity between the proportion of favorable and unfavorable reviews highlights a high degree of general customer satisfaction. The low proportion of unfavorable reviews suggests that overall, customers' expectations have been fulfilled or surpassed, which reflects positively on the product. This sentiment analysis sheds light on the favorable customer experiences that customers experienced with this particular product which was purchased directly from the Manufacturer's listing on the Amazon platform.

4.2.3 Word Frequency Analysis – Amazon

The word frequency analysis of sentiments comprises several outputs including a word cloud, frequency table, and hierarchy chart of codes. These methods reveal customers' intentions and concerns, while providing insights into the frequency of words and phrases in their reviews. The words and phrases can lend deeper insights into customer purchase intention and sentiment. For companies to successfully connect with their customers, they must comprehend these word dynamics. A comprehensive tree map was produced in the NVivo-assisted analysis process by examining the reviews left by Amazon customers for the product. This graphic depiction carefully lined up auto-coded themes as meaningful branches, while the leaves consist of commonly used terms below each theme cluster.

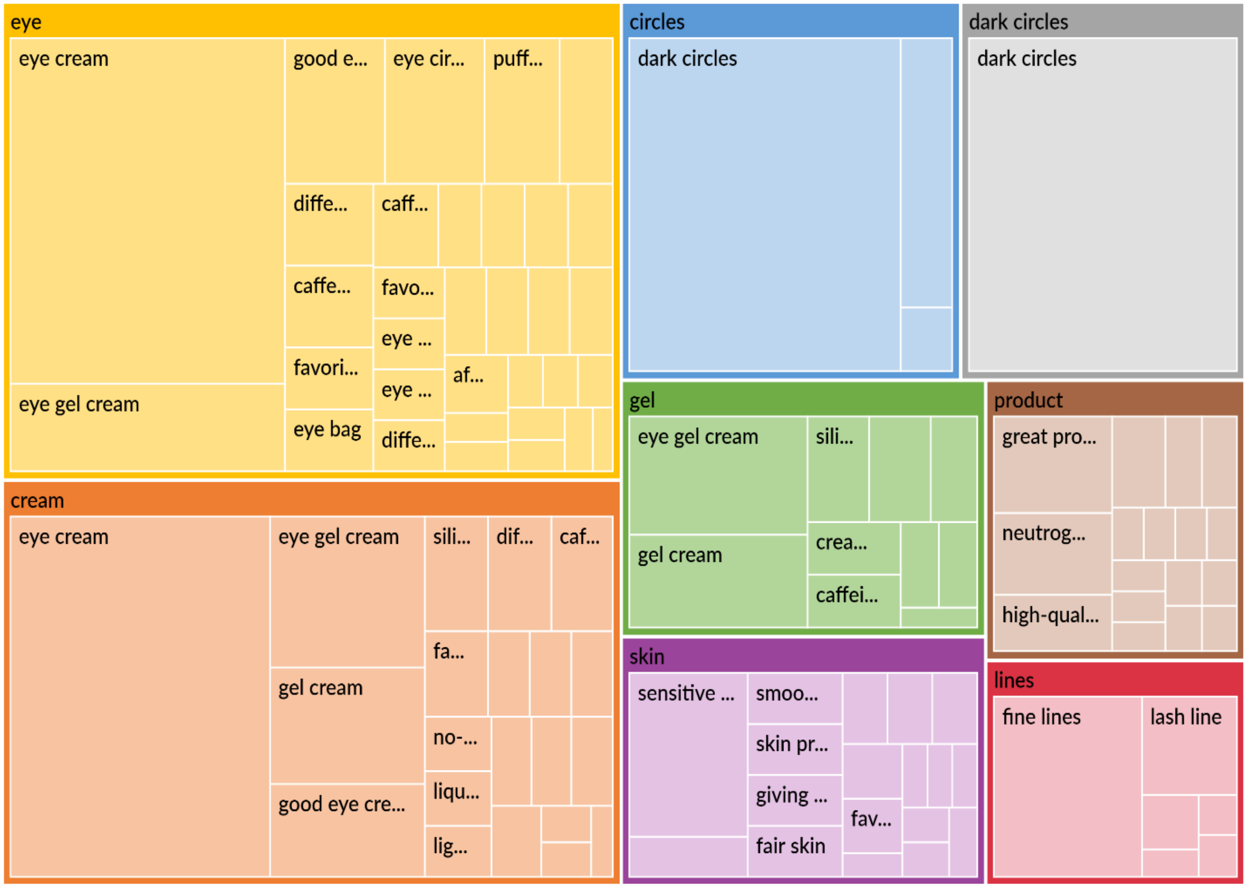

Figure 6. Tree Map of Amazon Reviews

Chart generated by NVivo (QSR International, Version 14, 2024)

Word trees provide an interpretive visual representation of the relationships between terms in the reviews, along with words that frequently occur alongside the pre-selected word.

Eye - Eye cream, Eye gel cream, Good eye cream, Different eye cream, Caffeine Eye gel cream, Favorite eye product, Eye bag, Eye circles, Caffeine Eye serum, Favorite eye, Eye Treatment, Eye water, Puffy eyes, Affordable eye cream

Cream - Eye cream, Eye cream gel, gel cream, good eye cream, silicon-based gel cream, face cream, no-frills eye cream, Liquid cream, lightweight cream, different eye cream, caffeine eye cream

Circles - Dark circles, eye circles, dark eye circles, tired circles, black circles

Gel - Eye gel cream, gel cream, silicon-based gel cream, creamy gel, caffeine eye gel cream

Skin - Sensitive skin, Smooth skin, Skin product, Giving skin, Fair skin, Favorite skincare items

Dark circles - dark circles

Product - Great product, Neutrogena Product, High-quality product

Lines - Fine lines, lash lines

The skillful use of NVivo's analytical algorithms highlights the importance of particular terms, clarifying the issues that customers are most concerned with. The prevalence of frequently used words, which are deliberately emphasized to define the most important topics in consumer discussions, highlights the strength of theme representation. The size of the associated rectangles for terms in this Tree map indicates the frequency in which the terms are found in the reviews. Words like "eye," "eye cream," "gel," and "circles" imply a heavy emphasis on issues relating to the eyes, such as dark circle treatment. It appears that "eye cream" and "gel cream" are the more commonly mentioned product categories based on their wider areas. The rectangles with the label "dark circles" indicate that customer feedback often addresses this particular situation or concern. There are also less common phrases like "puffiness," and "sensitive," which may relate to the intended results of the product which is perceived as an eye cream or gel.

The Tree map highlights popular product categories, customer sentiment, as well as the most frequently mentioned features of the skincare product. In general, it functions as a visual summary of the main topics of Amazon's users' evaluations. It enables the quick recognition of the prominent characteristics of client feedback regarding this eye skincare product.

Table 3. Frequency of Words in Amazon Reviews

Amazon Review	Frequency of Words
A : Circles	23
B : Cream	45
C : Dark Circles	20
D : Eye	61
E : Gel	16
F : Lines	15
G : Product	22
H : Skin	25

(Jason Raphael, 2024)

Table 3, along with the tree map in Figure 6 provides useful insights into recurring themes and customer concerns by displaying the prevalence of particular terms taken from the Amazon reviews. Interestingly, with 61 references, the term “Eye” (entry D) occurs the most frequently, correctly suggesting the focus is on a product associated with eye area care. Additionally, the terms “Cream” and “Dark Circles” (B and C) repeatedly reoccur with 45 and 20 mentions, respectively, indicating a considerable concern of consumers for the skincare product which addresses dark circles under the eyes. Sixteen mentions of the word “Gel” (E) indicate a portion of the consumer base who mentions gel-based skincare products. Furthermore, terms such as “Skin” (H) and “Lines” (F) have 25 and 15 references, respectively, suggesting problems with skin texture and wrinkle lines are the main focus. This frequency table offers a summary of the most frequently occurring terms in the Amazon reviews, highlighting user concerns about the skincare product, eye care, dark circles, and associated skin conditions.

Figure 7. Word Cloud of Amazon Reviews

Chart generated by NVivo (QSR International, Version 14, 2024)

The Word Cloud illustrated in Figure 7 was created using NVivo. It visually represents common phrases and recurrent words found in customer reviews on Amazon for the product. This graphic effectively captures the overall feelings of customers and highlights the priorities and buying behavior that appear in the reviews of Amazon consumers (Al-Kindi and Al-Khanjari, 2020, pp. 1-15) for the product. The word cloud graphic condenses the overall themes of the customer reviews and the most significant issues that span the individual reviews of Amazon for the chosen product which was the focus of this study.

Based on the represented keywords, it can be presumed they are key topical elements in the reviews: eyes, cream, skin, and product. These terms allude to the effects of eye cream on skin health and hence, it can be considered that these terms are somewhat associated with the main problems and concerns of the customers. Their significant size indicates they are mentioned frequently, suggesting their direct and significant relation to customer experiences and interests. Surrounding these dominant words are terms such as, “puffiness,” “dark circles,” “caffeine,” and “sensitive;” these words might be referring to particular skin issues that consumers are trying to solve with this product. “Caffeine” seems to refer to an active component in the product known to have benefits in skincare, such as ridding dark circles under the eyes and reducing puffiness. In addition, there are brand-specific mentions in the word cloud that, although not as noticeable, possibly indicate some customer loyalty or brand recognition. The use of descriptive phrases such as “fragrance-free,” “hydrating,” and “lightweight” indicate attributes that consumers value or seek in skincare products.

4.3 Sentiment Analysis of Manufacturer’s Reviews

Sentiment analysis for the same product sold on the Manufacturer’s retail e-commerce website started with the reviews. The process was the same as the Amazon review analysis, in which essential data was uploaded to the NVivo software following careful data cleaning and preprocessing, which included the eradication of Customer ID, review links, and other identifying details. Subsequently, the data was transformed into a useful format using the auto-coding method in NVivo. Using word clouds, tree maps, bar charts, and hierarchy charts, NVivo streamlined the analysis process. The graphical results were exported and carefully analyzed, providing important insights from the Manufacturer’s reviews. This technique made use of NVivo’s relatively rapid data processing and visualization features to ensure thorough comprehension of customer sentiments.

4.3.1 Overview of Sentiments – Manufacturer’s Website

The detailed analysis of sentiments started with the overall distribution of sentiments presenting ‘Positive,’ ‘Negative,’ ‘Neutral,’ and ‘Mixed’ emotions. The hierarchy chart of text reviews derived from the Manufacturer's online store for the product shows a range of opinions, with a clear focus on 'Positive' ratings. It also displays aspects that reflect both mixed opinions and a low percentage of unfavorable reviews.

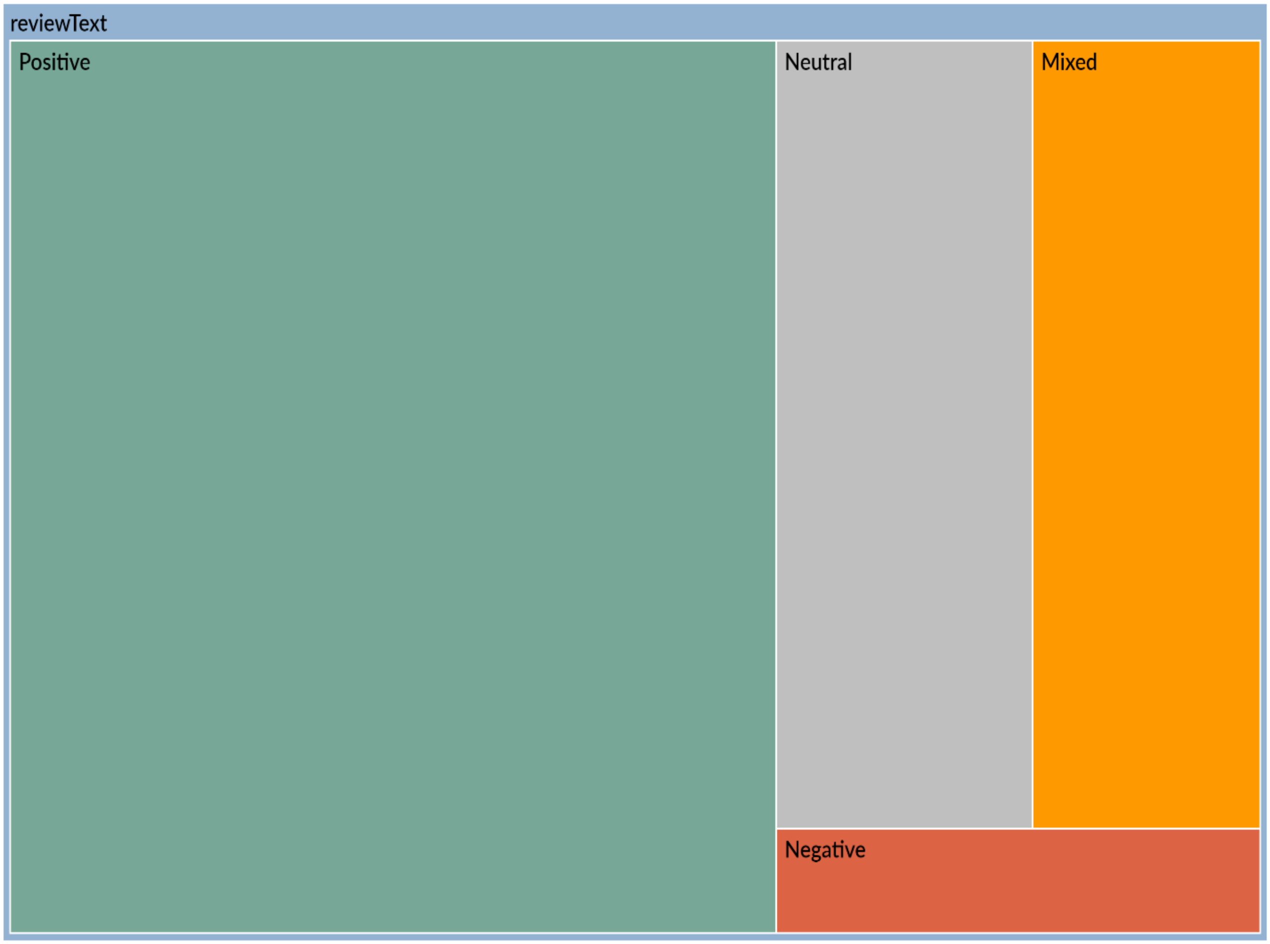

Figure 8. Hierarchy Chart of Sentiments – Manufacturer Reviews

Chart generated by NVivo (QSR International, Version 14, 2024)

As seen in Figure 8, a large green area labeled 'Positive' is devoted to agreeable thoughts that dominate the overall chart. This signifies a substantial proportion of satisfaction conveyed by customers who have had favorable experiences with the product they purchased from the Manufacturer's online store.

Adjacent to ‘Positive,’ there is a smaller, gray-colored area labeled ‘Neutral,’ which represents content that is neither favorable nor unfavorable and could include neutral or factual comments. Similar to the ‘Neutral’ portion in size, a ’Mixed’ sentiment (orange) occupies a vertical slice, suggesting that a meaningful proportion of evaluations are a combination of both positive and negative sentiments. This can be composed of customer reviews in which both appealing features and drawbacks of products are demonstrated simultaneously. On the contrary, the smallest area is occupied by ‘Negative’ comments which is denoted by the color red and represents discontent customers. However, the red area also exemplifies the opportunity for product improvement by interpreting consumer experiences and the issues encountered leading to negative sentiment. Thus, a comprehensive illustration of sentiments in the consumer reviews on the Manufacturer’s site for the product is provided by the hierarchy chart of sentiment, which endorses the high degree of positivity, distinguishes mixed sentiments from neutral comments, which are similar portion sizes on the chart, and the smallest region which contains negative sentiments in the Manufacturer’s product reviews.

4.3.2 Detailed Analysis and Classification of Sentiments – Manufacturer

For the sentiment analysis of the Manufacturer’s reviews, the subject data was processed by NVivo 14, which implemented lexical analysis to identify the valence of reviews. Reviews can be categorized as negative due to the presence of critical and unpleasant language, whereas positive reviews are measured by the existence of gratitude, appreciation, and admired words. These lexicons used for the identification of sentiments and feelings were specified by the auto-coding feature of NVivo for sentiment analysis, which determined the positive and negative sentiments along with their percentage coverage, reference of codes, and regularity in their pattern. Sentiment data offers useful information about the Manufacturer’s product by analyzing the reviews and opinions of customers. This method not only identified the major themes and emotional polarity in the reviews but also elucidated the view of the customers' perceptions and evaluations of the product.

The evaluated data from sentiment analysis by NVivo provided an extensive snapshot of the dynamics of customers' attitudes. Table 4 displays selected extracts of the sentiment classification (positive and negative) along with their coverage percentage. The positive percentage coverage is a percentage of the total positive manufacturer reviews. The displayed coverage percentage of the negative sentiments is a percentage of the total negative manufacturer reviews.

Table 4. Review Classification of Sentiment Analysis – Manufacturer Review

MANUFACTURER REVIEW SURVEY		
Emotions	**Reviews**	**Coverage**
Positive	It helped soothe some dry skin I had under my eye and brightened it up	0.08%
Positive	I loved it and it layers very well	0.03%
Negative	I was excited to see an improvement but saw no change	0.06%
Positive	Great product and affordable	0.02%
Negative	I didn't feel any significant difference by using this product in comparison with my other eye creams	0.07%
Positive	Overall a great product	0.01%

Negative	I have super dry skin and lately super baggy eyes	0.03%
Positive	I love a good eye cream especially one that my skin agrees with	0.05%
Negative	I've been using it for a week now so hard to tell if it will really make a difference	0.08%
Positive	I would recommend this to a friend and think this is a good one	0.03%

(Jason Raphael, 2024)

Table 4 illustrates excerpts of the sentiment analysis results of the Manufacturer's website reviews collected for this study of the product. It classifies opinions as either 'Positive' or 'Negative' and includes quotes from the reviews along with the coverage percentage of each sentiment type, that is, 'Negative' and 'Positive' in the customers' reviews on the Manufacturer's website. Positive reviews include optimistic points about how well the product works, how affordable it is, and how well it suits delicate skin. The advantages and application qualities of the product have been highlighted by reviewers. On the other hand, there were also unfavorable comments. Reviewers cite issues such as puffiness, dry skin, and dark circles, indicating places where the product might not have lived up to their expectations. Certain reviews seem cautiously optimistic, but others express doubts about the product's long-term effectiveness.

Sentiment analysis provides insightful information about customer opinions and experiences regarding the Manufacturer's product. This makes it possible to pinpoint a product's strong points and potential areas for improvement. Businesses can customize their product offers and marketing efforts by classifying reviews according to emotions (Lee and Bradlow, 2011, pp. 881-894). Using sentiment analysis software such as NVivo 14 makes it possible to analyze vast amounts of text data quickly and efficiently, revealing important themes and patterns in the reviews. Companies can enhance their customer experience and make well-informed improvement decisions by employing sentiment analysis of product evaluations, which provides valuable insights.

For a detailed analysis of the sentiments, a hierarchal chart was constructed using NVivo's function to show further classification of the required sentiments. As shown in Figure 9 below, the chart offers a fine-grained classification of customer attitudes from the text reviews, building on the sentiment analysis found in Figure 8, the hierarchy chart that was previously examined. To represent the intensity of the customer's sentiments, the sentiment spectrum was split into two overarching categories: 'Positive' and 'Negative,' as well as their respective strengths as seen in Figure 9.

Figure 9. Subcategories of Sentiments – Manufacturer Reviews

Chart generated by NVivo (QSR International, Version 14, 2024)

The ‘Positive’ sentiment is subdivided into ‘Very Positive’ and ‘Moderately Positive’ in the left section. ‘Moderately Positive’ feedback, represented by the color orange in the upper left quadrant, includes comments that are generally positive but may include some recommendations for enhancement or other less positive comments. On the other hand, the ‘Very Positive’ area denotes a portion of reviews that are overwhelmingly positive, demonstrating a high degree of customer satisfaction with the product.

The ‘Negative’ sentiment is represented on the chart’s right side, divided into ‘Moderately Negative’ and ‘Very Negative.’ The ‘Moderately Negative’ portion (highlighted in blue) represents less intense or less severe criticisms that are not critical. Reviews in the ‘Very Negative’ section express severe disappointment or significant concerns regarding the product. The lower frequency of negative attitudes highlights the fact that, while serious problems or significant discontent are less common, they nevertheless need to be addressed to improve overall sentiment polarity. In total, this hierarchy chart offers a clear visual summary that highlights the majority of favorable client attitudes, while alerting the company to negative reviews which can be focused on to improve the product.

The NVivo software generated a bar chart, seen in Figure 10, to refine the distribution of positive and negative attitudes. This refinement aims to improve the accuracy of the data presented in Figure 9. This bar chart data visualization enables rapid and accurate comprehension of sentiment trends in customer reviews.

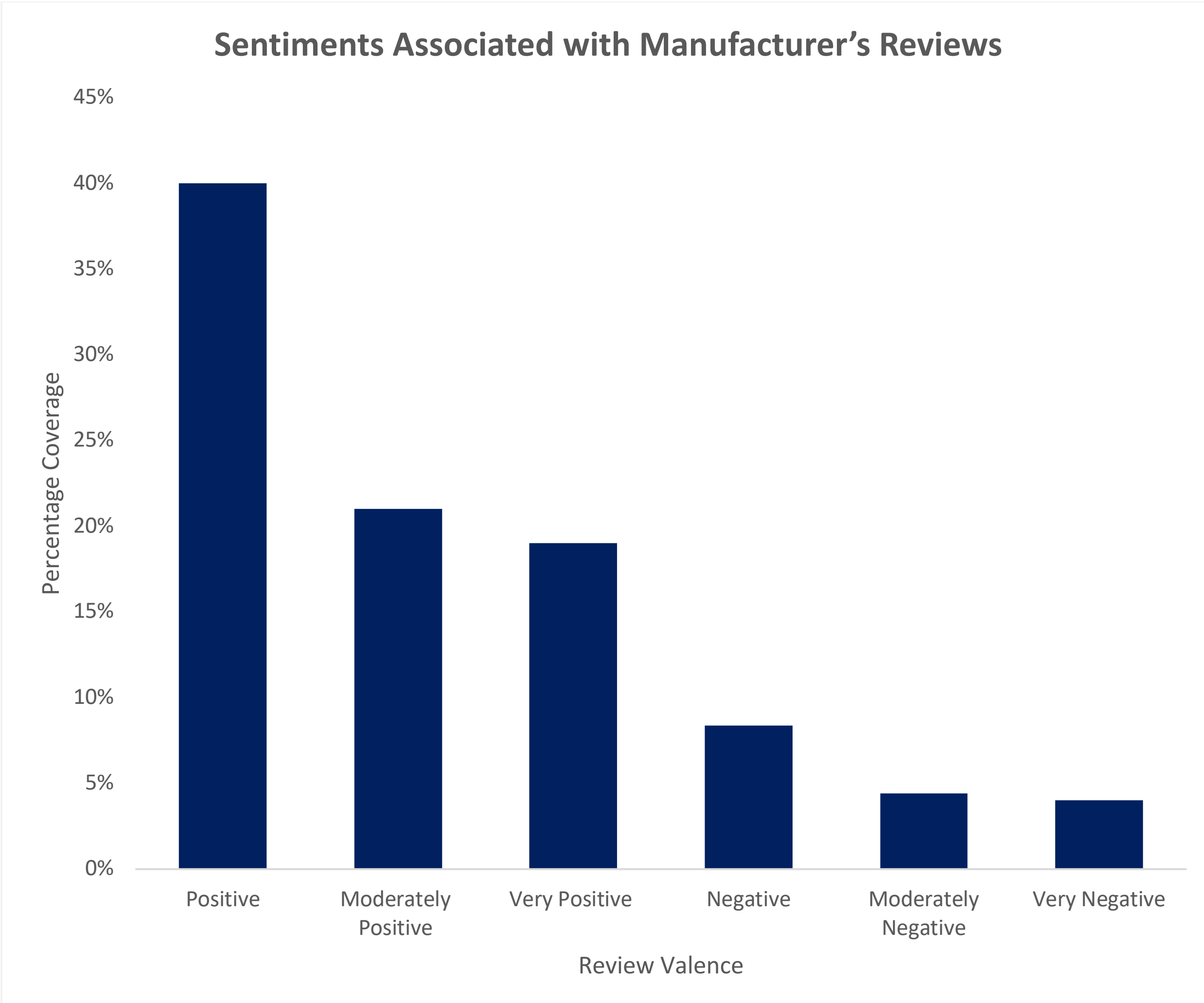

Figure 10. Bar Chart of Sentiment Analysis - Manufacturer Reviews

Chart generated by NVivo (QSR International, Version 14, 2024)

The bar chart depicting the sentiment analysis of the Manufacturer's evaluations indicates a mainly positive reception among customers. Specifically, 39.90% of the context in reviews expressed 'Positive' sentiments, indicating a substantial and enthusiastic endorsement of the Manufacturer's product sold on its website. Bifurcating the distribution of 'Positive' into 'Moderately Positive' and 'Very Positive' sentiments, 20.38% of the portion provided 'Moderately Positive' reviews, reflecting a favorable but perhaps more measured satisfaction level. However, 19.51% of the total ‘Positive’ reviews conveyed ‘Very Positive’ sentiments, highlighting a significant proportion of highly satisfied individuals. On the contrary, the negative responses were notably lower, with only 8.39% of the review data expressing ‘Negative’ sentiments. This negativity was further divided into 4.34% responding with ‘Moderately Negative’ feedback, and 4.04% providing ‘Very Negative’ reviews. The relatively low percentage of ‘Negative’ responses underscores the overall positive sentiment surrounding the Manufacturer’s product on its website.

4.3.3 Word Frequency Analysis – Manufacturer

Word frequency analysis is another step in NVivo’s sentiment analysis, which produces outputs such as word clouds and frequency tables to reveal consumer intentions. Auto-coded themes from the customer reviews of the product on the Manufacturer’s website were aligned in a tree map to showcase user feedback. The Tree map visualization in Figure 11, which was examined using NVivo software, shows a coded compilation of important terms taken from product reviews found on the web-based store of the Manufacturer. This type of qualitative data visualization shows the relative significance and frequency of terms or phrases that appear in the customer review dataset.

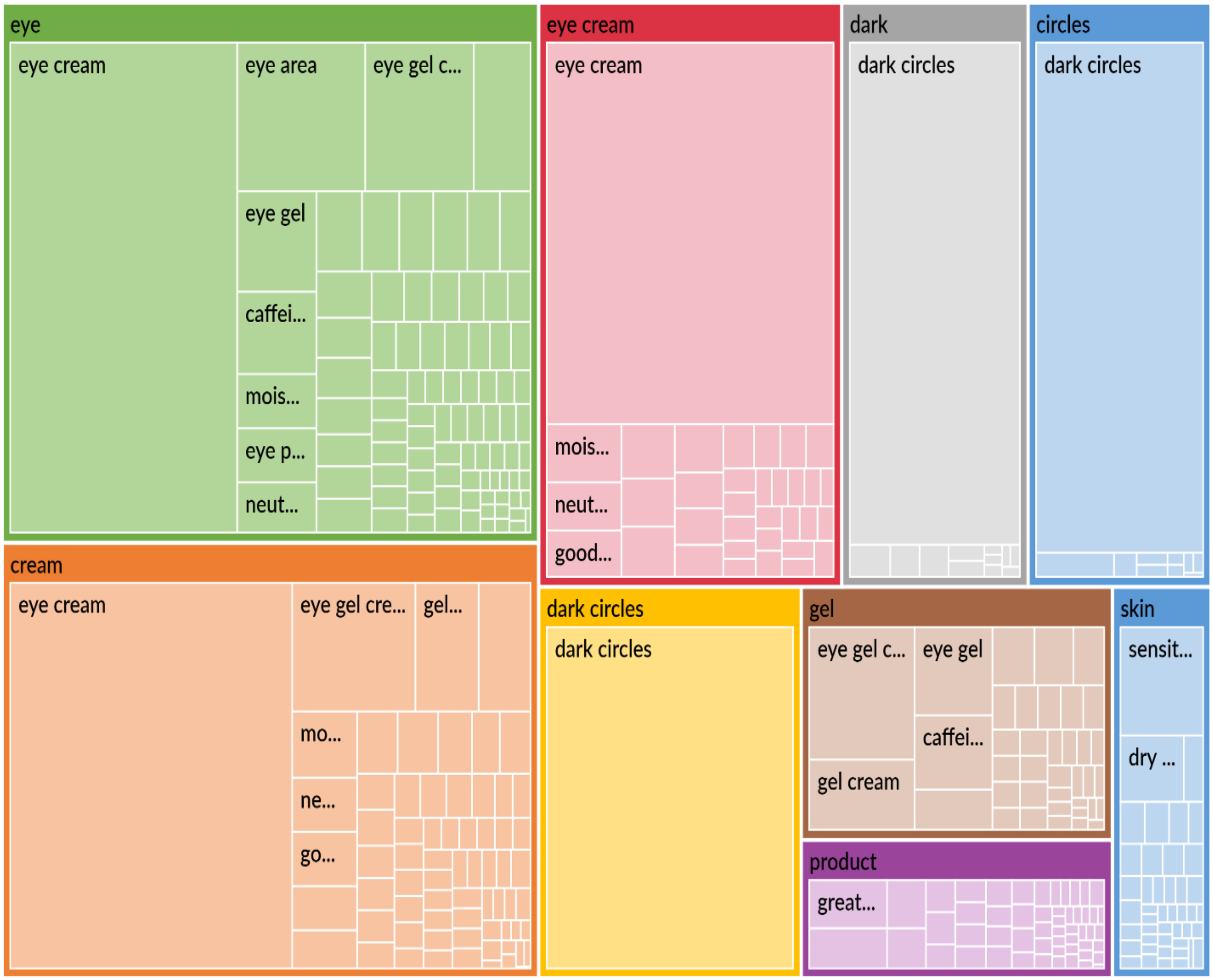

Figure 11. Tree Map of Manufacturer Reviews

Chart generated by NVivo (QSR International, Version 14, 2024)

Word trees provide an interpretive visual representation of the relationships between terms in the reviews, along with words that frequently occur alongside the pre-selected word.

Eye - Eye cream, eye area, eye gel, caffeine eye cream, moisturizing eye cream, eye product, Neutrogena eye cream, eye gel cream

Cream - Eye cream, eye gel cream, moisturizing eye cream, Neutrogena eye cream, good eye cream, gel cream

Eye cream - Eye cream, moisturizing eye cream, Neutrogena eye cream, good eye cream

Dark circles - dark circles

Dark - dark circles, dark area, dark eye bags, actual darkness

Gel - Eye gel cream, gel cream, eye gel, caffeine eye gel cream

Product - Great product, eye product, good product

Circles - dark circles, eye circles, black circles

Skin - Sensitive skin, dry skin, skincare, thin skin

A distinct category of codes is represented by each of the colored blocks that make up the tree map; the size of a block indicates how frequently the related term appears in the evaluations. The largest block, which is dedicated to the "eye" product category is labeled with the color green. Terms such as "cream," "moisturizing," and "good" are found in adjacent blocks, which are colored orange and red. This suggests that customers also use these descriptors frequently. The word "good" is used to imply favorable comments about the qualities of the product.

In addition, the tree map includes terms such as "dark circles," which denote a particular issue that consumers attempted to resolve by using this product, and "great," which was likely used to convey contentment with the effectiveness or quality of the product. Smaller categories are also displayed in the graphic, denoted by the terms "skin sensitivity" and "dry," coded in blue and purple, respectively, emphasizing both as less common but noteworthy references in customer feedback. These represent particular advantages of the product or problems that a percentage of users encounter.

Regarding business areas such as customer service, marketing strategy, and product development, this data offers invaluable insights. The frequency of particular words extracted from reviews of the Manufacturer's product are listed in Table 5 below, which was also highlighted in Figure 11 in the hierarchy chart. The table provides a quantitative understanding of the most common words found in the reviews. This lends insight to the priorities of the customers and commonalities in their experiences.

Table 5. Frequency of Words in Manufacturer Reviews

Manufacturer's Reviews	Frequency of Words
A : Circles	141
B : Cream	323
C : Dark	143
D : Dark Circles	129
E : Eye	455
F : Eye Cream	232
G : Gel	125
H : Product	107
I : Skin	108

(Jason Raphael, 2024)

Evidently, "Eye" (entity E) appears to be the most commonly appearing word with a count of 455. This is related to eye care or the eye region. "Eye Cream" (F) is closely connected, with a frequency of 232, indicating correctly that this particular product and possibly its category is frequently discussed in reviews. There were 323 mentions of the word "Cream" (B), suggesting a significant emphasis on the consistency of the product. The term "Dark Circles" (D) is referenced 129 times, suggesting that customers have a specific concern about it, which may influence the overall review content about this beauty product which is correlated to the eye region.

When paired with the 129 mentions of the combined phrase "Dark Circles" (D), the independent words "Circles" (A) and "Dark" (C) which occur 141 and 143 times respectively, underscore the significance of this specific issue in customer feedback. The word "Gel" (G) has been tallied 125 times indicating, while not as much as creams, users perceive the item to have a gel-based component. Some reviews reference skin issues or outcomes, suggesting a more extensive but infrequent conversation regarding a complete range of items and how they affect the skin. For instance, a reviewer might have indicated this beauty product works well in conjunction other skincare products they use on a regular basis.

The manufacturer can utilize this information to extract information about this product or which challenges to focus on first for product improvement, development, marketing, and customer support. The emphasis on words related to the eyes and issues around dark circles could, for instance, lead the Manufacturer to dedicate resources towards improving the significance and integrity of their line of eye care products, possibly leading to the development of more targeted and effective treatments for dark circles under the eyes.

One of the fascinating features of the NVivo software is a word cloud, which is a text data visual representation where each word's size represents its significance or recurrence within the dataset. As seen in Figure 12, the word cloud represents recurring phrases or words mentioned in the reviews of customers who purchased the selected product directly from the Manufacturer's web store.

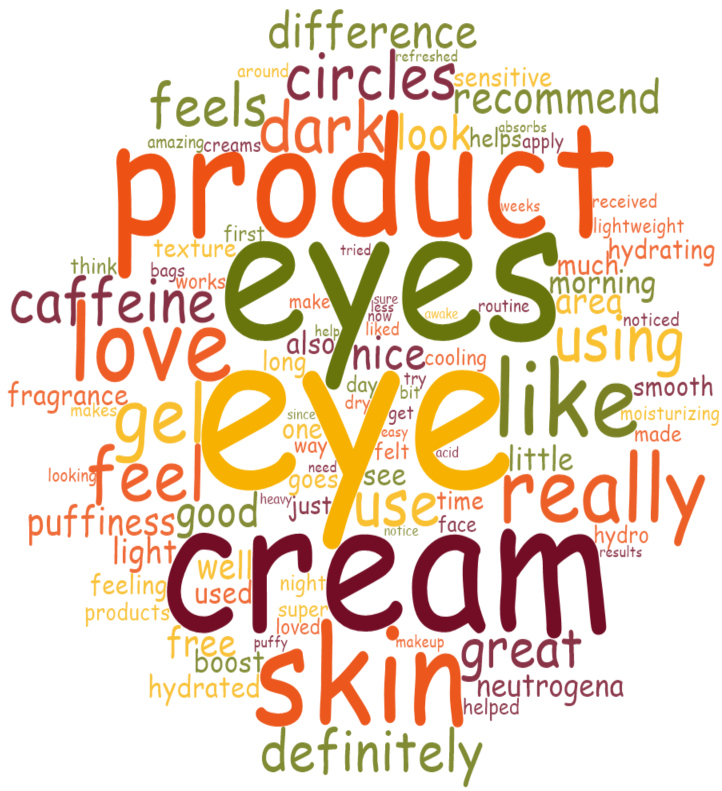

Figure 12. Word Cloud of Manufacturer Reviews

Chart generated by NVivo (QSR International, Version 14, 2024)

Words such as “eyes,” “product,” “cream,” “skin,” and “feel” are prominently featured and larger in size, indicating that they are the most often stated terms in the reviews. The high proportion of “eyes” and “cream” is consistent with the previous quantitative data as seen in Table 5, indicating a notable emphasis on eye creams or related items. “Product” is a generic term likely connected to both good and bad ratings. Descriptors such as “love,” “like,” “great,” and “definitely” surround the most prominent keywords, indicating positive customer opinion. These statements suggest that customers are quite content with the product.

Furthermore, certain aspects or worries such as “dark circles,” “puffiness,” “hydrated,” and “caffeine” are apparent, indicating these characteristics or difficulties are important to consumers. The term “caffeine” is likely referring to an ingredient in the product that minimizes dark circles or puffiness, indicating that consumers are aware of, and attracted by this ingredient and its effects. Words such as “sensitive,” “light,” “hydrating,” and “fragrance-free” imply this product’s consumers favor formulations that are non-irritating, effective, and mild, particularly for the delicate eye area. In summary, the word cloud provides a qualitative understanding of the entire customer experience and perception by highlighting the features of the skincare item that are most appreciated or disliked.

4.4 Comparative Analysis of Sentiments

To enhance the interpretation and understanding of the sentiment analysis results obtained from customer reviews on Amazon and the Manufacturer’s website for the product, a comparison study was conducted by thoroughly examining the data. The dataset studied displays a clear difference in the sentiment distribution between the two platforms, with the Manufacturer’s website depicting a sentiment bias that is noticeably more favorable. The purpose of this comparative analysis is to clarify the complexity of these results by providing a compelling analysis of the sentiment distribution on both platforms.

The comparative analysis is comprised of the assessment of positive sentiments of both platforms and, afterward, the comparison of negative sentiments in a similar manner. First, positive sentiments were considered for analysis from the given survey data, and positive sentiments were compared in parallel to determine the customer satisfaction intensity. Simultaneously, negative opinions were carefully contrasted to offer a detailed comprehension of the shortcomings according to the reviews of each platform. This methodology ensured an impartial assessment, permitting noticeable differentiation in the frequency and strength of opinion polarity, while enabling an all-encompassing assessment of customer contentment levels across each platform. The distribution of sentiment coding for reviews from Amazon and the Manufacturer’s website is shown in the Bar Graphs of Figures 13 and 14. These figures represent the coverage percentage of positive and negative attitudes.

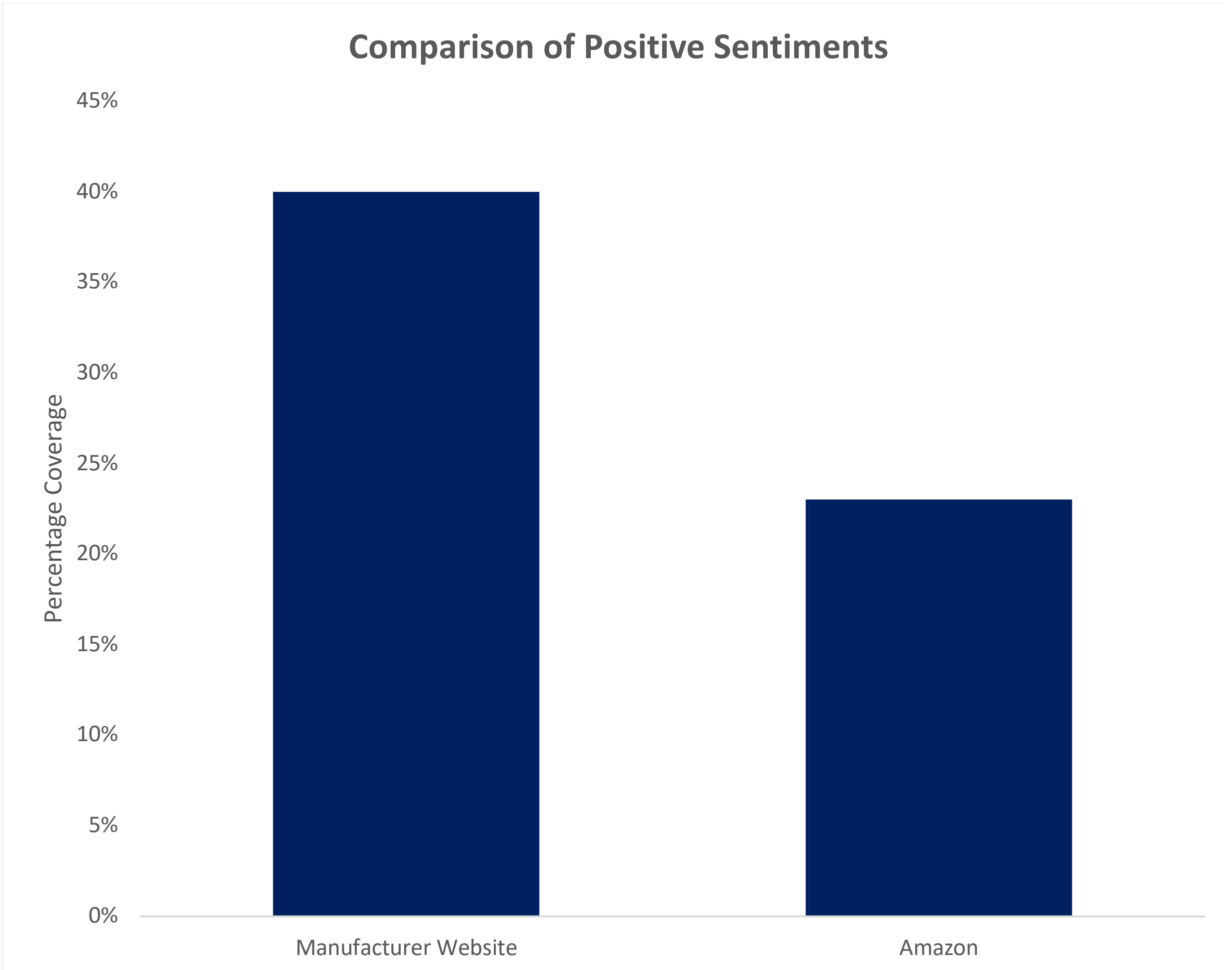

Figure 13. Comparative Chart for Positive Sentiments of Both Platforms

Chart generated by NVivo (QSR International, Version 14, 2024)

The first bar chart, titled 'Comparative Chart for Positive Sentiments of Both Platforms' displays a notable difference between the percentage of positive sentiment in reviews on the Manufacturer's website and Amazon for the product. This chart indicates that customers who leave reviews on the Manufacturer's website are more likely to have a positive experience with the product. This could be due to previous knowledge of product, a greater engagement with the brand, higher quality post-purchase customer service, or being a loyal repeat customer of the product.

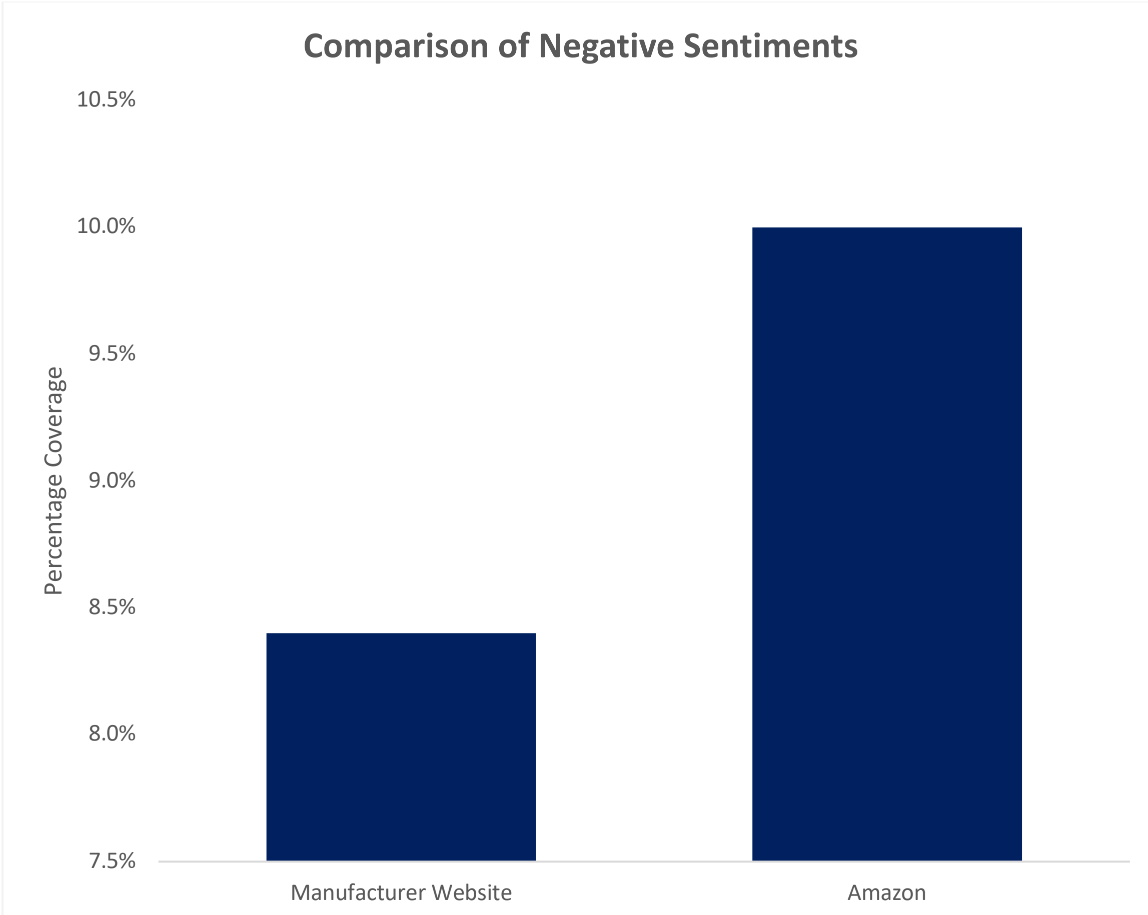

Figure 14. Comparative Chart for Negative Sentiments of Both Platforms

Chart generated by NVivo (QSR International, Version 14, 2024)

The second bar graph, 'Comparative Chart for Negative Sentiments of Both Platforms' indicates that, in comparison to evaluations from the Manufacturer's direct shoppers, a significantly higher percentage proportion of Amazon reviews are negative for the product. This may be a reflection of the larger and more diverse Amazon user base, which might be less familiar with the brand than the clientele of the Manufacturer's website, where consumers may be selective or swayed by the reputation of the brand.

Table 6 complements the bar graphs in Figures 13 and 14 with coverage percentages.

Table 6. Percentage of Coverage in Both Reviews

Name	References	Coverage	Sentiment
Manufacturer Reviews	918	39.90%	Positive
Amazon Reviews	113	23.33%	Positive
Manufacturer Reviews	172	8.39%	Negative
Amazon Reviews	63	10.16%	Negative

(Jason Raphael, 2024)

The data in the table displays that the proportion of positive sentiments in the reviews on Amazon for the product is 23.33%, which is lower than the proportion of positive sentiments in the reviews from the Manufacturer at 39.90%. This aligns with the Bar Chart depicted in Figure 13, which compares the positive sentiments on both platforms and indicates the Manufacturer's website has a higher proportion of positive emotions in reviews for this cosmetic product. However, the Amazon reviews contain negative sentiments at a rate of 10.16%, which is marginally higher than the 8.39% coverage of the Manufacturer reviews. This shows that, although there is negative feedback on both sites, there is a slightly larger proportion of unfavorable evaluations on Amazon for the product on a percentage basis.

Numerous reasons may be responsible for the observed differences in the sentiment distribution between the evaluations from the Manufacturer's e-commerce shop and Amazon for the product. The Manufacturer's website may be ornamented with more precise consumer marketing tactics specifically targeted to the customers' demographic, behavioral, or psychographic makeup. This is likely to align with the brand image that consumers expect, which may increase customer loyalty and brand kinship (Bilgihan and Bujisic, 2015, pp. 222-232).

Further, customers who are already loyal to the brand might prefer to purchase directly from the Manufacturer's e-store which may result in satisfactory reviews. In contrast, Amazon's store is frequented by a wide range of customers and preferences. The Amazon platform also has listings for numerous brands and comparable items, including those that are privately labeled, which may lead to more diverse expressions of sentiment in the reviews. This results in a more comprehensive understanding of emotions that encompasses the whole beauty care market. In the comparison of emotions on Amazon and the Manufacturer's reviews, there is a greater margin of positive reviews found on the Manufacturer's website for this item. Customer sentiments vary across both platforms and are clarified by this comparative analysis.

4.5 Logistic Regression of Amazon Reviews

To examine specific attributes of the reviews as indicators of sentiment polarity of customer reviews on the Amazon store, a logistic regression model was selected. The categorical nature of the variables in the dataset can be handled efficiently using this model. The variables selected in this model include sentiment valence (ST) as the dependent variable, and the effects of other independent variables as predictors of sentiment were analyzed. These variables included Vine-free product (VNF), total character count (TCC), and image attachment (IMG). The regression model is statistically meaningful at the 1% level by continual log-likelihood optimization, and the results of the Likelihood Ratio chi-square test show that (LR chi2(4) = 23.88, probability > chi2 = 0.0001). The model predicted the substantial importance of the Vine-free program (VNF) and customer image uploads (IMG) in feedback as predictors of customers' polarity in reviews. Further, the analysis also clarified that sentiment valence is not indicated by the length of the reviews.

In addition to statistical significance, the analysis proves useful in aiding manufacturers and sellers in maximizing the customer satisfaction ratio in reviews. This can be achieved by emphasizing the significant review factors that indicate sentiment direction on Amazon. The findings highlight the importance of the Vine program in collecting positive feedback and the impact of nonmonetary benefits on the quality and helpfulness of reviews. These results provide guidance for developing business improvement initiatives (Dorner, Giamattei, and Greiff, 2020, pp. 397-435; Garnefeld, 2021, pp. 703-722).

4.5.1 Marginal Effect Analysis - Amazon

The results of the predetermined logistic regression model are further analyzed by marginal effects that assess the systematic change in the probability of the dependent variable (sentiment valence) by the change in one unit of each of the independent variables while the others are held constant (Mize, Doan and Long, 2019, pp. 152-189). This partial differential of independent variables against sentiments was useful in providing a deeper understanding of the variable dynamics. Consequently, the prescriptive implications of the model were evaluated by computing the marginal effects.

The results of the marginal effect analysis reveal the impact of the independent variables on the probability of sentiment. The delta approach was utilized to predict the effective behavior of each variable, and the unit change of each variable was estimated based on the probability of the desired variable. The discontinuous pattern was measured by setting the mean values of the remaining variable constant. More precisely, perceptions of how the unit changes in the values of total character count (TCC), Vine-free product (VNF), and image attachment (IMG) affect the probability of having positive or negative sentiments in Amazon reviews for the product.

Table 7 displays the outcomes of logistic regression and their estimated marginal effects. The coefficients and standard errors are displayed for each variable. The significance and scope of the impact of each variable was elucidated using the coefficients and marginal effects of the model.

Table 7. Regression Results of Logistic Model for Amazon

Explanatory Variables	Coefficients	Marginal Effects
Constant (Intercept)	.007 (.229)	
Total Character Count (TCC)	-.000 (.000)	-0.000 (.000)
Vine Free Product (VNF)	3.229 (.964) *	.469 (.064) *
Image Attached (IMG)	-1.791 (.922) **	-.321 (.119) *
Chi-square	23.88	
Log-likelihood value	-72.574	

Note: Coefficients with a 10% significance level are denoted by ***, those with a 5% significance level are denoted by **, and those with a 1% significance level are denoted by *. Standard errors are in parentheses.

(Jason Raphael, 2024)

The significance of the chosen review attribute variables and their impact on customer sentiment was determined by this model. Among all explanatory variables, the Vine-free product has a strong and significant effect on customer sentiment. The significant effect of Vine-free product implies that a positive sentiment bias appears when reviewers received a free product in exchange for honest opinions in online reviews. Profoundly, the product was given to the consumers for free and asked to give their honest reviews in order to make the public aware of the quality of the products (Karabas, 2021, pp. 685-715). Therefore, in this case, people who were selected for a Vine-free product experience were expected to leave honest feedback and were influenced by the free giveaway product, resulting in positive review sentiments. Moreover, the statistical significance and coefficient of image attachment (IMG) also influenced review sentiments, but in a negative manner. The negative coefficient suggests an inverse relationship between the dependent variable (customer sentiment valence) and the existence of picture attachments. A negative value implies that the existence of picture attachments may indicate negative feelings. The variables illustrated in Table 7, which were found to be statistically significant and non-significant, are further explained in the following discussion to evaluate their specific impacts.

4.5.2 Significance of the Model - Amazon

The Model's statistical significance, as shown by the Chi-square test for the Likelihood Ratio, confirms the significance of the chosen variables in explaining the variation in sentiments. The model was statistically significant at the 1% significance level. Furthermore, it's a significant contribution to the understanding of the dynamics of sentiment expression in Amazon customer reviews for the product, as evidenced by its capacity to explain the observed variation in feelings predicted by the pseudo r-squared value of 0.1413.

Conclusively, this logistic regression study revealed the complex association between multiple review attributes and the attitudes in Amazon customer reviews for this product. The results underline the importance of utilizing Vine-free product distribution to help form favorable customer attitudes. Equally important is the adverse influence of image attachments by reviewers on the Amazon platform for this product. The length of reviews, which is an accepted factor known to convey an increase in sentiment intensity, is not a relevant indicator of sentiment valence for this product. Although the model makes a substantial contribution to the explanation of sentiment variability, more research into the elements influencing consumer sentiment on the Amazon platform is necessary to account for variance that cannot be explained with these chosen variables. These insights serve as a basis for focused tactics based on a sophisticated understanding of customer behavior in the context of online reviews on Amazon, which is also beneficial for sellers seeking to improve customer satisfaction and receive more positive feedback.

4.5.3 Significance of Variables - Amazon

The key finding of the analysis is that Vine-free product giveaway is a significant indicator of review sentiments. Customers who obtained the product for free through the Vine program are more than three times more likely to express favorable thoughts in reviews than those who did not receive a free product, according to the positive coefficient of 3.229. According to the reciprocity principle, customers typically return a favor when they receive a complimentary product and leave positive reviews (Hemetsberger, 2002, pp. 354-356). This outcome has considerable implications for companies looking to use the Vine program to obtain favorable online reviews. Subsequently, the Vine-free product had a considerable impact on the likelihood of favorable attitudes, as seen by their substantial marginal effect of 0.469 and highly significant p-value ($P<0.000$). Customers who took part in the Vine program and received the product without charge were over 46% more inclined to provide favorable feedback for this particular product.

With a p-value of 0.052, the image attachment variable (IMG) showed a significant negative coefficient of -1.791627. This strongly implies that customers' feelings are noticeably tempered when including a picture attachment in their reviews for this product on Amazon. In other words, customers who wanted to show the adverse side of the product often intentionally added images to their feedback.

This study does not question the conventional notions about the influence of the total character count (TCC) as an indicator of sentiment intensity. Nevertheless, the study demonstrates that the length of a review does not serve as a significant signal of review sentiment polarity for this particular product on Amazon, which presents a unique application of review length analysis. The low values of the coefficients indicate that there is no substantial correlation between the probability of emotion polarity and the length of the review.

4.6 Logistic Regression of Manufacturer Reviews

This study employed an identical logistic regression analysis model to that utilized for the Amazon reviews. The model was used to analyze the review attributes of customers collected from the Manufacturer's e-commerce shop for the product. This model tests the relationship between the review sentiment valence (ST) which is the dependent variable and the independent variables which are total character count (TCC), incentivized reviews (VNF), and user uploaded image attachment (IMG).

Using the likelihood ratio chi-square test, the regression model for the Manufacturer's reviews is statistically significant at a 5% level (LR chi2 (4) = 11.19, probability > chi2 = 0.0245). The variables introduced in the model, namely, incentivized reviews (VNF), and image attachment (IMG), are the dynamic variables that indicate sentiment direction and emotion in the review of a customer; nevertheless, total character count (TCC) was incorporated into the model to determine its significance as an indicator of sentiment polarity. However, a review's character count does not statistically foretell sentiment according to this model.

4.6.1 Marginal Effect Analysis – Manufacturer Reviews

The logistic regression analysis was then extended to include the steps for the estimation of marginal effects. In the context of the logistic regression analysis, the coefficients of the variables illustrate how the variables indicate the probability of receiving negative or positive feedback. Insights about the extracted attitudinal data were explored, with details about total character count (TCC), incentivized reviews (VNF), and image attachments (IMG). Marginal effect analysis assisted with identifying the likelihood of either positive or negative feedback based on changes to these variables, while all the other variables were controlled. Understanding the feelings contained in the reviews on the Manufacturer's website for this product was useful for gaining strategic insights into new possibilities for marketing this and similar products to further satisfy the needs of consumers. The results obtained from the estimation of the marginal effect for each independent variable and logistic regression are listed below in Table 8. The incorporation of the coefficients and marginal effects against each explanatory variable provides valuable insights into the outcomes and impact of each chosen individual variable on sentiment.

Table 8. Regression Results of Logistic Model for Manufacturer

Explanatory Variables	**Coefficients**	**Marginal Effects**
Constant (Intercept)	1.028 (.605)	
Total Character Count (TCC)	-.000 (.001)	-0.000 (.000)
Incentivized Reviews (VNF)	1.789 (.593) *	.188 (.101) ***
Image Attached (IMG)	.666 (.386) ***	.031 (.017) ***
Chi-square	11.19	
Log-likelihood value	-148.194	

Note: *** denotes the 10% significance level of coefficients, ** denotes the 5% significance level of coefficients, and * denotes the 1% significance level of coefficients. In parenthesis, standard errors are displayed.

(Jason Raphael, 2024)

Similar to the regression analysis of the Amazon reviews, the above-described Table 8 effectively comprises meaningful results extracted from logistic regression and the marginal effects estimation for each explanatory variable. The significance of each variable was analyzed and its effectiveness was gauged with the assistance of coefficients and their p-values. The dependent variable, sentiment valence (ST), is indicated by two of the independent variables which are incentivized reviews (VNF) and image attachment (IMG), thus, these variables have significance in the model about the reviews from the Manufacturer's website for this product. Incentivized reviews (VNF) play a vital role in indicating positivity in the reviews of the customers. Thus, the presence of incentivized reviews increases the probability of positive sentiments in the reviews. The Manufacturer offers a free product to some consumers to get feedback in the form of reviews, and subsequently, the free products positively influence the customers which is reflected in the positive sentiments in their reviews. The user-generated images submitted by customers in their reviews are also indicators of customer sentiment valence, positively influencing the overall sentiment of the reviews. This effect is contrary to the influence observed in Amazon reviews when a customer uploads images. This implies that reviews with images typically have higher values of positive sentiments than reviews without images on the Manufacturer's e-commerce store for the product. This may potentially impact shoppers' attitudes or thoughts about the product when reading reviews before purchase.

4.6.2 Significance of Model – Manufacturer Reviews

The purpose of the logistic regression analysis and marginal effects estimation was to examine the effects of total character count (TCC), incentivized product (VNF), and image attachment (IMG) as indicators of sentiment polarity present in the Manufacturer e-commerce shop's feedback for the product. The likelihood ratio chi-square test (LR chi2(4) = 11.19, p = 0.0245) indicates that the model is statistically significant overall, revealing that at least one of the independent variables has a discernible effect on the outcome. However, the model appears to be significant at the 5% level, according to the pseudo-R-squared value of 0.0364. This highlights the model's capacity to clarify the aspects driving the prediction of sentiment expression in customer evaluations, offering insightful information about the variables affecting customer views. However, the low pseudo-R-squared value suggests that even while the model explains a portion of the sentiment variation, there may be other unaccounted for factors that also influence consumer attitudes.

4.6.3 Significance of Variables – Manufacturer Reviews

An extensive examination of the variables involved in the dataset influencing the sentiment of the customer reviews is well explained by the logistic regression model. Their significance and importance are also indicated by the model. Specifically, the provision of free products in return for reviews is dominantly significant at a 1% level of significance ($p = 0.003$). This outcome demonstrates that there is a strong impact of giveaways and incentives on the opinions of customers. The reviewers were provided with the product free of charge in order to obtain their purportedly impartial opinions and feedback. However, it is evident that the potential influence is heavily skewed towards the product, as customers tend to provide positive feedback in exchange for the gift. This significantly enhances the brand image and success rate of the product.

Furthermore, the image attachment in the reviews describes a marginal impact on the emotions and sentiments of the customers, thus, is statistically significant bearing a p-value of 0.084, having significance at a 10% level. This behavior predicts that the visual addition in the reviews plays a role in driving the positive sentiments and opinions of the customer, however, the impact is not as strong as that of incentivized reviews.

Furthermore, the variable total character count (TCC) was categorized as non-significant as an indicator of review valence.

Overall, these adjusted results highlight the importance of incentivized reviews and image attachments in influencing feedback from the reviews on the Manufacturer's retail e-commerce store. However, the total character count does not show any discernible influence on sentiment during the estimation for this product's reviews on the Manufacturer's e-shop.

4.7 Comparative Analysis of Regressions

The same logistic regression and estimation of their marginal effects was conducted on the reviews extracted from both platforms, Amazon and the Manufacturer's website for the product. The comparative analysis of the results from the regression models was carried out to provide valuable insights by highlighting the factors influencing the sentiments of reviews across two different e-commerce platforms and gauging the commonalities shared by them for the same product.

Overall statistical significance is shown by the likelihood ratio chi-square tests for both models. The LR chi-square value in the Manufacturer reviews model was 11.19 ($p = 0.0245$), whereas it was 23.88 ($p < 0.0001$) in the Amazon reviews model, suggesting the regression model for the Manufacturer's website has meaningful significance at a 5% level and that of Amazon is at 1% significance level. It is noteworthy that the pseudo-R-squared value of the Manufacturer's product reviews model was 0.0364, which suggests a moderate amount of explained variance. In contrast, the Amazon reviews model has a significantly higher pseudo-R-squared value of 0.1413, indicating a superior fit to the data.

Upon analyzing the influence of the diverse independent variables on sentiment expression, intriguing results were obtained:

Total Character Count (TCC) - The total character count of reviews does not show up as a statistically significant predictor of sentiment polarity in either the Manufacturer or Amazon reviews models.

Incentivized Reviews (VNF) - Obtaining a complimentary product via the Vine-free program on the Amazon platform or via the Manufacturer's e-commerce platform appears to be an immensely significant predictor of sentiment in both models. This illustrates the impact of incentive schemes on customer feedback and raises the possibility of a bias towards favorable reviews of the product.

Image Attachment (IMG) - In both models, picture attachment has a slightly significant impact on sentiment expression, but it has less of an impact than receiving a free product. The inclusion of images seems to have a minimal impact on sentiment in both Amazon and Manufacturer evaluations, indicating that customers' perceptions may be shaped by visual information, though not as much as by free product incentives. However, the impact of this variable as an indicator of sentiment direction is found to be different in both models. There is a negative impact on sentiment observed in Amazon's model while a slightly positive influence on sentiment is evident in the Manufacturer's model. Meanwhile, the photos attached by the consumers in the reviews are found significant in both regression models.

Thus, a comparison of both regression models of Amazon and the Manufacturer's reviews was carried out to extract valuable information about the factors influencing the sentiments and emotions of the customers. The Vine program or offering of free products in exchange for reviews was found as the most significant variable in aligning the customers' attitudes toward positive. However, the duration of reviews has no significant use for indicating or impacting the sentiments of the customer reviews on either platform. The inclusion of the images attached in the reviews has a minor impact on the sentiments, signifying that images in the feedback play a role in determining the sentiment polarity of customer opinions.

4.8 Hypothesis Testing

The research was conducted on the evaluation of sentiments in customer reviews on two different platforms, namely, Amazon and the Manufacturer's e-commerce website for the same beauty product, and select review factors affecting the sentiments of reviews. The hypotheses of the study were evaluated by further extending the research based on the obtained results. Sentiment analysis for Amazon and the Manufacturer evaluations was first carried out independently using NVivo 14 for qualitative data analysis, utilizing information gathered from reviews on both platforms. The prevailing positive and negative attitudes within the customer reviews were then explained through the creation of word clouds and hierarchical charts.

After comparing the outcomes from each platform, noticeable differences in the distribution of customer sentiment became apparent. Interestingly, consumers are more likely to post favorable reviews on the Manufacturer's website for the product than on Amazon. In particular, 39.90% of positive sentiments were expressed in the total reviews on the Manufacturer's website for the product, which is significantly higher than 23.33% of positive evaluations on

Amazon. On the other hand, negative reviews make up only 8.39% of the total reviews on the Manufacturer's website, while 10.16% of the sentiments in reviews on Amazon are negative.

Hypothesis 1 -

H1 - Customer opinions on Amazon differ significantly from those on the Manufacturer's online store in terms of sentiment for the same product.

The results support the theories that were put forth in the study. Starting from the first hypothesis (H1), which seems to be supported by the findings. There were notable differences in consumer opinions between Amazon and the Manufacturer's online store for the same product. The results derived from sentiment analysis highlighted the fact that customers showed a disparity of sentiment in their reviews for the same product when sold on two different e-commerce platforms, Amazon and the Manufacturer's online store. Customers expressed more positive sentiments in their reviews on the Manufacturer's e-commerce shop on a percentage basis of total reviews in the dataset. Specifically, the Manufacturer's percentage of positive reviews was 39.90% while the percentage of total Amazon reviews for the product was 23.33%. Further, to support this outcome, the study of Sung, Chung and Lee (2023, pp. 1-10) found that the customers who visited a manufacturer's website directly expressed greater levels of satisfaction and as a result, a higher possibility of expressing positive emotions. Whereas, Amazon buyers were less likely to give positive reviews as per the alignment with the results. Sebastianelli and Tamimi (2018, pp. 506-519) explored the impact of online shopping platforms on customers' beliefs and perceptions. They found a significant impact of platform differences on customer sentiment as well as their purchasing decisions which aligns with the research contained in this study. Customer opinions in this study differ for the same beauty cosmetic product sold on the Amazon platform and the Manufacturer's retail e-commerce website.

Hypothesis 2 -

H2 - There is a significant relationship between shoppers' previous knowledge of the product or brand and the sentiment valence of customer reviews for the product on the Amazon platform and the Manufacturer's online retail store.

The research in this study validated the second hypothesis, thus, there is a significant relationship between the product perception of the shopper including previous knowledge of the product or brand, and the aggregated sentiment polarity of reviews. On a percentage basis, more positive reviews of the product were found on the Manufacturer's website compared to Amazon which proves that higher satisfaction with the product is related to brand or product awareness.

Known brands or product-specific websites have higher favorable evaluations which equates to positive sentiments. This revealed that manufacturers who sell products directly to consumers online nurture a more positive brand perception, and customers tend to perceive more value in their products, which leads to more positive reviews.

The specific interactions of consumers with Amazon as opposed to the Manufacturer's online site also have significance. Consumers who browse Amazon may come across a product while shopping for something else or just perusing alternatives, thus the reviews that users write on Amazon may be less intentional without previous knowledge of the brand or product. On a manufacturer's online store, however, buyers are usually more deliberate and targeted (Amine, 1998, pp. 305-319). Consumers deliberately go to the product website to browse specific products and possibly make a targeted purchase. Customers who purchase directly from the Manufacturer's retail e-commerce shop are therefore more likely to be directly interested in the product due to this targeted connection, which results in more positive reviews.

Hypothesis 3 -

H3 - The provision of Vine-free or incentivized products increases the probability of positive valence in the reviews either on Amazon or the Manufacturer's website.

The research was expanded to include a logistic regression examination of the effects of selected review attributes on sentiment in the reviews using STATA software. These variables included review length (TCC), vine-free or incentivized product (VNF), and image attachment (IMG) by the customers in their reviews. The offer of vine-free or incentivized products was found to positively affect sentiments for both websites, suggesting that giveaways and free products did influence reviews and introduce positive bias. The results of the regression analyses supported Hypothesis 3, proving that providing free products via initiatives like Amazon's Vine significantly raises the likelihood of receiving positive reviews. Garnefeld (2021, pp. 703-722) investigated the positive effect of marketing tactics - more specifically, giving away free products, and receiving positive ratings. Their study found that although there is a definite attempt made to obtain favorable evaluations through product samples, the cost of the product given away has a substantial impact on the reviews. It was discovered, namely, that items with higher prices typically garner positive evaluations. This implies that sellers are using a dual strategy: using free product offers to boost positive reviews and taking advantage of the higher perceived value that comes with more expensive products.

The research in this study revealed that giving away the cosmetic product for free in exchange for reviews definitively resulted in a greater percentage of positive reviews on both the Amazon platform and the Manufacturer's retail e-commerce shop.

Hypothesis 4 -

H4 - The total character count, also referred to as the duration of reviews is not an indication of sentiment polarity on Amazon and the Manufacturer's platform.

Finally, by demonstrating the non-significance of review length as an indicator of review sentiment polarity, the regression results validated Hypothesis 4. The results of the regression models for both platforms revealed that the length of a review had no discernible effect on sentiment valence.

Findings of the Research

This study offers insightful information about the dynamics of customer attitudes on two distinct e-commerce sites, namely Amazon and the Manufacturer's website for an identical product. It clarifies which of the chosen variables were indicators of the opinion polarity expressed in customer reviews. The results reveal the importance of customer reviews for shoppers and brands, particularly noting the divergence of customer attitudes on the Amazon platform and the Manufacturer's e-commerce store. Further, the impact of the review attributes such as Vine-free or incentivized products positively indicates the customer sentiment valence contained in reviews on both platforms, unlike the length of a review, which does not indicate customer sentiment on either platform. The Manufacturer's product page received more positive reviews as compared to Amazon on a percentage basis.

Nevertheless, subtleties about the influence of image attachments on sentiment were also shown by the investigation in this study. Image attachments have been observed to be indicative of unfavorable opinions in Amazon reviews. This is most likely because customers tend to express significant discontent with the product when uploading a photo, and might be unfamiliar with the brand or the intended level of results that are reasonable for the product. On the other hand, customers tended to commend the product and attach positive pictures to their reviews on the Manufacturer's website. Overall, there were significant effects of picture attachments on sentiment valence in customer reviews, both positive and negative, particularly for each platform.

4.9 Chapter Conclusion

The research in the study assists with the investigation of the behavior of online buyers, concentrating on customers' feedback in reviews on Amazon and the Manufacturer's website for the same beauty cosmetic product. For qualitative data analysis, NVivo 14 was utilized to evaluate the customer's sentiments found in reviews of the skin care product. Additionally, applied logistic regression analysis was conducted using STATA for sentiment analysis to observe the influence of specific review qualities and attributes on the sentiment polarity of reviews, specifically, total character count (TCC), obtainability of Vine-free or incentivized products (VNF), and the attachment of images (IMG). According to this research analysis, there is divergence observed in the reviews on both platforms. Thus, the total percentage of positive sentiments in the customer reviews on the Manufacturer's website is greater than those on the Amazon store.

This disparity highlights a customer's relation that is specific to a platform and has a wide and substantial effect on sentiment reviews. On the Manufacturer's website, there are favorable reviews that show the likelihood of previous brand or product exposure leading to positive reviews. Whereas Amazon's less prejudiced sentiment representation shows the diverse range of its buyers as its platform has a wider reach. The logistic regression result of the research revealed that review sentiments of both platforms had been substantially impacted by a Vine-free or incentivized product, showing a higher probability of expressing positive sentiments after receiving the product for free in exchange for a review.

The research also explored how the overall polarity of review sentiments differed with the presence of image attachments in customer reviews on both platforms. This infers that customers have clear expectations and intentions when providing image attachments within their review text. The research neither confirmed nor invalidated the accepted hypothesis that longer reviews contain more emotional intensity. However, the results of this study revealed that the length of reviews is not an indicator of sentiment polarity, that is, positive or negative for this particular product on either platform. Users left longer reviews to show positive and negative feelings without an overall leaning towards a specific direction. By applying a logistic regression model and sentiment analysis, the research proposed a thorough understanding of the divergence of feedback from customers on both platforms of e-commerce.

The results display the importance of understanding the behavior of customers about platform specificity, and how sentiments are affected by the review attributes chosen for this research. This comprehension gives businesses the ability to understand a customer's feedback from new perspectives and use it to enhance customer experiences related to the product, leading to more positive reviews in the future.

Conclusively, this research offers brands that sell online better insight into e-commerce customer attitudes and gives the necessary information for businesses seeking to enhance customer satisfaction and their online occurrence of positive reviews. The research examined the challenging relationship between customer reviews and e-commerce dynamics by investigating the complexities of online feedback and some of the variables that affect them.

CHAPTER V

DISCUSSION

The fifth chapter embarks on an in-depth discussion of the findings and interpretation of the results obtained from the sentiment analyses of Amazon and the Manufacturer's reviews for the specific cosmetic product used in this study. For the qualitative analysis of data and sentiment analysis, NVivo 14 was utilized. This chapter provides a broader understanding of the interpretation of the results, recognizes the theoretical implications of the findings, explores the application of the study in the practical world, acknowledges the limitations and challenges of the study, and opens the channel for recommendations for future research projects.

The findings of sentiment analysis from the customer reviews are found in this chapter in detail. The aim was to discover hidden trends and views by analyzing the sentiment of the reviews retrieved from both Amazon and Manufacturer's online retail e-commerce store. Also, through regression analysis, the study examines the implications of these results on the customers' behavior, the evaluation of the product, and the decision-making process of the customers. The discussion then turns to the implications at a theoretical and practical level. It then explains how industries employ sentiment analysis and subsequent analyses of consumers' behavior in enhancing product experience and marketing strategies in managing the consumers. In addition, the research explains the ways through which customers can use these evaluations to their benefit in their purchasing activities.

The limitations of this study are then discussed. Factors that might have influenced the perceived outcome were included. This gives an insight into the enormity of the research that is to be done and the consequences of it. Furthermore, the study outcomes can be examined with the other aspects in future research. However, this chapter is considered to play a significant role in the analysis of the findings of sentiment analysis, examining their effect and discussing directions for further research. In this way, the research aims to increase the understanding of customers' attitudes and perceptions toward a particular product.

5.1 Interpretation of the Results

This research work employs both qualitative and quantitative research approaches. Consequently, both kinds of assessments were used in this research, and the previous chapters offer details on how the evaluations were conducted and the steps taken to guarantee the accuracy of the data. Additionally, the findings of the analysis techniques such as sentiment analysis and logistic regression were also within the scope of the previous chapters. In this section, the further interpretation of the obtained results of the sentiment analysis and logistic regression for both platforms have been reviewed separately and compared with the features of the results from both platforms to analyze the collected reviews from both platforms. The discussion also included a comparison of the results that both platforms have given.

5.1.1 Interpretation of Sentiment Results

Sentiment analysis is the extraction of the valence and the classification of the reviews into positive, neutral, or negative. It helps to evaluate the perception that the customers have about this particular product. Sentiment Analysis enables businesses to acquire more information about a customer's perception of a particular product. The textual data sets were used to perform sentiment analysis and the actual data from the review that were used in this research were collected by a Python script. Based on the findings of the given sentimental analysis of reviews, companies can reach certain decisions based on consumer feedback (Medhat, Hassan, and Korashy 2014, pp. 1093-1113). Sentiment analysis is often employed by companies and marketers to identify positive or negative reviews or feedback.

The sentiment analysis of the collected feedback serves as an important instrument for decoding the subtleties of customers' attitudes and perceptive of products (Taboada, 2016, pp. 325-347). To summarize, the present study applied the sentiment analysis of the reviews collected from both platforms with the help of NVivo 14 software for the qualitative analysis and Manual coding for the logistic regression. However, before using the dataset, the set was preprocessed, with special emphasis to removing unwanted features like the links to other reviews and the customer screen name that was not useful in the data set. The use of auto-coding to made the testing process more efficient by restructuring the data.

NVivo software was selected as it is transparent and has credible results when used in version 14. It was an important tool for this research, providing a dynamic structure for separating and clarifying the sentiments extracted from the reviews. Robust visualizations, such as bar charts, tree maps, word clouds, and hierarchy charts present a comprehensive depiction that facilitates the analysis of customer sentiment. This graphical demonstration provides a top-down view of the distribution of sentiments and simplifies sentiment trends and patterns.

- **For Amazon Reviews**

The results displayed were derived from sentiment analysis conducted on reviews of the beauty cosmetic product sold by the Manufacturer's via their own listing page on Amazon using NVivo, referenced in this paper as Amazon reviews. The hierarchy chart of sentiment as seen in Figure 3, reveals a complete summary of the attributes categorized as 'Positive,' 'Negative,' 'Mixed,' and 'Neutral.' Figure 3 provides a schematic of all sentiments in the Amazon dataset. It was revealed that a substantial percentage of the chart emphasizes the neutral section, indicating that most reviewers refrain from providing any strong valence in their comments. The second most prominent aspect is the positive emotion, which indicates that customers are generally satisfied with the product. The content of reviews that contain both favorable and negative sentiments simultaneously are categorized as mixed sentiment and contain the third largest portion sentiment. However, unfavorable feelings constitute the smallest percentage. Therefore, the depiction of this hierarchical arrangement of sentiments in Amazon evaluations accurately displays the equitable values of clients that purchased the product and left reviews. The substantial volume of neutral feedback represents reviews from consumers who neither left positive or negative comments about the product. The positive sentiment, which follows the neutral valence, indicates a higher degree of customer satisfaction, either due to the product's qualities, value, or effective marketing strategies. The opportunity for further improvement and product branding is also present, as confirmed by the negative sentiment of some reviews. The developed hierarchy chart was then further subdivided by NVivo to obtain deep insights into positive and negative sentiments as seen in Figure 4. Thus, it is subdivided into 'Very Positive,' 'Moderately Positive,' 'Very Negative,' and 'Moderately Negative' categories to provide a more detailed view.

The results of sentiment analysis were presented using hierarchical charts and a bar chart. These charts represent the percentage distribution of each sentiment category, including 'Positive' (divided into 'Very Positive' and 'Moderately Positive') and 'Negative' (divided into 'Very Negative' and 'Moderately Negative'). The results as seen in Figure 5 show that a significant number of Amazon customers had positive experiences with the product, according to the Bar Chart results of sentiment analysis, with 23.33% of the reviews as 'Positive.' In contrast, the percentage of 'Negative' sentiment in reviews remained at only 10.16%, and it can be interpreted that positive emotions are viably leading in the reviews, eventually more than double when compared with negative sentiments.

The formation of word trees or tree maps as an output for all identified themes and codes underlines the concerns and preferences of consumers in their reviews. This strategy skillfully gathered popular subjects and themes from the customer reviews. Each theme and code are emphasized by occupying a block; thus, the most prominent thoughts of reviewers can be seen simultaneously in the largest blocks. With the assistance of this map, as seen in Figure 4, the Manufacturer can evaluate its product quality and identify customer complaints, product categories, and consumer preferences for this skincare product via the Amazon platform.

NVivo's sentiment analysis function included a word frequency chart as seen in Table 3, that plays a crucial role in identifying the intensity of customer opinion expressed in reviews.
This inclusive study clarifies the most frequently used words and reveals the central motifs that

filter customer attitudes from product quality to buyer experience. Word clouds, hierarchy charts, and frequency tables illustrate the fundamental ideas and themes of reviews. Companies must build a positive customer experience based on consumer feedback, and this process can begin through sentiment analysis of reviews. E-commerce competition is fierce in most verticals, so companies need to study the attitudes of customers toward their products, allowing them to satisfy their customers' needs and wants with enhanced product quality and perception.

The provision of a word cloud as seen in Figure 7 was produced in the output by NVivo 14 and it summarizes all frequently used terms in Amazon reviews for the given product, indicating consumer interests, concerns, and preferences in selecting this skincare product. This is useful for seeing all relevant terms related to a product from the viewpoint of customers at a glance.

- **For Manufacturer's Reviews**

The sentiment analysis of the reviews of the same product sold on the Manufacturer's retail e-commerce shop initiated with an investigation of customers' review sentiment. Sentiment analysis was again performed by employing NVivo's sentiment identification features based on Natural Language Processing (NLP). By leveraging the auto-coding mechanism, the data was analyzed, and various types of outputs were produced for qualitative analysis. NVivo processed data from the Manufacturer's review dataset via sentiment recognition, hierarchy charts, bar charts, tree maps, and word frequency clouds.

The comprehensive sentiment analysis of the Manufacturer's customer reviews began with a hierarchy chart as seen in Figure 8, of feelings expressed in open-ended reviews whose chart is distributed as 'Positive,' 'Negative,' 'Neutral,' or 'Mixed' sentiments. Positive comments express a favorable review of the product, and show the customers' experience was satisfactory; a negative comment extracts an unfavorable review of the product, indicating their dissatisfactory experience; whereas neutral comments do not show any significant leaning towards either sentiment polarity according to NVivo's process. The greatest portion of this chart is shared by positive sentiments, which depict the success rate of the product and the high level of customer satisfaction. The negative sentiment proportion was the smallest, indicating that the smallest group of reviewers exhibited adverse views and dissatisfaction levels. The existing hierarchy chart was then subdivided into a more detailed chart, as seen in Figure 9, consisting of only 'Positive' and 'Negative' attitude blocks, resulting in portions of 'Moderately Positive,' 'Very Positive,' 'Moderately Negative,' and 'Very Negative.'

Subsequently, the proportional distribution of the identified sentiments was determined using a bar chart, in Figure 10, that represents the actual share of each portion of sentiment depicted in the previous hierarchy chart. The bar chart of sentiment analysis comprised the percentage coverage of 'Positive,' 'Moderately Positive,' 'Very Positive,' 'Negative,' 'Moderately Negative,' and 'Very Negative' sentiments. The results of the bar chart clarify the dominant nature of positive sentiments in the reviews; the measured percentage of positive sentiment is 39.90%, highlighting the customers' optimistic experience with the product and a higher satisfaction ratio. Among the 39.90% positive sentiments, 20.38% showed contentment with the product with a moderate attitude; however, approximately 19.51% expressed strong gratification with the product, which is possibly due to brand perception and the customer's website experience. However, a smaller percentage, 8.39%, of the sentiment in the customer reviews expressed adverse feelings. This sentiment breakdown provides a nuanced understanding of customer perceptions, emphasizing the overwhelmingly positive nature of reviews, with only a minority expressing negative sentiments. The Manufacturer can use this analysis to better understand consumer attitudes overall, pinpoint areas for future product development or improvements, and highlights strengths that can be incorporated into marketing plans.

A tree map, in Figure 11, exposed the customers' preferences, intentions, and recurring concerns with either the product or packaging. It provided the hierarchal vision of customer reviews by organizing the themes and codes extracted from the reviews in a tree form. The visualization of the tree map is constructed with the themes as branches, while the codes can be referred to as leaves, which show the frequency of single words along with their composite words present in the review of customers. The block size within the tree map indicates the frequency of terms that occur in the assessment.

Thus, the tree map provides a hierarchical view of customer feedback, enabling the Manufacturer to rapidly identify the most frequently mentioned characteristics or attributes of the product as well as the general opinions of customers regarding them. For priority areas such as customer service, marketing strategy, and product development, this data can offer invaluable insights.

In Figure 12, the word frequency of prominent words was measured and graphically represented by a word cloud. The word cloud chart provides a clear representation of the cluster of terms that are commonly used in reviews, with the most common themes represented by larger text. Furthermore, the formation of a frequency table elucidates the most recurrent words in the dataset of reviews leading to a priority list of the most popular topics among customers.

Thus, the analysis and obtained results deliver a qualitative perception of the consumers' experiences prominent in the performance of this skincare product. Customers approaching the Manufacturer's platform were likely already familiar with the product and knew the brand. The Manufacturer's objective should be to ensure that consumers value the product's characteristics and quality, make a purchase, and are henceforth persuaded to make subsequent purchases. The findings found in the qualitative investigation indicate that customers value the product's characteristics and quality.

5.1.2 Interpretation of Regression Results

The quantitative aspect of the study was facilitated by logistic regression analysis based on manual sentiment valence coding, which was performed by utilizing the collected web data consisting of review attributes from both platforms. The outcomes of logistic regression for both models of Amazon and the Manufacturer reviews were discussed in the previous chapter; however, the interpretation of results is included as part of this section. The sentiment polarity found in the reviews of each platform was correlated with the contributing review attribute factors.

- **For Amazon Reviews**

The logistic regression results performed on the Amazon reviews provided a significant understanding of the review factors indicating consumer sentiment polarity. The model involved the independent variables: total character count (TCC), Vine-free product/incentivized product (VNF), and image attachment (IMG), along with the dependent variable sentiment valence (ST). Validating theses independent variables as indications on consumer sentiment polarity in reviews was an outcome of the logistic regression.

The Vine-free product (VNF) is an important correlated factor, highlighting customers who received the product by the Vine-free (VNF) program are more likely to show positive feedback in their reviews on Amazon for this product. The significance of the variable indicates that customers likely feel motivated to respond to the acceptance of complementary products with satisfactory feedback. The marginal effect and significance of the coefficient of the Vine-free product (VNF) underlines its substantial influence on customer opinions, emphasizing its ability as a tactical tool for businesses looking for a favorable online appraisal in feedbacks. The presence of image attachments (IMG) in reviews indicates negativity on Amazon for this product, which is contrary to the sentiment valence indication of the Vine-free (VNF) variable. Images attached by customers may be more biased toward underlining the negative attributes of products in their reviews. This outcome is incongruent with the assumption that visual representation improves the sentiment towards the positive in reviews, and underlines the necessity of understanding its correlation to consumer opinions, and the effect on future shoppers reading the reviews. Overall, customers of this product on Amazon possess a more neutral nature according to the qualitative section of this study. This seems to imply that shoppers looking at reviews begin with a neutral attitude, but they can be adversely swayed by the images in the reviews since these are indicative of negative sentiment. The total character count (TCC) is an insignificant indicator of positive or negative sentiments. This argues that the length of reviews does not statistically indicate the direction or leanings of review valence.

The significance of the review variables selected for research in this study is confirmed by describing the difference in positive or negative sentiments as they relate to each variable. The regression model for the Amazon reviews is statistically meaningful at the 1% level.

The results of the logistic regression analysis provided noteworthy insights for the Manufacturer in aiming to improve customer positivity and perception, which will lead to more positive online reviews if utilized. By identifying the effect of multiple factors, such as Vine-free product (VNF) participation and image attachments (IMG), as indicators of positive or negative sentiment, companies can upgrade their approaches to increase positive sentiment and lessen negative reviews. However, insignificant factors as indicators of sentiment polarity observed in the results can be ignored by marketers and businesses. This will allow for greater efficiency in considering other relevant factors when researching customer sentiments and their indicators or influence. The outcome of the logistic regression of Amazon, along with the variable significance and interpretation, is provided in Table 9 for clarity.

Table 9. Interpretation of Logistic Regression Model Results for Amazon

Explanatory Variables	**Significance**	**Interpretation**
Total Character Count (TCC)	Insignificant	This attribute is not an indicator regarding sentiment polarity of Amazon customer reviews.
Vine Free Product/Incentivized Products (VNF)	Positively Significant	The attribute is correlated to positivity among Amazon customers in their reviews.

Image Attached (IMG)	Negatively Significant	The attribute is correlated to negativity among Amazon customers in their reviews.

(Jason Raphael, 2024)

- **For Manufacturer Reviews**

The results were gathered by employing the logistic regression model on customer reviews gathered from the Manufacturer's online store for the product to analyze sentiments, the same as the Amazon reviews method. This model examines the indication of sentiment polarity of independent variables including total character count (TCC), Vine-free product/incentivized products (VNF), and picture attachment (IMG) on the dependent variable sentiment valence (ST). For the Manufacturer reviews, the regression model validates at a 5% statistical significance level, indicating some of the chosen independent variables are significant indicators of sentiment polarity of reviews.

Incentivized reviews (VNF) are a significant variable of sentiment, with a strong indication of positive emotions in reviews. In exchange for supposedly honest reviews, the provision of a free product is correlated and indicative of positive consumer sentiment, which improves the brand image and product reviews. Likewise, in reviews, image attachment (IMG) plays a significant role indicating the presence of positive sentiment. Images uploaded by customers in their reviews indicates greater positive attitudes compared to reviews without images. Meanwhile, sentiment valence is not significantly indicated by the total character count (TCC) variable.

A broader understanding of the correlation of each variable on the indication of sentiment expression was developed with a marginal effect analysis. Companies can better understand the changing aspects of customer emotions or feedback by examining how a change in individual variables is linked to the probability of positive or negative responses; while keeping other variables constant.

Table 10 comprises independent variables in addition to each variable's significance and interpretation, gained from the marginal effects estimation and logistic regression analysis.

Table 10. Interpretation of Logistic Regression Model Results for Manufacturer

Explanatory Variables	Significance	Interpretation
Total Character Count (TCC)	Insignificant	This attribute is not an indicator regarding sentiment polarity of the Manufacturer's customer reviews.
Vine Free Product/Incentivized Products (VNF)	Positively Significant	The attribute is correlated to positivity among the Manufacturer's customers in their reviews.
Image Attached (IMG)	Positively Significant	The attribute is correlated to positivity among the Manufacturer's customers in their reviews.

(Jason Raphael, 2024)

5.1.3 Comparison of Platforms

To make a comparison between both the platforms, the sentiment analysis conducted on both the e-commerce platforms was made to comprehend the distinction in the behavior patterns of the customers of Amazon and the Manufacturer of the product. The comparative analysis of different sources of reviews also presented a greater percentage of positive feelings found in reviews that were obtained from the Manufacturer's website, which suggests that the customers who left these remarks were likely to have had a more enjoyable experience in dealing with the product or brand they are most likely familiar with. Such customers likely wanted the product or brand and probably went to the Manufacturer's website with the purpose of finding the product with a clear commercial intent. On the same note, it could be noted that on a comparative percentage basis, Amazon rated less than the Manufacturer's sales platform on the positive reviews. Amazon is an expansive marketplace that offers products from various brands. The consumer base on Amazon consists of a significant proportion of casual or incidental shoppers who may not be actively seeking a particular brand's product. These customers may have come across the brand's product by chance or through algorithmic recommendations. Therefore, the variation in customer behavior is likely due to product or brand perception, resulting in 39.90% of positive sentiment in Manufacturer's reviews versus that of 23.33% in Amazon's reviews. For the same reason, the population of negative sentiments in reviews from the Manufacturer's website is less than Amazon, with 8.39% coverage of overall comments, while the negative sentiment population in Amazon is around 10.16%. Relevant to this comparison, 21.60% of reviews on the Amazon product page were incentivized (VNF) versus 96.46% of the reviews on the Manufacturer's retail e-commerce page for the product. Henceforth, the higher distribution of reviews based on free product distribution on the Manufacturer's website is also a seemingly significant factor in the greater customer satisfaction at the Manufacturer's online shop compared to Amazon.

The comparative analysis of platforms was further extended by comparing and contrasting the logistic regression results of Amazon and the Manufacturer's models. This comparison aimed to analyze the results and provide valuable platform specific insights through the independent review variables of review length (TCC), Vine-free product/incentivized reviews (VNF), and image attachment in reviews (IMG), indicating the sentiment polarity of reviews in two different e-commerce platform settings, and gauging the commonalities shared by them. The interpretation of the results can be initiated by the correlation of review length, also referred to as total character count (TCC) on polarity; it had no significant impact as an indicator of the sentiment of customers in either model. This implies that consumer sentiment valence is not considerably indicated by the length of reviews, that is, longer or shorter. The next variable analyzed was Vine-free product/incentivized reviews (VNF), which show positive significance in the models of both platforms, confirming that the provision of incentivized products and giving away free goods via programs such as Amazon Vine was a major indicator of the emotional valence expressed by the Manufacturer's and Amazon reviewers. Finally, the attachment of images in the reviews had a slight correlation to review sentiment polarity in both models. However, the indication of this variable is found to be different in both models, with a negative indicator of sentiment observed in Amazon's model, while a slightly positive indication on sentiment is evident in the Manufacturer's model. It predicts the brand or product consciousness of customers; thus, the images attached by the Manufacturer's customers are intended to show the effectiveness of the product and express positivity with the images. Nevertheless, there are skeptical customers on Amazon who may seek to undermine the product's implied usefulness by sharing photographs depicting its negative effects or deficiencies in the product packaging.

Conclusively, the interpretation of results obtained from both the qualitative and quantitative analyses of both platforms suggest the sentiment of customers is also correlated to the platform in which they are interacting. Apart from the platform, other influencing factors can also possibly indicate variance in customers' feelings which are beyond the scope of this study. The results serve as potential indicators of future marketing tactics and methods for influencing evaluations in a positive way, hence enhancing firm profitability. Further research could entail analyzing customer attitudes affected by other sentiment indicating variables not addressed in this research study.

5.2 Theoretical Implications of Study

The study of sentiment analysis and select review attributes as indicators of sentiment valence found in Amazon and the Manufacturer's customer reviews has theoretical implications that reach beyond the domain of marketing and customer behavior. By exposing the multifaceted relationship between these variables and highlighting the fundamental mechanisms compelling sentiment behavior, this research provides deep insights into human perception and sentiment in the digital era. Furthermore, theoretical understanding of this study can lead to the expansion of a more dynamic framework of sentiment analysis and encourage companies to enhance their knowledge of customer behavior and their responses to customer reviews and experience.

To increase positive review outcomes, sentiment analysis lends significant theoretical implications specifically relevant to customer reviews on the website of the Manufacturer's e-commerce site and Amazon for this product, impelling advertising and sales schemes, and ultimately improving customer gratification. Thus, the study for evaluating the sentiments of reviews from different platforms aligns with various existing theories, and the results of this study can be used as a pathway for elaborating and further exploring key aspects of theories. Upon examining the logistic regression analyses performed on both Amazon and the Manufacturer's reviews, the information relevant in the greater theoretical framework of sentiment analysis was extracted. Further, the recognition of the behavior of consumers, factors influencing their attitude, and the relationship between customers and platform attributes should be further examined. In doing so, the independent variables utilized in this study and their significant results can lead to a broader perspective of indicators regarding consumer review sentiment polarity. The following theories, methods, and strategies link directly to the practicality and usefulness of this study. It also provides possible future research opportunities when combined with independent review variables, and their indications of sentiment valence in customer reviews.

5.2.2 Consumer Behavior Theory

The theoretical implications of this research concern the function of online platforms in determining customer emotions and sentiments. One of the most frequented e-commerce websites globally is Amazon, whose extensive constituency and vast product base create a significant impact on product and brand perception. However, manufacturers' retail e-commerce platforms are built on various backend technologies and offer a direct link for the interaction between consumers and brands, allowing more flexibility in the appearance of product pages and brand imaging. This research study highlights the influence of platform review features on consumer sentiment by evaluating feedback across these two distinct e-commerce websites for the same product. This research can be considered a gateway to better understanding consumer behavior theory, which plays a vital role in defining the buying or purchasing decisions of customers. Consumer behavior provides an idea about the perception of customers related to the product. Businesses should understand the Consumer Behavior Theory to increase demand for their products. If businesses comprehend the purchasing patterns, preferences, or dislikes of the customer, it is possible to increase sales. This research study offers the opportunity to examine a particular effect of review variables on the variability of sentiments expressed in the reviews that affect the customer's buying behavior. In the context of the present work, consumer behavior is understood to mean the buying behavior of individual consumers in terms of the way they choose certain products or services to satisfy certain needs. Firms might employ this study to assess consumers' reactions to various setups of the marketing platform (Manuere, Chikazhe and Manyeruke, 2022, pp. 105-112). According to Bray (2008, pp. 2-33), customer behavior defines the process of the purchase, evaluation, consumption, and disposal of a product may be influenced by the perception of customers regarding the brand and the product.

5.2.3 Brand Management and Reputation Theory

This research contributes to the knowledge of understanding consumer behavior and brand images in the realm of e-commerce. Evaluations given by users of products constitute a good point through which customers' attitudes toward a company can be established. This information can be used and compiled to formulate good strategies and frameworks for the improvement of brand image and the development of long-term consumer relations. For instance, such information helps identify sentiment themes and provide insights into what could be potential trends in positive feedback to develop a more robust brand image and work on certain aspects to ensure consumers' loyalty and satisfaction.

Brand reputation theory refers to a person's attitude towards a particular brand. Brand reputation corresponds with the trust level and the assurance received from the customers and is influenced by various factors (Veloutsou and Moutinho, 2009, pp. 314-322). The concept of brand reputation requires the analysis of how people make a decision about a brand, as well as appraise it, by reference to certain parameters such as brand identity, brand perception, or brand image (Sääksjärvi, and Samiee, 2011, pp. 169-177). The importance of brand management in the context of digital business environments cannot be overemphasized, thus, ensuring positive attitudes among consumers requires constant efforts in diverse aspects. For long-term achievements, the importance of customer loyalty and trust is extremely important for them because customers anticipate firms and their products perform satisfactorily. According to Zehir (2011, pp. 1218-1231), it is important to manage reviews and build trust with brand reputation theory. A positive reputation for a brand leads to increased sales, customer loyalty, and long-run brand success. Brand reputation theory also focuses on individual user-generated content more specifically any form of negative remarks about a product to fashion solutions and brand reputation (Olaleye, Sanusi and Salo, 2018, pp. 85-102). An effective approach to managing brand reputation involves analyzing the online reviews of the brand's products and using the insights gained to improve the consumer experience. Aligning with this study, the importance of online website reviews helps identify online reputations. The main focus is to increase positive brand perceptions among customers (Colleoni , 2011, pp. 1-25). The insights revealed in this study will serve as a springboard for enhancing a brand’s reputation and improving customer service through sentiment analysis and impactful review variable identification.

5.2.3 Visual Semiotic Theory in Sentiment Analysis

Broadly determining emotion can be challenging, particularly considering the individual evaluations, which makes automatic identification more challenging. This type of analysis employs both the NLP and lexicon methods in addition to several codes on actual data derived from two different websites. Semiotics as a field of study addresses itself to the various ways in which meaning is constructed and conveyed. The processes of categorization involve semiotic structures of written language, visuals, as well as the effect of sounds, expressions, and space (Kumar , 2020, Article 102141). This research presents a mixed method where sentiment analysis is adopted and image attachments as the variable in evaluations. This research draws its theoretical basis from Semiotics Theory to look at the implication of using user-generated content in the form of uploaded images in customer reviews as an indication of the valence of the reviews. As this research also points out the impact of e-commerce on individuals’ feelings and attitudes, it acknowledges that companies need to grasp various approaches of semiotic theory that distinguish how written and graphic forms are utilized in expressing emotions (Aziz and Mohamed, 2023, 1-52). This study sought to employ a hybrid approach that entails a mixing of sentiment analysis and images in the reviews. When applying Semiotics Theory in sentiment analysis, this study identifies those four elements; the tone of language, the valence of words, and image attachment, which are the processes that foster the collective sentiments in the reviews. This study also reveals the great influence of e-commerce on a person’s feelings and attitudes. This underlines the relevance of the Semiotic Theory that enables organizations to observe how language, images, and gestural signs are employed to convey emotion (Aziz and Mohamed, 2023, 1-52).

5.2.4 Alignment with Human Sentiment Methods

Human sentiment methods incorporate complex systems to identify people's feelings and passion in writing. These methods analyze all the details and nuances of the given text with the same efficiency as in the case of human analysis. This work shows the relevance of employing reviews to assess the custodian's perception of a certain product. Text mining and machine learning are the theoretical approaches that imply a favorable future for the new sentiment analysis models that can take into account the complexity of human emotions inherent in the language. Duan (2016, pp. 282-296) suggested that the effects of consumer reviews on customer evaluation are also different. The weak signal for sentiment polarity of the variable review length detected in this study points to the possible limitations of traditional approaches to sentiment analysis. Sometimes emotions may be conveyed in indirect ways, hence traditional strategies of how to dissect and sum up the results may be insufficient and require more elaborated and delicate systematic methods. Therefore, this study forms part of the advanced sentiment analysis theories that employ Natural language Processing (NLP) and Machine Learning (ML) to seek better methods of human sentiment learning. This research is a way forward toward enhancing an understanding of complex sentiment analysis, with a particular focus on identifying the specific review-based variables as indicators of sentiment polarity in the text.

5.2.5 Implications for Marketing Strategies

The results of this study have direct implications for marketing strategies and provide a deeper insight into review variables that companies can utilize and exploit resulting in higher customer satisfaction levels and boosting favorable online evaluations. Therefore, understanding the impact of positive or negative comments helps companies change their marketing strategies to achieve higher rates of satisfaction among customers. For example, providing samples to customers who in turn are likely to post favorable opinions on social media platforms is beneficial in enhancing the popularity of the favorable opinions and equally helps in enhancing the reputation of the brand.

According to Sheykh Abbasi, Abdolvand and Rajaee Harandi (2022, pp. 141-163), the opinions and information of the buyers are essential in firms responding to complaints, assessing products and services, and for marketing and business development. The significance of sentiment analysis has increased significantly because it is used to analyze customer feedback that is provided through reviewing products or services. The sentiment analysis technique used in this study was taken to classify the comments into the Positive and Negative. The outcomes of such sentiment polarity sorting may help in handling consumer complaints, encouraging market increase, and evaluation of products. There are marketing strategies whom target the positive aspects derived from the analysis of the customer reviews hence satisfying the customers. It means that these product attributes can become the foundation for positioning and advertising communication both online and offline.

Therefore, the understanding of the findings of sentiment analysis of the reviews gathered from Amazon and the Manufacturer's online portal opens an imperative view to examine customer behavior, brand image, and marketing strategies. Based on the way how the consumer emotions are segmented on different e-commerce sites and how the attributes of reviews signal the emotion, they offer valuable information and knowledge for sentiment analysis. Besides, the outcomes described in this study can be used to help businesses pay more attention to enhancing customer satisfaction levels and brand confidence in the era of digital environment prevalence.

5.3 Practical Implications of the Study

Sentiment Analysis can be considered a developing area in natural language processing and has numerous pragmatic connotations when it comes to evaluating the reviews of an e-commerce platform from a manufacturer and multiple Amazon reviews of the same product. Understanding the feelings conveyed through the words used in the reviews is an important task in an open and uninterrupted platform like Amazon which is an important place where people go to view products and make purchases. The feedback posted to the website by the buyers does influence the decisions of many shoppers, while sentiment analysis does offer important impressions of user attitudes, concerns, and satisfaction. It displays the ability of marketers to sort reviews analytically based on the divergence of sentiment as well as experience the trends that manifest the level of satisfaction and dissatisfaction from the consumers through the application of sentiment analysis processes (Puschmann and Powell, 2018, pp. 1-12). This helps the platform in providing product guides, recommending consumer-generated content, and creating individual recommendations for individual customers hence enhancing the shopping experience. Moreover, sentiment analysis helps Amazon to solve negative feedback and prevent disasters in its online marketplace. Amazon can leverage this knowledge towards the progress of the more significant review characteristics that reflect product success and control the consumers.

Sentiment analysis implies massive significance for the manufacturers in terms of customer emotions and product reviews. This assists manufacturers in improving product quality and in also changing their advertising policies and marketing strategies. Using sentiment analysis one can see how a brand is perceived, track the competitors' performance, and identify emerging market trends. The findings of this research can be used by manufacturers to focus on the positives from reviews on their platforms of the statistically significant factors that pertain to the success and buying influence of products.

5.3.1 Encouraging SMEs to Leverage Sentiment Analysis

This research study can also help SMEs including start-up businesses to make a decision on which retail platforms they should market their products, and measure the competition in the market space in which they operate through sentiment analysis, thus saving the cost of engaging in more expensive market research. Due to the high cost of carrying out market research, small businesses cannot afford to purchase costly software and time-consuming large volumes of data and hire outside consultants to conduct research. This study provides a direction for small brands and start-ups to learn and gain insight into consumer behavior and their perception of products in various channels (Rambocas and Pacheco, 2018, pp. 146-163), in a relatively cheaper way compared to other research methods.

In the e-commerce field, small business faces the challenge of selecting the right sites to sell products which is compounded by resource constraints. They are required to select the right platforms to drive more sales of their products as well as enhance or establish a brand image. The use of sentiment analysis is particularly valuable in research and the tool has presented itself as a possibility of gaining insights into the customers' perception and the general dynamics of e-commerce. Sentiment Analysis is therefore cheaper than other forms of research and businesses.

Sentiment analysis helps small businesses to sustain their online status of brand with the positive reviews collection on various platforms. By observing the trends in sentiments SMEs can concentrate on consumer preferences and perceptions (Pollak, Dorcak, and Markovic, 2021, pp. 1-16).

5.3.2 Voice of Customer and Product Features

Regarding product development techniques, customer-oriented features have been identified as a significant factor in the techniques for product development because they assist in forming product characteristics and enhancing buyer priorities through the use of responses from questionnaires provided online by customers (Cao, Dewan and Lin, 2023). When users are asked to freely express their feelings about some companies' products on feedback forums or different websites and then analyzed in groups, companies end up with trends or broad attitudes that point out the needs and wants of the segment. Medhat, Hassan, and Korashy (2014, pp. 1093-1113) disclosed that the techniques of sentiment analysis help in the identification of aspects and qualities of the product that are highly appealing to clients. Consequently, the research conducted in this study provides a framework for the subsequent mapping of future product formation and development. By prioritizing customer-centric product development stages, companies may strengthen the ties between their brands and customers, resulting in increased consumer contentment, loyalty, and a more positive brand image in the marketplace (Fiiwe , 2023, pp. 19-28). The application of consumer-oriented product attributes obtained from product reviews provides significant benefits. It allows companies to evaluate customer priorities and industry trends. If utilized productively, this can result in business growth. By understanding consumer perceptions, firms can allocate resources with more efficiency to improve brand reputation. The customer-oriented approach creates a deeper emotional connection in customers because their response to the product impacts the development tactics for the product and creates long-term benefits. This results in a company's innovation and close to real-time improvements where possible. Businesses can create value for their stakeholder's profit by completing consumer expectations regarding products that discriminate them from market competition.

5.3.3 Adjusting Product Pricing

The sentiment analysis of the reviews gives a perception of the value of the products about the prices. It can be a significant factor affecting the concepts of pricing; therefore, it allows businesses to change prices due to the obtained knowledge of consumers and can lead to higher levels of revenues (Wu, Chiang and Chang, 2024, pp. 1927-1936). Based on the analysis of positive and negative sentiments, companies can use available price changes depending on consumers' satisfaction and competitor prices for similar products. The given activity of sentiment analysis and further determination of its value, particularly when it goes beyond simple positive/negative or useful/harmful categorization, can sometimes be completed and justified only with price differentiation. This is because sentiment analysis introduces some elements such as the price factor of the product and the value that customers expect as far as the reviews are concerned. Sometimes the variation in the sentiment can be justified by external factors, these may be the activities and products of competitors and seasonal factors indicating that companies need to perform the sentiment analysis not only over days or weeks but over months or even years. The sentiment analysis serves as a review loop of the price optimization which enables the change of policies and pricing strategies to generate positive consumer sentiments (Huang, Zavareh and Mustafa, 2023, pp. 90367-90382).

5.3.4 Recognizing Competitive Benefits

The practical implications of sentiment analysis based on customer reviews can lead to the recognition of competitive advantages. Sentiment analysis helps companies maintain product standards for their competitors. By evaluating the sentiments conveyed in feedback on competitive products, firms can examine the areas where there's an opportunity to upgrade their products against competitors (Trivedi and Singh, 2021, pp. 891-910). For businesses, strategic decision-making can be emboldened by competitive intelligence from online reviews. Amarouche, Benbrahim and Kassou (2015, pp. 358-365) discussed that businesses can increase their competitive advantage of the products they offer through comparing reviews. Thus, for the success of a business that sells online, it is necessary to evaluate the sentiments of customers found in reviews about the product and its competition. Firms can better understand product experience and leverage it with the assistance of sentiment analysis.

5.3.5 Forecasting Product Demand

The reviews collected from Amazon and a Manufacturer's e-commerce website act as a repository from which analyzing customer sentiments is possible. The practical implication of this study appears to strengthen the forecasting and demand for a product, which is crucial for businesses that want to anticipate future requirements and adjust their manufacturing processes to meet client expectations. Forecasting customer demand is one of the vital activities for any business since it enables the company to produce goods to meet the needs of the customers. Lau, Zhang and Xu (2018, pp. 1775-1794) explained that the application of sentiment analysis leads to a cycle of continuous improvement when it comes to demand projection to help the e-commerce markets and manufacturers predict demand in the future. In the highly competitive and volatile e-commerce environment, the conclusion of this work could be of help to the various organizations embarking on setting up production based on the demand and enhancing its sales forecasting. This finally leads to the overall achievement of goals such as gaining maximum profits for the business. Thus, using trends of sentiment companies can build changes in customer sentiment and predict changes in demand using overall positive or negative reviews. For demand prediction the right assessment of consumer behavior is crucial to manage corresponding decision-making and shaping its results that influence the distribution of the resources (Amellal, 2024, pp. 237-248). Sentiment analysis of customers' feedback plays a crucial role in predicting customers' purchasing behavior for product positioning and the strategic management of product supply (Wu, 2022, pp. 795-816). Overall, it enables e-commerce businesses to grow through gradual enhancement and results in the accumulation of a positive reputation in the somewhat saturated e-commerce industry.

5.4 Limitations of the Study

Conducting a comparative analysis of reviews of similar products on Amazon and the Manufacturer's retail e-commerce shop gives a valuable understanding of customer behavior and opinion in the area of digital platforms. However, it is also crucial to identify the limitations of this research, concentrating on the areas where additional understanding and learning are possible through future study.

5.4.1 Sample Bias

One important limitation of this study is the potential for sample bias in the reviews occupied by the Manufacturer's and Amazon's platforms. While some measures were taken to get an unbiased sample, there is always a probability of intrinsic bias in the reviews due to the arrangement and placement of the product on the e-commerce website. This bias can lead to an overestimate or underestimation of the product's quality, thereby influencing the results of sentiment analysis. For example, higher sales of products or higher prominence may be a reason for the unequal proportion of reviews compared to a product with a lower prominence or listing categorization. Additionally, the locale of the consumers giving feedback on these websites may not be representative of larger, more diverse user populations, which can create biases in sentiment analysis.

5.4.2 General Applicability

This research offers insights into the sentiment dynamics based on feedback from Amazon and the Manufacturer's e-commerce site for a specific product only. The generalizability of this analysis to other product categories or online platforms may be limited. Changes in customer preferences, product features, and platform characteristics in various market domains can positively or negatively impact the causes of dynamic sentiment. Hence, further research should be conducted in the form of future studies to broaden the scope and application of this study by including contexts that were not examined in this research.

5.4.3 Possibility of Fake Reviews

The quality of the feedback obtained from both the Manufacturer and Amazon websites was given critical attention and focus in this analysis. The existence of false or fake feedback can demoralize the authenticity and credibility of sentiment evaluations, possibly resulting in inaccurate results. Although efforts have been made to lessen the risk via thorough cleaning of the data and authentication measures, the intrinsic variation in review accuracy on various platforms persists as a continuous challenge in the study of sentiment analysis of customer reviews. There is no overt indication that fake reviews were a prevailing active component of the reviews on either platform for this beauty skin care product.

5.4.4 Platform Differences

Amazon and the Manufacturer's platforms contain diverse customer demographics, review guidelines and rules, and the culture of the community that impacts customer sentiment expression. Platform-specific variation leads to unique factors that can add complex layers in the comparison of both Amazon and the Manufacturer's platform reviews. For instance, consumers may inherit diverse linguistic types and norms of communication while interacting within the constraints of each website, hence molding the content and tone of reviews in specific ways. Avoiding these specific platform distinctions can resolve the reliability and legitimacy of the comparative analysis results. The platforms utilized in this study do not appear to contain overt platform-specific semantics. However, platform-specific semantics and culture can play a significant role in future studies regarding cross-platform consumer sentiment comparisons.

5.4.5 Exclusion of Other Features

The research in this study focused on specific review attributes and features including total character count (TCC), Vine-free and incentivized product (VNF) giveaways, and image attachments (IMG) which have the possibility of indicating the valence of sentiments in online reviews. It is noteworthy to identify the existence of other variables that were not included in this analysis. For example, influencing factors such as the user experience of the websites, ease of the buying process, demographic features of users, product pricing, shipping options, and packaging aesthetics may have significant impacts on sentiments, but were generally beyond the scope of this study.

5.4.6 Temporal Effects

For sentiment expression, the temporal effect shows other dimensions beyond the focus of this research. For instance, reviews obtained at separate time intervals may reveal changes in customer sentiment impacted by elements such as variations in market trends, changes in customer priorities, and product updates. Neglecting these temporal dynamics can lead to imperfect or quasi-ambiguous results due to the sentiment trends highlighted in reviews of the product on Amazon and the Manufacturer's site. Exertions should be made in future research to focus on analyzing reviews from different time durations to account for the possible temporal nature of customer sentiments.

5.4.7 Model's Shortcoming

The sentiment analysis model applied in this research may demonstrate limitations in describing the tone of customer sentiment expressed in online feedback from reviews. Specific linguistic components of speech in the reviews including sarcasm, insincerity, and confusing language can create situations in which the polarity of sentiments may not be readily visible in the text. This research study is mainly based on the presence of a sentiment demonstration to categorize reviews, which can superintend indirect sentiments expressed through unbiased language. For instance, expressions such as "product as described" may seem neutral but can possess positive sentiment within the perspective of a satisfactory review. Future researchers can utilize more complex techniques of sentiment analysis to enable the decoding of hidden sentiments in the text of reviews.

5.4.8 Interpretation Challenges

Analyzing the impact of multiple factors on sentiment expression is a noteworthy challenge in this research. Creating underlying relations among variables and the results of sentiment is intrinsically challenging because of the complex attitude of customer behavior and the interaction of various impacting factors which are correlative in this study, not causative. However, the connection among numerous variables may lead to complications that were not completely discovered in this research. Future researchers should use additional statistical tools, such as structural equation models or causative implication techniques, to clarify the fundamental mechanism of sentiment expression obtained through online feedback further strengthening the systematic approach.

Thus, by summing up the limitations of this study on sentiment analysis of Amazon and the Manufacturer's reviews, it yields key insights regarding customer opinions in the digital e-commerce realm. Therefore, it is necessary to identify and point out the intrinsic limitations faced during the investigation process.

Biases in sampling, general applicability, possible presence of fake reviews, platform differences, exclusion of other features, temporal effects, model shortcomings, and interpretation challenges are crucial areas for future examination and modification. Recognizing these study limitations and implementing additional techniques in research plans, data collection, and interpretation of future research can further improve the credibility and consistency of sentiment analysis in online customer reviews. Prospective researchers should focus on solving these limitations through a methodological, innovative approach to increase the perception and strategic use of customer sentiment.

5.5 Recommendations for Future Research

The field of digital marketing is constantly evolving, driven by modernization and advances in technology. As changes occur in the formats of customer feedback and several customer reviews, the requirement for advanced methodologies to analyze consumer sentiments becomes more crucial. This study's thorough review of the existing literature highlights the further expansion and research of sentiment analysis in marketing-related studies. Emphasizing the perceptions obtained from this analysis, this research presents several recommendations for future researchers in this field. These recommendations are designed to highlight unresolved questions, overcome methodological limitations, and enhance the perception of human behavior.

This study bridges the research gap by providing a precise examination and comparison of two online platforms for the same product highlighting variations, as well as the relevancy of specific review attributes as indicators of sentiment valence. Huang, Zavareh and Mustafa (2023, pp. 90367-90382) acknowledged several challenges that researchers would face in future studies, particularly with situation-centric sentiment analysis. With the increase in customer reviews on e-commerce platforms, it is essential to classify sentiments both in the review text as a whole and at the aspect level. One of the challenges is encountering sentiments that are difficult to classify as negative or positive due to the occurrence of various aspects. In recent years, aspect extraction is a critical phase that has emerged in sentiment analysis. Implicit aspects can be gathered from the context of the text as well as the generally accepted common lexicon. Maitama (2020, pp. 194166-194191) found methods for obtaining explicit aspects, implicit aspects, or both. As techniques in ML such as vector machines and neural networks progress, future researchers should utilize them for more accurate sentiment polarity assessment.

5.5.1 Website-Specific Study

Future research should include an in-depth investigation of the specific platform elements that indicate and influence consumer sentiment on various e-commerce platforms. By performing a comparative analysis between several platforms, such as eBay, Amazon, Walmart, and the Manufacturers' e-commerce platform, researchers can analyze the specific methods, review collection techniques, and consumer demographics that impact the attitude and tone of consumer feedback. Focusing on the influences of specific platform features is necessary for planning customized strategies to enhance consumer satisfaction on a platform basis.

As for the future researchers who will investigate the given field of comparative analysis, they can emphasize how the different websites impact the sentiments of the customers. For example, future research can reveal whether the reviews arranged for consideration and written on different websites are more positive or are positively biased compared to the spontaneous reviews, not arranged with the company and whether it is the same or differ when it comes to a large number of various websites and products. Besides, examining the customers through the websites can illustrate how characteristics like gender, age, or location may influence the kinds of sentiments of the given categories as well as the language of the feedback. Thus, the separation of the influence into these categories can help brands create platform-specific strategies with better results and in a more efficient manner by focusing on each website/ platform's target audience.

5.5.2 Longitudinal Studies

The ability to employ a longitudinal method to acquire more information on consumer perceptions of service quality and on potential temporal changes and progression of customer characteristics have been highlighted as crucial (Ebadi, 2021, pp. 725-739). Through tracking how sentiments change with time, research activities can uncover seasonal shifts, product performance over time, or external factors that may influence consumer concepts or beliefs. The longitudinal surveys also give a better picture in depicting the changing moods of the customers and the business needs to remedy the changing tides in the market from time to time.

Furthermore, longitudinal studies can also facilitate the identification of some key factors that drive the shifts in customer perception, like advertisement campaign, new product release or other actions that are either able to create positive or negative emotional responses among customers. By understanding customer trends, researchers can identify the influence of the evolutions in marketing campaigns on consumer perceptions. Furthermore, longitudinal data can simplify the understanding of long-term patterns that may not be revealed in cross-sectional data analyses, thereby contributing to or shaping long-term strategic policies.

5.5.3 Cross-Cultural Study

Prospective research should investigate cross-cultural variations in consumer attitudes expressed in reviews, given the global reach of some e-commerce platforms. The expression and interpretation of consumer feedback might be influenced by cultural considerations including linguistic preferences, means of communication, and cultural norms. Conducting comparative research in various cultural contexts will assist with clarifying whether consumer feelings and their expressions are universal or culturally specific, which can help multinational firms with their localization and global brand management initiatives (Rosillo-Diaz, Blanco-Encomienda and Crespo-Almendros, 2020, pp. 139-160).

Cross-cultural studies can also be used to express how social conventions and principles influence consumer groups' perceptions of products, services, and brand quality. For example, views and perceptions concerning exclusivity, social status, and distinction might be explained by a comparative analysis of consumers' attitudes toward higher-end products across cultures. By paying attention to such elements of culture, manufacturers can elevate their brands and their positions on the global market with different advertising and marketing strategies reflecting the culture-specificities of the target regions.

5.5.4 Incorporation of Multimodal Dataset

Using multimodal data which is a combination of images, video, text, and audio can assist in improving insights of consumer sentiment towards online platforms. Thus, through the identification of visuals including product photographs and user-generated images alongside feedback, future researchers can determine additional dimensions of customer experience that may not be inferable from textual feedback alone. By including multiple modes of data, more in depth information and a holistic view of the total consumer and customer is possible. It is believed that this analysis could uncover nonstandard indicators uncovered in various modes that enrich the existing models and techniques of manners of how to express different kinds of sentiments inclusively (Gandhi, 2023, pp. 424-444). For example, to include facial expressions of consumers when giving video reviews on products, gives a better understanding of the valence in the reviews and satisfaction levels. Similarly, when analyzing customer service telephone calls or video-based reviews in very detail it is possible to take into consideration voice tone, pitch, and emotional undertones, which are filtered when the text of the conversation is transcribed. Descriptive researchers may therefore potentially achieve a deeper and broader perspective of the customer sentiments and emotions in online markets by incorporating all the modes of data collection into a research dataset.

5.5.5 Advanced Methodology with Machine Learning

The efficiency and effectiveness of consumers' sentiment in e-commerce can be evaluated more objectively by employing artificial intelligence techs such as neural networks and deep learning (Ghorbani, 2020, pp. 1-12). After the present research works, other research studies may explore the application of neural network frameworks and machine learning designs for categorizing consumer feedback as well as analyzing and archiving the various feedbacks at a greater capacity. By applying sophisticated machinery of machine learning, the researchers can pinpoint the subtle trends and changes in consumers' attitudes, which in turn provide access to more accurate and useful knowledge.

Through algorithms for machine learning, researchers may successfully identify sentiment-containing expressions and feelings in several scenarios including the following for automated processing and analyzing large amounts of textual data. Namely, deep-learning models are observed to be more accurate than traditional approaches to sentiment assessment regarding intricate patterns and relations between semantically related words in text. One way through which researchers can counter the challenges posed by manual coding and annotation is through algorithms that are based on the latest machine learning techniques that can assist in sentiment analysis of the various web stores and other related platforms.

5.5.6 Impact of Intrinsic Review Characteristics

Review characteristics such as the lexical choice of language, emotional intensity as well as the user's reliability can all help in the acquisition of more information on the specific consumer sentiment and their purchase intention. Subsequent researchers might collaborate with commercial entities and platforms to conduct such experiments to systematically force customers to write reviews with given characteristics and assess the impact on the sentiment polarity. Approaches to enhance the reliability, integrity, and efficiency of the reviews in the e-commerce context can be derived depending on how changes in the image attributes influence the perceptions of customers (Felbermayr and Nanopoulos, 2016, pp. 60-76).

The aspects are quantifiable and researchers can specify those that impact on the consumer sentiment valence the most and conduct experiments focused on certain facets of the review characteristics and their impact on customer perception and behavior. For instance, adjustments in the in-review items, such as details of feedback, politeness, and formality, can uncover how communication impacts the consumer perception of the quality of products and brands. Comparing reviewers' competence or credibility (e.g., expertise, verified or unverified), enables elaborating on the nuances of how customers' perceived confidence and reliability affect shopper's decisions to purchase products. Thus, the research can help scholars offer practical recommendations for increasing review valence and quality over the Internet by systematically altering and highlighting various attributes of the reviews and evaluating the resulting changes in customers' attitudes.

The aforementioned suggestions offer invite more productive paths for further research on the sentiment of customers in online markets. More contributions can be made by the researchers towards the goal of understanding consumer behavior in the digital age with a focus on the following aspects; website specific factors, long-term methods, cross-cultural and multi-method replicate studies, multimodal dataset analysis including methods such as machine learning methods and a study of how intrinsic characteristics of reviews affect sentiment. The future research can produce new knowledge and contribute to the development of e-commerce scholarship based on interdisciplinary perceptions and modern methods.

CHAPTER VI

CONCLUSION

The purpose of this study was to explore and analyze the disparity of customer sentiments in reviews and their purchasing decisions across two different online platforms for the same product in the skincare category. The study focuses on the discrepancy in sentiment valence in customer reviews between Amazon and the e-commerce platform of the product Manufacturer. This study analyzed how specific review attributes reflect the positive or negative sentiment of reviews on each site. This research provides a preliminary background for the discussion of consumer behavior and attitudes towards a beauty cosmetic product sold in the digital e-commerce market by employing both qualitative and quantitative methods. This chapter presents a comprehensive summary of the research findings, conclusions, and contributions to the field of e-commerce and marketing. It also includes final thoughts.

6.1 Summary of Findings

The primary finding of the investigation demonstrates significantly different sentiment of the consumers across both platforms for the same product: Amazon and the Manufacturer's online store. There is more variability found in the reviews of consumers on Amazon relative to the Manufacturer's site, with a much greater emphasis on factors such as product quality and effectiveness. Amazon's platform, which is recognized for its substantial range of product categories and brands likely attracts consumers who depend heavily on product reviews for deciding on their purchase. The sentiment analysis of Amazon reviews demonstrated a balanced mixture of positive and negative sentiments. In particular, the sentiment conveyed for the selected product on Amazon displayed 23.33% positive reviews and 10.16% negative reviews.

Conversely, customers from the Manufacturer's web store appeared to arrive at the website with predetermined perceptions of the brand or product, and a greater degree of brand trustworthiness. This pre-existing belief led to a higher percentage of satisfactory reviews, with

39.90% positive reviews and only 8.39% negative reviews. The inconsistency in review valence suggests that consumers on Amazon are stricter and more diverse in their reviews, likely due to Amazon's product selection, recommendation engine, and competitive nature. Conversely, consumers on the Manufacturer's website seem to have a pre-existing positive perception of the product, resulting in more positive reviews.

The sentiment analysis performed with NVivo 14 discovered that positive sentiments on Amazon often revealed the product's efficiency, ease of use, and reasonable price. Negative reviews highlighted discontentment with product quality, packing, and customer service concerns related directly to the product. Neutral reviews were often comprised of well-adjusted feedback, indicating both pros and cons. The Manufacturer's website reviews primarily underlined the product's advantages and overall satisfaction level, with fewer mentions of unfavorable experiences. This distinct behavior suggested that product perception and customer loyalty considerably affected consumer reviews on the Manufacturer's website.

The study also found the significant influence of specific valence indicators of consumer sentiments. Firstly, incentivized products, such as those offered by Amazon Vine were used to gather product reviews, positively correlated with sentiments of consumer reviews on both websites. This outcome revealed that complimentary products or free products in exchange for reviews can reflect positive sentiment and enhance product awareness. Customers who received incentivized products often conveyed appreciation and gratitude, which was parlayed to more positive reviews. This phenomenon exemplified that the practice of giving incentivized products in exchange for feedback can efficiently indicate positive responses and increase product ratings on different platforms for the same product.

Secondly, the length of reviews was analyzed as another variable which potentially indicates customer sentiment, and found only negligible influence on sentiment, representing that lengthy and detailed reviews do not effectively indicate review sentiment polarity. Both short reviews and long reviews have similar allocations of positive and negative feedback, suggesting that customer sentiments are linked closer to the content of the review rather than the length of reviews.

Subsequently, the study found that image attachments in customer reviews were an indication sentiment in both Amazon and the Manufacturer reviews. However, the indication of sentiment was more significant on Amazon and suggested negative sentiment, while the indication of sentiment was less significant on the Manufacturer's e-commerce shop and suggested positive sentiment. At Amazon, images were frequently used to document faults, inadequate packaging, or disappointment with the product. However, images attached to reviews on the Manufacturer's platform were usually more positive or leaning towards neutral, highlighting the product's success at the intended outcomes. This variance implies that the platform context impacts how visual features are utilized and potentially perceived in consumer reviews.

Conclusively, the study highlighted the intricate relationship between the characteristics of the platform, product perception, and consumer sentiment, and found a positive relationship between product perception and the sentiment of customers. It determined that some platform review factors indicate the sentiment polarity of consumer reviews and customer loyalty, and ultimately play a fundamental role in influencing consumer behavior and buying decisions, yet can differ per platform. The research focuses on the significance of considering both the website context and the intrinsic biases of consumers when leaving reviews online.

6.2 Contribution to Knowledge

This research contributes significantly to the existing literature and knowledge regarding the analysis of sentiments in e-commerce, and the investigation of customers' behaviors. Firstly, it provides practical knowledge of the variation in the feelings of customers towards one e-commerce website compared to another for the same product. Focusing on a single product and linking the reviews on Amazon and the platform owned by the Manufacturer assists this investigational study with minimizing the biases caused by other factors, including product variation and single platform bias. This method offers a greater insight into how platform differences impinge on customers' emotions and sentiment found in customer reviews.

This study adds to the stream of e-commerce customer behavior knowledge, highlighting how platform differences affect customer behavior and consequently shape buying behavior. The conclusion drawn from the outcomes of the current research as well as the differences between Amazon and the Manufacturer's website is that consumers are influenced by the perspective in which they encountered and engage with the product on different platforms. Such findings are imperative to any researcher who aims to understand customer shopping behavior in the online environment, and the factors that define customer satisfaction and reliability.

Secondly, the research yields the information necessary to get favorable sentiments in product reviews via incentivized products. The impact of incentivized products or giveaways on both websites suggests the efficacy of this strategy for enhancing product knowledge amongst consumers, along with creating enthusiasm for positive reviews. This result has implications for companies and brands, which can either promote incentivized or Vine-free products to drive improvement in consumer opinion and further advance the reputation of the brand. Through tactics such as this, involving free products in exchange for reviews, brands can further create a positive image about their products by utilizing user generated feedback in the form of positive ratings while advertising a product. Furthermore, companies aiming to enhance their profits by better comprehending customers' apprehensions and grievances regarding their goods can employ this study to identify specific aspects for product enhancement, resulting in review improvement and potentially increase sales.

The study also provides insight into the ethical considerations associated with incentivized reviews. While incentivized products can create positive feedback, firms need to guarantee clearness and trustworthiness in their review collection practices. Incentivized reviews should be marked as such by the platform to keep faith and credibility in customer reviews. This ethical aspect is critical for maintaining the long-term reliability and trustworthiness of brands.

Thirdly, the research sheds light on the limited viability of review length as an indicator of consumer sentiment polarity. By proving this determinant does not significantly infer customer review polarity, the study compliments common assumptions about the depth or intensity of sentiment in detailed and lengthy reviews. Longer reviews may contain greater depth of sentiment or a more complete understanding of feelings, however, these longer reviews do not indicate whether the valence is more likely to be positive or negative. This information can be utilized to update the design of review systems, and shift the focus to other elements, such as review content and genuineness, to affect consumer sentiment polarity. Brands and platform designers can concentrate on the quality and applicability of review content over the word counts.

The study offers an understanding of visual factors in online reviews. The contradictory impact of image attachments in reviews on Amazon and the Manufacturer's platform emphasizes the importance of platform context when examining image content in reviews. This suggests that businesses should carefully observe and manage the visual aspects of consumer reviews to make sure they accurately reflect the product quality and consumer sentiment.

Furthermore, the study advances methodological development in e-commerce research by retaining a mixed-methods approach. The mixture of qualitative sentiment analysis by NVivo 14 and quantitative analysis using STATA offers a more complete understanding of consumer sentiment and associated factors. This methodological template serves as an illustrative pattern that can unite future academics in their efforts to understand complex buyer behavior. Qualitative and quantitative research methods used together forge a more wholesome assessment of consumer characteristics and perceptions.

The applicability of NVivo for qualitative sentiment analysis facilitated the extraction and elaboration of sentiment content from the consumer reviews obtained from Amazon and the Manufacturer's shop. Further, the analysis of NVivo in this research brings to light the most significant aspects of the emotions and feelings that makeup customers' perceptions. The second analysis leveraged quantitative examination of manually coded data with STATA and explored the more profound facets of review variables indicating customer sentiment polarity. Future research can utilize these findings as a lens through which customer feelings such as emotional strength and tone can be viewed for other products and platforms.

The study is further enhanced by the quantitative analysis that employed STATA software to provide statistical evidence of the link between the features of the reviews as indicators of customer sentiment polarity towards the product. Exact assessment has made it possible to determine the impact of each factor as an indicator of sentiment by employing marginal effect estimations along with correlation analysis. The effectiveness of quantitative analysis strengthens the conclusion's validation and reliability while expressing a solid foundation for more research and practical applications.

Ultimately, the research provides valuable advice to companies that want to enhance their online brand positing, increase customer engagement, or want to establish a deeper relationship with consumers. By taking into account the review attributes that are indicative of customer attitudes, sellers can promote initiatives to construct more positive opinions in reviews about their products, consequently, enhancing product success. The research has shown that it is essential to emphasize the variables or methods that can enhance the positive sentiments of customer reviews. This, in turn, will serve as a catalyst for generating more sales. For instance, businesses can offer promotions, giveaways, or incentive programs to improve reviews sentiments, and the review ratings of their products.

6.3 Concluding Remarks

To summarize, this study reveals the variations in customer review sentiment for a particular product sold on two distinct e-commerce platforms. Additionally, it highlights the efficacy of selected review factors in indicating the emotional tone of the reviews. The research revealed pertinent variations in the sentiment exhibited towards a particular skincare product by customers from the two platforms. However, a portion of the review features play a role in indicating the sentiment polarity of customers' reviews of the product on both Amazon and the Manufacturer's e-commerce website.

Thus, the study supports the centrality of understanding review features and their indications about product perception, and encouraging incentivized product distribution to craft positive sentiments reflected in consumer reviews. The study's methodological approach is a combination of quantitative and qualitative strategies, which enables one to gain a comprehensive understanding of buyers' attitudes across multiple platforms for the same product, and specific review variables as indicators of review sentiment. This is beneficial for both academic and practical business applications. This study bridges the gap in evaluating customers' reviews cross platform for the same product by revealing differences in sentiment which can impact strategic business choices. The findings presented in this study illustrates specific review attributes indicating the perception of the products, which justifies the application of nuanced strategies for developing marketing campaigns and engaging customers.

Future research on consumer behavior and attitude change can explore additional factors that indicate the evolving dynamics in consumer sentiment. These factors may include cultural differences, product categories, and the impact of emerging technologies on e-commerce website platforms. In this perspective, as the research on customer behavior continues to reveal new insights about online platforms and consumer sentiment, more efficient ways of bridging the gap between the increasing needs and the preferences of online customers will be revealed.

It is also possible for future research to assess the influence of different e-commerce platforms, their specific review attributes, and other digital channels on the formation of consumer attitudes and behavior. As the digital world unites and expands, studying the links between distinct online websites and customer perception can impact the future of e-commerce design and development. Future research could explore the impact of giving away incentivized products relative to their costs, and the highly probable increase in credibility through online reviews, thus enhancing the long-term reputation of the product. Incentivized reviews can also help to generate a higher number of customer reviews as well as create free publicity in the short term. The sustainability and effectiveness of these strategies should be further investigated by research and development.

In addition to the aforementioned points, future study can also investigate the latest applications of AI and ML models in the examination and evaluation of online reviews. Advanced analytical tools can provide a deeper insight of customer attitudes and behaviors, leading to more effective and streamlined strategies in expanding brand perception and enhancing customer reviews. By conducting research that utilizes advanced AI and ML, researchers can provide new and valuable solutions to the various difficulties often associated with the e-commerce industry.

Thus, the current study explores an incremental improvement of e-commerce sentiment analysis, and valuable recommendations are offered for companies desiring to expand their product sales and enhance their online presence. Executives and marketers stand to benefit from the findings of this study to make well-informed decisions that can enhance product perception, achieve superior evaluations, and eventually boost sales.

In summary, this paper provides a literature review and empirical evidence about variations and similarities in consumer behaviors and attitudes toward a specific product sold on two different e-commerce websites, Amazon and the Manufacturer's online store, and identifies overall key factors that indicate consumer review polarity. Attributes specific to customer reviews and consumer perception including visual content in the form of images included in reviews and products that are incentivized are more important as sentiment indicators as per the findings. This paradigm shift over previous quantitative and qualitative approaches can provide significant contributions to academic research and real-world application in e-commerce contexts. It is recommended that future researchers explore other factors impacting consumer sentiment and develop improved strategies for customer engagement leading to more satisfied experiences.

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