IMPACT OF E-WOM ON PURCHASE INTENTION OF KURTIS IN INDIAN E-COMMERCE CONTEXT: A MIXED METHOD APPROACH

ABSTRACT

Online shopping has changed the current structure of shopping for many customers. Shopping from e-commerce websites is not only confined as a trend, but it's the utmost need of the hour. The current study will be done in two phases. In phase one, a conceptual model will be made, which will be used for testing the impact of online reviews belonging to Indian ethnic dresses on the purchase decision of the consumer. The conceptual model will be tested using a survey-based primary data collection. A descriptive analysis and hypothesis testing would be performed based on the data collected. In the second phase of the study, the online review will be web-scrapped from the different e-commerce portals like Amazon, Flipkart and Snap deal. The reviews both in textual nature and image forms (as well as videos) will be retrieved from these e-commerce portals. Different levels of analysis will be performed for textual and image datasets. Once the textual reviews are retrieved, the data is pre-processed both computationally and to some extent manually. The data collected for the Indian ethnic dresses will be binned under different price bands so as to ensure further comparative analysis. The next analytical steps involved would be product feature extraction, emotional classification of the reviews, text classification model for a recommendation, and topic modelling. There lie opportunities for optimization in text feature selection, text classification model, and topic modelling. The findings from this study would throw a lot of insights on the consumer behaviour in e-businesses and get provide data-driven pointers for managerial decision making.

Keywords: Online Shopping; Indian ethnic dresses; e-commerce; Consumer behavior; Text feature selection; Text classification model; Topic modelling

CONTENTS

LIST OF ABBREVIATIONS

AGFI	Adjusted goodness of fit index
CFA	Confirmatory Factor Analysis
CFI	Comparative fit index
COD	Cash on Delivery
e-WOM	electronic Word of Mouth
GFI	Goodness of fit index
RMSEA	Root-mean-square error of approximation
SEM	Structural Equation Modelling
TRA	Theory of Reason Actioned

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CHAPTER 1

INTRODUCTION

Globalisation and technological upgradation are the pillars of the modern world. People could not have predicted the extent of the internet's impact on human life when it first existed. Millions of people use the internet to communicate, conduct studies, find amusement, and, most currently, purchase and offer products and services for sale.

People in today's world are so preoccupied with their daily lives that going out to shop for themselves is tough. Adding to that online store gives people a plethora of options to choose from while sitting in the comfort of their own homes, including savings that a traditional store would never be able to offer. Online purchasing has gotten more convenient as mobile phone penetration, particularly smartphone penetration, has increased, as has mobile internet use. Concerning fashion-related consumption, are getting regular existence, a change that ought to urge us to focus our attention around the diverge range of online consumption possibilities. Within ten years, India's online consumer base of roughly 20 million buyers might grow by 1400 per cent, reaching 300 million (Kanchan et al., 2015).

Online reviews have also become a significant basis for product comparison. Consumers are accustomed to relying on internet reviews to determine whether or not to make an e-commerce purchase. 97.7% of users check relevant reviews before completing an online purchase, according to a survey. These reviews, as buyer feedback, have a significant impact on potential consumers' purchasing intent or behaviour (Zhang et al., 2020). Consumers can get detailed feedback on goods and services from other consumers, while merchants and producers can get information from their customers on the benefits and drawbacks of their products in order to better understand their needs and identify areas for development. As a result, online marketers and advertisers are spending money on social media advertising in improving consumer trust in the source of information and so influence their online purchase decisions.

The internet swallows' new tools and technology like a black hole. Many industries concentrate on the factors that can influence Indian customers' purchasing decisions. The Internet has caused enormous changes in business, as conversations are increasingly held between individuals rather than by marketers. Word of mouth refers to verbal communication about products and companies that has a positive and significant impact on consumer purchase behaviour. Because it comes from other customers, shoppers find it more credible. As a result, because the average consumer talks about products 212 times each year, it is advised that Electronic Word of Mouth and Purchase Intention of Fashion Products reputable marketers take advantage of the benefits of word of mouth (Keller et al., 2007).

The relevance of electronic word of mouth has also been recognised by marketing experts. Customers are discovered to highlight the bad and positive reviews of other users' experiences who purchased a similar product earlier in the electronic word of mouth set. These favourable and negative comments have an impact on potential buyers' purchasing intentions for fashion products. As a result, it's crucial to understand the factors that can influence electronic word of mouth and buy intent in the ethnic market. This paper looks into the factors that influence customers of Indian ethnic dresses through online review sources and collects reviews of ethnic dresses (i.e., Kurtis) on e-commerce portals (i.e., Amazon, Flipkart, and Snap deal) to see how online reviews influence purchase behaviour during the purchasing process.

1.1 Motivation for the Study

The impact of electronic word-of-mouth (e-WOM) on the online purchase decision is a well-researched area. However, the impact of e-WOM on the purchase of Indian ethnic dresses have not been given due importance in past literature. Additionally, the insights hidden in the online reviewers regarding the behavioural characteristics of female buyers, especially in the context of Indian ethnic dresses, is not yet studied in extant literature. In fact, this is the motivation for the current study to understand the factors that impact the purchase decision of buyers during e-buying of Kurtis and further examine the e-WOM or online reviews scrapped by prominent e-retailers in India by adopting a text mining approach.

1.2 Scope of the Study

The study's scope is limited to just female Kurtis from all Indian ethnic garments. For this study, the online reviews are analyzed from only three e-commerce portals: Amazon, Flipkart, and Snapdeal.

1.3 Problem Statement

Though e-commerce companies have stabilized their foothold in the shopping list of many, it also has some drawbacks. It's true that it provides a large assortment of products, but it creates confusion as well. People often couldn't determine what to choose and what not to choose between so many variables, and what could have been done in an hour takes hours and hours of contemplation in vain. There is also the matter of accurate representation of the product. Many people complain that the digital picture given on the shopping sites sometimes vary greatly from the product that was delivered. It creates a bad impression on the minds of people and refrains them from online shopping. Choosing a perfect product to buy requires many things, and among them, importance is mostly given to the product reviews. People browse through many positive and negative reviews before buying the product, so they get confused about whether to buy the product or not.

1.4 Organization of thesis

The remainder of this thesis is arranged in the following chapter.

Chapter 2 presents a review of related literature, which aids in the development of the theoretical framework.

Chapter 3 describes the research objectives and hypotheses proposed.

Chapter 4 outlines the research methodology.

Chapter 5 presents data analysis and its results

Chapter 6 provides the discussion and implications of the study.

Chapter 7 discusses conclusion and scope for future research.

1.5 Summary

This chapter begins with an overview of online purchasing, the significance of reviews, and the role of e-WOM. Following that, the study's motivation, scope, and problem statement are outlined. Based on the problem description, a complete literature review is conducted in Chapter 2.

CHAPTER 2

LITERATURE REVIEW

2.1 Theoretical background

Online product reviews and online product ratings will influence consumer purchasing decisions based on online reviews (Lackermair et al., 2013). Online reviews have a substantial impact on buyer purchase frequency and decision, according to (Vimaladevi & Dhanabhakaym, 2012). Because they serve as the foundation for influencing consumers' psychological and social traits, online product reviews and ratings have an impact on consumer purchase decisions (Micheal & Alrasheed, 2011). Reviews reflect or form a product's, brand's, or company's reputation, which can be thought of as a summary of the company's previous customer experiences, customer perceptions, and business activities, and is usually a solid basis for purchasing decisions (Becker and Nobre, 2014; Dellarocas, 2010; Lee and Bradlow, 2011). The majority of the studies looked on the impact of e-WOM characteristics including quantity, quality, and relevance on purchase intent (Lin et al., 2013). (Wolny and Mueller, 2013) investigated the motives for customers engaging in electronic word of mouth in the context of fashion brands using an enhanced Theory of Reasoned Action (TRA) model. Quality, credibility, source appeal, and style are all essential criteria in electronic word of mouth messages that buyers use to make future purchase decisions, according to (Teng et al., 2014). (Vahdati and Nejad, 2016) found that e-WOM had a favourable and significant impact on bank customers' purchase intentions in a recent study. As a result, customer e-WOM has a substantial influence on their purchasing intent. As a result, it is possible to speculate that e-WOM participation has a large beneficial impact on fashion product purchase intent.

2.2 Importance of online reviews in e-commerce purchase behaviour

Online reviews are arguably are the most useful way to eliminate the one-sided view of the product i.e. the marketer's view. Majority of the e-commerce business customers trade through these reviews provided by the other customers. When a customer wants to buy any product in any offline shop, he prefers for the trustworthy shopkeepers who would provide them the good products. While in online shopping trust plays the major role in a successful and a vanished brand. In the online platform reviews play an important role of building trust among the customers because in online platform it’s only the customer and the marketer who performs their works. Introduction of the review system in the online markets acted as a boon to both customers as well the marketers. Review system helped to build trust among the customers and helped the marketers to improve their product. It gave insight to many marketers to do business using the Product Concept. Product concept helped the firms to increase their profits by enhancing the quality of the product. Review sites like e-WOM has reduced the loss incurred by the online selling shops, they provide useful information to the product which has lessen the returning of product.

When customers decide to shop on the internet, they go through the online purchasing procedure. The internet has evolved into a new distribution channel and has highlighted the evolution of this channel, e-commerce, as the most significant contribution of the information revolution. Today, the internet has become a highly competitive industry, and the first step in making an impression on customers and keeping them is to identify specific influencing variables when purchasing online, which can be regarded considerations. The behaviour that inspires a person to take a given action is known as intention (Rezvani et al., 2012). What a customer anticipates he or she will buy is referred to as purchase intention. It can also be defined as the act of acquiring a goods and the physiological reaction to it (Lin & Lu, 2010). "Ajzen (1991) argued that intentions are considered to be an indicator of how far people are willing to approach specific behaviour and how many tries they are making in order to do certain behaviour," according to (Lim et al., 2016) in theory of reasoned action and theory of planned behaviour. This intention is based on the person's or consumer's positive attitude toward executing that behaviour, according to theories of reasoned action and planned behaviour; hence, if they hear positive electronic word of mouth, their purchase intention is likely to be high.

2.3 Study of e-WOM analysis in the e-commerce portals

Word-of-mouth communication is one of the earliest forms of communication (Dellarocas, 2003), and it has been characterised in a variety of ways. The ever-increasing population of internet users increased with the coming of the online shops and it grew when these online businesses introduced the review system in their service. This is because online shopping depends upon these reviews systems such as the e-WOMs. Online reviews may be positive or may be negative which are provided by the company, past customers or those customers who researched about the product. Online reviews not only help in marketing, also for research work. It was found by the people that online reviews are more persuasive in online marketing. Previously researches were conducted to analyse which review was more persuading and it was found that people were more persuaded by the negative reviews than the positive reviews. When a potential consumer reads a lot of unfavourable internet reviews, he or she creates a poor impression of the product. Furthermore, (Lee et al., 2008) found that unfavourable internet reviews lower customers' positive feelings about a product. These research, on the other hand, were limited to non-classified general products.

e-WOM analysis can be divided into two parts valence and volume. A product becomes famous due to valence or volume of sale done by the marketer. Valence is important in the luxurious or the costly products whereas volume of sale is important for the daily use products. E-commerce portals such as Amazon, Flipkart, Snapdeal, etc created their empire in the online market as they worked upon their lacunas by using these e-WOMs, also the companies who have tied up with them got the early warning signals about their products and worked upon it to gain the targeted customers.

2.4 Impact of online e-WOM on online purchase of apparels

Before independence India was known for its textile industry, also it was one of the greatest producers of textile until the colonial rule devastated it. Today, after the IT industry, the apparel and textile industries are the second largest in India, accounting for up to 26 percent of the country's foreign exchange. Textile and apparel are that industry whose market capitalisation is vast and is the most profitable. India has changed into wellspring of apparel industry due its well fortune of low-cost fabric and well bonding with the other countries. Indian attire is largely demanded by the customers because of its designs, its fabric work, its stitching and knitting, etc. The most demanded among them are the ethnic dresses, ethnic designs have their market all over the world for their traditionally profoundness and their designs. Ethnic wears are mostly used during the festivals and in India is full of festivals. Ethnic industry was earlier bounded to limited areas such are the rich families, when E-commerce introduced ethnic industry got the opportunity to expand its business not only in India but also throughout the world. More and more textile companies came into the market when the saw the growing demand of the ethnic dresses. But during the initial period people lacked to trust the apparel industry product when it entered into the E-commerce world. Many clothes were found to be defective and hence people found to be reluctant of buying dresses from the e-portals.

Introduction of e-WOM helped these businesses to withstand during the time of loss. e-WOMs helped the customers to give assurance about the product. The customers who were satisfied with the product gave their reviews about the product and hence it helped many more potential customers to buy those apparels. Customers also gave many negative reviews which helped the industries to work upon it and enhanced their products. Indian ethnic industries endeavours to maintain its product quality and customer satisfaction. The expansion of the local business segment's enthusiasm for clothing is linked to the achievement of the retailing range in India. e-WOM played a crucial role for the industries to win the international markets. Globalisation enabled apparel industries to get famous all over the world. The reviews of the past customers were elucidated by the businesses and presented to the new customers as India's tradition is famous all over the world it gave an easy base for the companies to persuade people to buy the ethnic dresses.

2.5 Trend of purchasing ethnic dresses in India on e-commerce portals

Indian culture is followed by its rituals in a simplest way. All over the country people adhere many beliefs and celebrate various festivals. Indian culture is followed by all over India as well many other parts of the world like the US. Ethnic clothing is an essential aspect of Indian culture. Indians wear traditional garments such as the ghagra-choli, dhoti-kurta, salwar-suit, kurta-pajama, and saree for weddings and other important occasions. People of all ages wear ethnic clothing. Indian ethnic clothing and Indian culture are two sides of the same coin, presenting Indian culture in various ways while serving the same objective. When people dress in Indian cultural attire, their Indian culture seeps through, making them look extremely lovely. India has a rich legacy of heritage of textile tradition and wide range of ethnic costumes which comprise of versatile techniques like silhouettes and classical tailoring famous across the subcontinent for its suitability of any terrain, weather and regional socio-cultural influences of its past invades. The new millennium has seen revolutionary change across the socio-economic Diasporas of India due to humongous efforts of the past and the globalization.

With globalisation and internet services all across the world e-commerce portals enabled themselves to add upon the opportunity to raid into the ethnic industry of India. Many e-commerce portals like the Amazon, Flipkart, etc tied up with the ethnic costume producing firms and helped them to increase their sales. These portals provided the producers a good amount of profit for their product as well to the customer with an affordable amount. Trading in the e-portal sites is more economical than the offline trades. E-portal reduced the cost of production for the companies and made the product economical for the customers by reducing the channels of distribution. Potential customers of the ethnic costumes gradually increased when they found their desired costumes in an economical rate. Moreover, when review upgradation like the e-WOM came into act in the e-portals people got to know about good brands selling the ethnic costumes and hence purchased from those marketers and made them popular all over the world.

2.6 Literature gap

According to the analysis of the literature reviews, (Baber et al., 2016) discovered that the majority of the studies on e-WOM were centred on the tourism business, film debates, or dining experiences. The extant studies on impact of e-WOM on purchase decision has also traditionally confined to electronic items, and apparels. However, the Indian ethnic dresses have not been given due attention in any of the past studies. However, to understand the online review for Indian ethnic dresses in the context of e-commerce portal is also necessary. The features that impact customer satisfaction/dissatisfaction during e-purchase of Indian ethnic dresses has not been identified in past studies. In summary, despite the extensive literature on e-WOM, researchers in the context of Indian ethnic dresses continue to make slow progress.

2.7 Summary

This chapter begins with a theoretical background. Following that, the importance of online reviews in e-commerce purchase behaviour, the study of e-WOM analysis in the e-commerce portals, the impact of online e-WOM on online purchase of apparel, and the trend of purchasing ethnic dresses in India on e-commerce portals are outlined. Following that, the literature was grouped, and a gap in the literature was identified, which was utilised to build the model and hypotheses in Chapter 3.

CHAPTER 3

RESEARCH OBJECTIVES & HYPOTHESES

3.1 Research objectives

For the research, the following objectives are defined:

1. Study the factors that impact the purchase decision of buyers of e-retail stores in the context of Indian ethnic wear
2. Develop a conceptual model to abstract the relationship of online purchase decision and its impacting factors
3. Identify the key product features that are more discussed in online reviews for Kurtis
4. Extract the sentiment polarity of various product features from online reviews and building a relationship on customer satisfaction
5. Develop an online purchase recommendation model based on textual features
6. Perform latent semantic analysis to identify critical factors that affect customer satisfaction
7. Explore the impact of extracted topics on consumers' evaluations

3.2 Hypotheses

3.2.1 Purchase intention

Purchase intent is usually thought to be a good predictor of actual purchase (Grewal et al., 1998). Studies confirming that e-WOM has a direct impact on purchasing intent abound in the study literature (Lee, Park & Han 2008). Consumers often seek external information on a product before making a purchase in order to lessen the risks of making a poor decision. Customer reviews on the internet include suggestions from people who have purchased and used the product, therefore the information provided may assist buyers in making better informed purchasing decisions (Xu and Chan, 2010). Negative online customer evaluations highlight the potential dangers and risks of purchasing a product, dramatically lowering buy intent (Lee, Park, and Han, 2008; Wu and Wang, 2011).

3.2.2 Review quality

The lack of a standard format for e-WOM has resulted in a variation in the quality of online customer reviews (Lee, Park, and Han, 2008). Review quality, also known as a message's persuasive strength, has been widely used as an antecedent of the central route (Cheung and

Thadani, 2012). The persuasive power of the e-WOM message was used to define review quality. Consumers will always strive to process every given piece of information in order to assess whether or not a message is true. These consumers believe that the review information is valuable when they believe that an argument is valid (Sussman and Siegal, 2003). Relevance, reliability, understandability, and sufficiency are the characteristics of review quality, according to (Lee, Park, and Han, 2008). There are two types of review quality: low quality and high quality. Low-quality online customer reviews are "emotional, subjective, lacking in factual information, and merely making a recommendation," whereas high-quality evaluations are "logical, compelling, and provide reasoning to back facts about the product" (Park, Lee and Han, 2007). Low-quality online customer reviews typically fail to assist consumers in evaluating a product since the information is deemed irrelevant, uninformative, and ambiguous, making it difficult to grasp (Lee, Park, and Han, 2008). On the other hand, high-quality online customer evaluations include more understandable and objective facts, as well as sufficient rationale (Lee, Park, and Han, 2008). As a result, a positive online customer review is more compelling than a negative one (Park, Lee, and Han, 2007). Prior research has consistently found a link between participation and argument quality (Park, Lee, and Han, 2007). Consumers are more inclined to commit the cognitive work required to analyse the genuine benefits of the product being reviewed when there is a high level of product participation, according to (Wu and Wang, 2011). (Wu and Wang, 2011; Lee, Park, and Han, 2008). Individuals that are driven to analyse a message are more likely to consider things through and make decisions based on the evaluation of persuasive arguments (Park, Lee, and Han, 2007). According to previous study, the quality of reviews has a beneficial impact on purchase intent (Lee and Shin, 2014; Park, Lee, and Han, 2007). Thus,

- H_1: Review quality has a significant positive effect on perceived value.

3.2.3 Review type

3.2.3.1 Negative reviews

Consumers can share their dissatisfaction with five people in a traditional context, but in a network environment, they can reach out to 6,000 or more people (Hanson, 2000). Negative WOM means that customers who are dissatisfied with a product would share their emotional experiences with others. (Liang and Chen, 2006), discussed that customer were not satisfied with their products and services and that they shared experience with friends and family and advised them not to buy the products or services. They were not satisfied with their customer's products or services. Therefore, informed, negative assessments lead to considerably little satisfaction of consumers. Based on past studies, Negative online commentary is characterised as an internet forum to share unhappy consumers with a product or service. (Hennig-Thurau, and Walsh, 2003) discuss that unfavourable customer reviews do not have a positive effect. The "negative effect" can be traced to this discovery (Lee and Cranage, 2014). When consumers are exposed to negative online customer reviews, (Lee, Park, and Han, 2008) believe that they are generally perceived as low quality. Given that favourable information for high, medium, and low-quality products is generally supplied, positive or neutral online customer reviews are often less helpful when establishing the perceived quality of the product (Lee, Park, and Han 2008). Consequently, negative online customer reviews are seen as more diagnostic to take decisions (Lee, Park, and Han, 2008). Many research of unfavourable internet reviews confirmed its harmful purchase behavioural impacts (Bambauer-Sachse and Mangold, 2011; Park, Lee, and Han, 2007). In their study, (Berger, Sorensen, and Rasmussen, 2010) show that the negative online evaluations can in fact be positive when product awareness is minimal. In the marketing sector, (Ahluwalia et al., 2000) discovered that consumers typically believe that bad information is worth more than good information; therefore, in their purchasing choices they would rely more on negative information. This development demonstrates the knowledge of internet users' rights in the improvement of the online shopping process. The contradictions in these findings are an opportunity for this study to clarify the impact on perceived value of an ethnic product of negative reviews. In the context of online consumer ethnic dresses reviews this phenomenon is particularly widespread. Thus,

- H_2: Negative reviews has a significant positive effect on perceived value.

3.2.3.2 Positive reviews

Positive customer reviews, according to (Hennig-Thurau, and Walsh, 2003), have a smaller influence than negative customer reviews. When a buyer sees positive online customer evaluations, according to (Lee, Park, and Han, 2008), they are more likely to think the product is of higher quality. Because positive information is regularly supplied for high, average, and low-quality products, favourable or neutral internet user reviews are less useful in determining product perceived quality (Lee, Park, and Han, 2008). Thus,

- H_3: Positive reviews has a significant positive effect on perceived value.

3.2.4 Review form

3.2.4.1 Textual reviews

Textual remarks are unstructured, user-generated written information regarding items and services that provide aspects of a customer's consuming experience and perceptions. Marketers can use online communications to encourage re-viewers to supply the online community with more relevant service-related information in this regard (Koo, 2016). Customers can write their opinions, which represent their level of pleasure, or inform others about their experiences in textual comments, which have since become an important source for making online decisions (Xie, Zhang, & Zhang, 2014). According to (Xie et al., 2014), 53% of customers will not make a hotel reservation until they have read information posted on SMPs, and 77% of customers regularly use text content to make booking decisions. Businesses can collect client feedback and improve their products and services as a consequence of this format, decreasing marketing expenses as a result of a better understanding of customer preferences (Xu et al., 2017). Thus,

- H_4: Textual reviews has a significant positive effect on perceived value.

3.2.4.2 Image reviews

Consumer reviews, which are one component of reviews, form pictures in the first or additional reviews. The photographs in the reviews show the genuine quality of the product, such as colour difficulties, inconsistencies in specs, or a high-quality, positive experience. Picture reviews reduce the consumer's risk when acquiring experiencing things. Picture reviews show actual purchase behaviour in the customer learning process (Mo, Li, & Fan, 2015).

A growing number of marketing operations, according to (Guitart and Hervet, 2017), rely on contextual photography to gauge client attitudes and purchase intentions. They claimed that contextual visuals enable people to recall a need related to a product, resulting in increased attention and processing fluency, as well as increased advertising efficacy. Because photographs account for 60% of all digital impressions and 70% of marketers use visual assets to develop fresh visual content, businesses are increasingly turning to SMPs. As a result, contextual photographs aid detailed mental imaging of a product, making them a critical component of online reviews.

Consumers' perceptions of a store are dependent on its environmental features and functional attributes. For almost 50 years, researchers have investigated retail store appearance and its association with consumers' buy intentions, finding a link between store image and buying intent (e.g., Agarwal & Teas, 2001; Bell, 1999; Grewal et al., 1998; Dodds et al., 1991). However, little study has been done on the impact of an online store's image on consumers' purchase intentions. Despite the fact that few studies have linked the holistic design of an online store's image to purchase intentions, specific aspects of the image have been shown to have a positive impact on purchase intentions. Another study focusing on multichannel businesses discovered a substantial correlation between an online store's image and consumer purchase intent (Kwon and Lennon, 2009; Verhagen and van Dolen, 2009). (Kwon and Lennon, 2009), for example, the impact of vertically-integrated specialty apparel brands' online store image on consumers' propensity to shop at their online store was investigated. (Verhagen and van Dolen, 2009) looked at the overall image of online stores, however they left out pure internet players, who make up a significant portion of online shopping. Thus,

- H_5: Image reviews has a significant positive effect on perceived value.

3.2.4.3 Video reviews

From a communication aspect, online product displays are defined as a certain type of communication that online retailers can use to engage with customers and offer product information (Wang et al., 2016). In similar research on online product displays, scholars concentrated on examining the distinctions between display formats and discovered that video displays, when compared to text, had a significant impact on those who browse for pleasure (Aljukhadar & Senecal, 2017). Some experts believe that visual displays, like as movies, have a more emotional impact on customers than text, which is beneficial for the emotional component of the customer relationship (Pera & Viglia, 2016). Certain scholars have contrasted consumer preferences to the effects of static images, dynamic video, and various display formats (such as slides). (Roggeveen et al., 2015) evaluated the three types of product presentation—static photos, slides, and dynamic video—and discovered that dynamic display forms were more likely to influence consumers to purchase hedonic products (Roggeveen et al., 2015). However, in the sphere of social media, some experts believe that the effects of photos and videos on consumer engagement can only result in compliant rather than interactive participation, but that the shift in consumer cognition brought on by text links will lead to more active participation (Viglia, Pera & Bigne, 2018). Despite this, only a few studies have evaluated video content to see how it affects customer behaviour. Video displays, in fact, combine bright colours, visual signals, dynamic movement, and a range of noises to convey a plethora of information to customers (Tang, 2012).

Consumers are introduced to products through online product displays, which help them understand them better (Jiang & Benbasat, 2007). Because consumers cannot touch or inspect actual objects in the internet environment, a strong online product image can assist them in identifying and understanding things (Xu, Chen & Santhanam, 2015). As a result, online product display is critical for retailers, as it can impact consumers' views and assist them in making relevant purchasing decisions. According to the vividness idea (Nisbett & Ross, 1980), vivid information causes consumers to have more mental images of things, which increases their imaginal consumption (Nowlis, Mandel & Mccabe, 2004). The dynamic display form is a more vibrant version of the static display form. When compared to a static display, it makes customers feel more like participants and allows them to better imagine how the products will feel when they use them (Pera & Vigilia, 2016). Thus,

- H_6: Video reviews has a significant positive effect on perceived value.

3.2.5 Perceived value

Online reviews are frequently used by internet shoppers to determine the value of a product (Archak et al., 2011). The likelihood of making a purchasing choice is increased when the product's perceived worth is high (Grewal et al., 1998). Not only product quality, but also perceived product value (the difference between quality and price) are influenced by online reviews (Li and Hitt, 2010). When the majority of the reviews for a high price product are positive, people may perceive the pricing to be reasonable and the product to be of good quality and value. When the bulk of the reviews are negative (i.e., there are a lot of negative reviews), customers may think the price is too high, the product is of low quality and value, and they refuse to buy it. Value is a trade-off between what consumers obtain (such as quality and benefits) and what they give up (such as money, time, and effort) (Zeithaml, 1988). Consumers' views of value are influenced by unfavourable pricing perceptions, which increase perceived expenses or sacrifice (Monroe, 2003). Consumers, on the other hand, will consider the goods as more valuable if the price is reasonable, acceptable, and fair. A high (vs. low) number of negative reviews would diminish consumers' pricing satisfaction, which would subsequently negatively (positively) affect their perceived product value and purchase intentions. As a result, there's a link between price satisfaction and perceived value (Xia and Monroe, 2004), as well as perceived value and buy intent (Xia and Monroe, 2004). (Grewal et al., 1998). Thus,

- H_7 (a): Perceived value has a significant positive effect on e-WOM engagement.
- H_7 (b): Perceived value has a significant positive effect on Purchase intention.

3.2.6 eWOM engagement

Oral communication, often known as word of mouth (WOM), occurs when information is shared in a social setting or circle. It's a sort of informal communication in which customers talk about their favourite companies, goods, and services. It comes in handy when it comes to marketing promotions (Nguyen & Romaniuk, 2014). eWOM has had a big impact on consumer buy intents since the advent of web 2.0 technology, as people trust eWOM before purchasing any product (Doh & Hwang, 2009). Purchase intention is a broad outcome variable of electronic word of mouth communication. They looked at purchase intention as a result of eWOM and discovered that 10 out of 25 research looked at purchase intention as a result of eWOM, with 10 of those studies concentrating on the impact of incentives on customer purchase intents. The bulk of studies looked at how eWOM characteristics including quantity, quality, and relevance influenced purchase intent (Lin et al., 2013). (Shabsogh, 2013) found that "correlations between source attributes and trustworthiness are generally unrelated to eWOM" and its impact on purchase intent in their research. (Wolny and Mueller, 2013) studied why customers engage in electronic word-of-mouth in the context of fashion companies on social networking sites using an upgraded Theory of Reasoned Action (TRA) model. In another study, (Teng et al., 2014) discovered that customers assess the quality, credibility, source attractiveness, and style of electronic word of mouth messages when making future purchase decisions. In a recent study, (Vahdati and Nejad, 2016) found that e-WOM had a positive and significant impact on bank customers' purchasing intent. As a result, client eWOM has a significant impact on their social networking site purchase intent.

Engagement refers to a consumer's emotional reactions to situations and other stimuli that create a bond or relationship with the stimulus (Kapoor and Kulshrestha, 2011). Customer involvement is described as a customer's behavioural manifestation toward a business, such as influencing the business in ways other than buying (Bijmolt et al., 2010; Doorn et al., 2010). WOM, referrals, assisting other consumers, blogging, posting reviews, and engagement and co-creation in brand communities are all examples of related occurrences (Doorn et al., 2010; Hollebeek et al., 2014). To rationalise the influence of eWOM on customers, we must examine user involvement with eWOM communication as a first step. This could lead to a better understanding of what each user needs for eWOM communication. The willingness to request or share eWOM information with other consumers is defined as eWOM participation in this study. Customers that engage in eWOM communication are more likely to make a purchase decision. The impact of eWOM on consumer purchasing intentions have been studied in a number of studies (Baber et al., 2016; Chen et al., 2014; Erkan and Evans, 2016; Mortazavi et al., 2014; Wu and Wang, 2011; Yu and Natalia, 2013). It has been claimed, for example, that eWOM and consumer purchase intent have a positive association (Sharifpour et al., 2016). Thus,

- H_8: eWOM engagement has a significant positive effect on Purchase intention.

This study attempted to fill a gap in the literature by investigating the factors influencing the customers of the Indian ethnic dresses through the online review sources. This study will comfort us to know how e-WOM not only helps the customers while purchasing ethnic dresses (Kurtis) online also how the marketer gets assistance to know more about his performance and can enhance his marketing mix procedures. The theoretical model, depicted in Figure 3.1, includes independent, mediator, and dependent variables. The independent variables come from the review quality, review type, and review form of online reviews. Review type refers to negative reviews and positive reviews. Review form refers to textual reviews, image reviews, and video reviews of ethnic products. Then, the mediator variable comes from the perceived value and the dependent variables come from the e-WOM engagement and purchase intention.

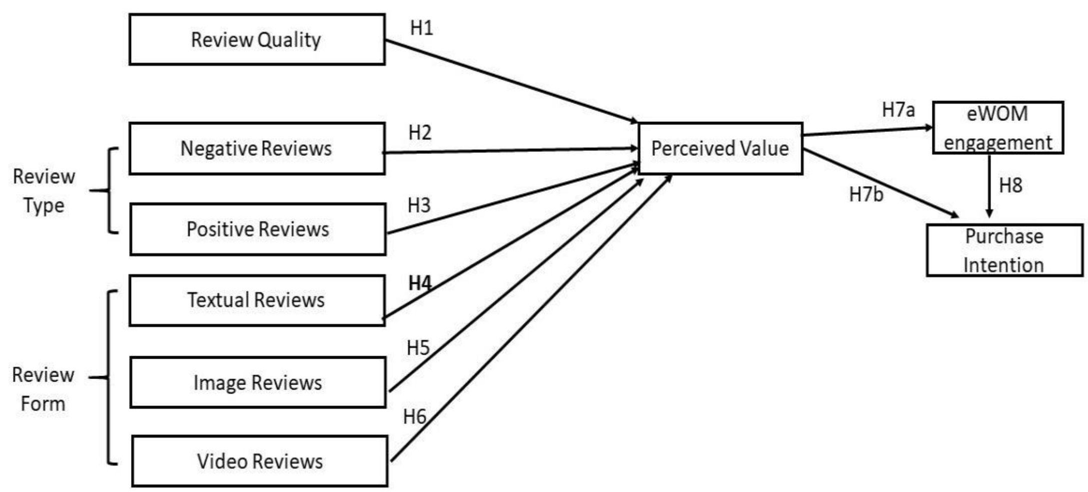

Figure 3.1 An illustrative diagram of the research model

3.3 Summary

This chapter begins with the research objective. Following that, hypothesis for different identified factors was formulated, and a research model was constructed. This research model aids us in moving on to the research methodology in Chapter 4.

CHAPTER 4
RESEARCH METHODOLOGY

4.1 Research Study 1

This study is a causal investigation into the impact of Review quality, Negative reviews, Positive reviews, Textual reviews, Image reviews, Video reviews, and Perceived value on e-WOM engagement and Purchase intention in ecommerce portal. This study's participants are female Facebook users. This study's population includes any female who has a Facebook account and is a frequent and active user.

4.1.1 Sampling Technique

The demographic of this study included every female person who has a Facebook account and is a frequent and active user. The sample for this study is made up of people over the age of 18 who have some online purchase experience or are familiar with online product reviews. Second, was it on design that only Facebook users were chosen as respondents? Because of its judgement or goal, the sampling technique used in this study falls within the non-probability sampling technique type, i.e., purposive or judgmental sampling technique. This study intended to assess the impact of e-WOM on ethnic product purchase intention on an ecommerce portal, although random sampling was impossible due to the fact that not every Facebook user is an online shopper.

4.1.2 Research Instrument

A five-point questionnaire was created. The data was collected using a Likert scale. Review quality has 4 items, negative reviews have 3 items, positive reviews have 3 items, textual reviews have 3 items, image reviews have 3 items, and video reviews have 3 items in the independent variables. There are 3 items in the mediator variable perceived value. There are 3 items in the dependent variable e-WOM engagement and 3 items in the dependent variable purchase intention. The other component of the questionnaire asked about the respondents' demographics, such as their age, gender, annual income, education level, nature of employment, internet experience, and online Kurtis purchase experience. To test the hypotheses, IBM SPSS 25 programme and its Structural Equation Modelling (SEM) by SPSS AMOS 23 programme were used for data analysis.

4.1.3 Data Collection

A closed-ended questionnaire was used to obtain information. To collect data, a web-based questionnaire was distributed among the respondents. "Google forms" were constructed to collect data electronically, and surveys were distributed to responders using social networking sites such as Facebook. First, with a sample of 30 asserters, a study was conducted to ensure the relevance of the questions in accords with the norms. As a result, some changes, deletion and additions of questions are made. A sample size of 250 were collected using a judgmental sampling process to acquire data.

4.2 Research Study 2

4.2.1 Data Collection

The dataset of customer reviews was extracted from 3 websites, Flipkart, Amazon, and Snapdeal. The reviews were collected for Kurtis and 2 price categories, price less than 2000 and price greater than 2000. The number of reviews retrieved under each category varied largely. A total of 6 data .csv files were prepared in the desired format for each dress under each price range. All the reviews are scrapped from the woman's Kurtis section under each category. Total 11450 reviews were scrapped in the price less than 2000 category, with 9883 positive reviews and 1567 negative reviews. Also, total 4311 reviews were scrapped in the price more than 2000 category, with 3539 positive reviews and 772 negative reviews.

The techniques of Web Scraping were used for the extraction of the same. For Web Scraping, library files of Beautiful Soup were used in Python.

4.2.2 Data Pre-processing

Upon data collection, each review was manually labeled as – 'Recommended' or 'Not Recommended' and checked for any misspelled words and use of Hinglish. These are further preprocessed using the regex library file to remove any non-alphabetic characters and emojis. All the reviews are converted into lower case and remove extra white spaces.

These preprocessed reviews are then tokenized into words and sentences, using nltk.sent_tokenize and nltk.word_tokenize. Each tokenized word is further stemmed using Porter Stemmer, nltk.stem.

Lemmatization is also done on tokenized words using WordNetLemmatizer, nltk.stem. Stopwords are removed from the data except 'not', because 'not' is a very important influencer through negation.

4.2.3 Data Balancing

Post pre-processing, data was balanced. All the duplicates in the data are removed in order to avoid over-fitting. After deleting duplicate data, there are 5513 positive reviews and 1095 negative reviews in the price less than 2000 category. Then, after deleting duplicate data in the price more than 2000 category, there are 2319 positive reviews and 618 negative reviews. The number of positive class samples is much greater than the number of negative class samples. So, to balance the data, the negative class is up-sampled by random oversampling technique. After oversampling, both positive and negative reviews in the price less than 2000 category had 5513 data, while both positive and negative reviews in the price greater than 2000 category had 2319 data.

4.3 Summary

This chapter is divided into 2 phases. In the first phase, a sampling technique, research technique, and data collection were done for the primary survey. Data collection, data pre-processing, and data balancing were done for online reviews analysis in the second phase. The data is then analysed, and the results are presented for both phases in Chapter 5.

CHAPTER 5

DATA ANALYSIS AND RESULTS

5.1 Research Study 1

5.1.1 Demographical Background

Age, gender, annual income, education level, nature of employment, internet experience, and online Kurtis purchase experience are the seven areas of the demographic section of the questionnaire. The results of the demographic portion of the questionnaire are shown in Table 5.1.

Table 5.1 Respondent's Demographic Background

Factor		Options	Frequency	Percentage
1	Age	16-24 Years	193	77.2%
		25-34 Years	56	22.4%
		35-44 Years	1	0.4%
		45-54 Years	0	0%
2	Gender	Male	0	0%
		Female	250	100%
3	Education	Less than or equal to higher secondary (10+2) education	21	8.4%
		Bachelor Degree	134	53.6%
		Master Degree	72	28.8%
		Professional Degree	23	9.2%
4	Annual Income	Less than 5 Lakh	188	75.2%
		5-10 Lakh	47	18.8%
		10-15 Lakh	10	4%
		15-20 Lakh	1	0.4%
		More than 20 Lakh	4	1.6%
5	Nature of Employment	Student	165	66%
		Service	66	26.4%
		Business	5	2%
		Freelance worker	5	2%
		Unemployed/Retired	4	1.6%
		Housewife	5	2%
6	Internet Experience	Less than 2 Years	32	12.8%
		2-4 Years	32	12.8%
		4-6 Years	59	23.6%
		6-8 Years	52	20.8%
		More than 8 Years	75	30%
7	Online Kurtis Purchase Experience	Last 2 Years	88	35.2%
		Last 2-4 Years	82	32.8%
		Last 4-6 Years	58	23.2%
		Last 6-8 Years	16	6.4%
		More than 8 Years	6	2.4%

5.1.2 Correlation Analysis

The term "correlation" is used to describe the relationship between two or more variables. Table **5.2** illustrates the Pearson correlation between all variables, indicating that they are all positively associated. The table also includes the mean, standard deviation, and reliability analysis data. Table 5.2 shows that the largest correlation (r=.716) exists between video and image reviews, while the lowest correlation (r=.383) appears between e-WOM and perceived value. The results also show that none of the inter-item correlations are more than 0.90, showing that there are no difficulties with multicollinearity.

5.1.3 Reliability Analysis

Cronbach's alpha was used to perform a reliability analysis on the items to ensure that they were internally consistent. Pilot testing was also carried out for this study. Table 5.2 demonstrates that all Cronbach's alpha values are greater than 0.7, indicating that the items in the questionnaire are consistent. Table 5.2 shows that reliability of e-WOM engagement was the highest (α= 0.91, M= 3.6, SD= 1.06) followed by Video reviews (α=.89, M= 4.1, SD= 0.85), Image reviews (α= 0.88, M= 4.2, SD= 0.84), Review quality (α=.85, M= 3.7, SD= 0.78), Textual reviews (α=.85, M= 4.0, SD= .79), Positive reviews (α=.84, M= 3.9, SD= 0.81), Perceived value (α=.82, M= 3.8, SD= 0.82), Purchase intention (α=.82, M= 3.8, SD= 0.82) and Negative reviews (α=.78, M= 4.0, SD= 0.79). Internal consistency of the items was validated because these reliabilities were more than 0.70.

Table 5.2 Correlation and Reliability Analysis of Study Variables

	Variables	M	S. D	1	2	3	4	5	6	7	8	9	α
1	Review quality	3.7	0.78	1									0.85
2	Negative reviews	4.0	0.79	.521**	1								0.78
3	Positive reviews	3.9	0.81	.562**	.554**	1							0.84
4	Textual reviews	4.0	0.79	.532**	.588**	.614**	1						0.85
5	Image reviews	4.2	0.84	.461**	.586**	.527**	.618**	1					0.88
6	Video reviews	4.1	0.85	.495**	.474**	.452**	.586**	.716**	1				0.89
7	Perceived value	3.8	0.82	.637**	.446**	.514**	.514**	.420**	.467**	1			0.82
8	e-WOM engagement	3.6	1.06	.538**	.342**	.436**	.419**	.438**	.504**	.383**	1		0.91
9	Purchase intention	3.8	0.82	.582**	.487**	.550**	.509**	.509**	.499**	.662**	.508**	1	0.82
M = Mean, S. D = Standard Deviation, α = Cronbach's alpha													

5.1.4 Validity Analysis

A few measures have been done to check the instrument's validity or accuracy, which are as follows:

Content validity: Experts' professional judgement was used to determine the instrument's content validity. Supervisors with good research backgrounds who occupy senior faculty positions were consulted for this reason.

Construct validity is divided into two types. Convergent and discriminant validity, for example, were calculated by theoretically constructing variables to be measured. The convergent validity test was designed to determine how large an indicator's share of a single concept was. When a factor loading value is large and substantial, an indicator is said to converge. It also has a higher than 0.5 standardised factor loading estimate. Discriminant validity is determined via factor analysis. For this purpose, confirmatory factor analysis (CFA) was used with AMOS 23 and maximum probability valuation. Fit indices for the model's quality of fit include the chi-square (χ^2), the root-mean-square error of approximation (RMSEA), the comparative fit index (CFI), goodness of fit index (GFI), and adjusted goodness of fit index (AGFI). The RMSEA is a calculation that calculates the average of residual variance and covariance; effective models have RMSEA values of 0.08 or below. The CFI scale spans from 0 to 1, with 0 being the lowest and 1 being the highest. When comparing models with the same number of degrees of freedom, a lower chi-square value indicates a better fit. The standardised loadings of each item on each factor were likewise determined using the CFA test. The results of this CFA showed that the model fit was satisfactory and that the constructs were legitimate. Table 5.3 displays the CFA model fit values.

Table 5.3 Confirmatory Factor Analysis

	χ^2	Df	χ^2/Df	CFI	GFI	AGFI	RMSEA
Default Model	589.016	324	1.818	0.942	0.860	0.824	0.057

5.1.5 Hypothesis Testing

A measurement modelling (CFA) was performed in the first phase, and it was discovered that all of the measures (items) adequately characterise (measure) their respective constructs. The second phase is structural modelling, which involves evaluating relationships between multiple latent variables using structural equation modelling (SEM). Following CFA, IBM-Amos 23 was used to perform SEM on the dataset. The following are the outcomes. (Table 5.4)

Table 5.4 SEM Results using AMOS

Predictors		Estimate	S.E.	t	p	Hypothesis acceptance
1	Review quality → Perceived value	.553	.088	6.283	.000	Significant
2	Negative reviews → Perceived value	-.046	.074	-.632	.527	Not significant
3	Positive reviews → Perceived value	.182	.087	2.101	.036	Significant
4	Textual reviews → Perceived value	.041	.086	.474	.635	Not significant
5	Image reviews → Perceived value	-.037	.103	-.354	.723	Not significant
6	Video reviews → Perceived value	.229	.086	2.660	.008	Significant
7a	Perceived value → e-WOM engagement	1.178	.145	8.140	.000	Significant
7b	Perceived value → Purchase intention	.612	.072	8.462	.000	Significant
8	e-WOM engagement → Purchase intention	.221	.043	5.193	.000	Significant

Table 5.4 shows that review quality (β =.553(.088) t= (6.283), p =.000) is strongly associated to perceived value (β =.553(.088) t= (6.283), p =.000.). As a result, the hypothesis 1, that review quality has a large positive effect on perceived value in ecommerce websites, was confirmed. Negative reviews were also found to have no influence on perceived value (β =-.046(.074), t=-.632, p=.527). Positive reviews had a substantial effect on perceived value (β =.182(.087), t=2.101, p=.036), confirming hypothesis 3 that positive reviews have a significant effect on perceived value of ethnic products in an ecommerce platform. The influence of textual reviews on perceived value was non-significant (β=.041(.086), t (.474), p=.635) when regressed on perceived value. The impact of image reviews on perceived value was also shown to be non-significant (β=-.037(.103), t=-.354, p=.723). The data also demonstrate that video reviews are substantially associated to perceived value (β =.229(.086), t (2.660), p=.008), supporting hypothesis 6. Additionally, the impact of perceived value on e-WOM engagement was shown to be significant (β=1.178(.145), t=8.140, p=.000). As a result, the study's hypothesis 7(a) is supported. The findings further confirm hypothesis 7(b) by demonstrating that perceived value (β=.612(.072), t (8.462), p=.000) is substantially related to purchase intention. Similarly, the study shows that e-WOM involvement is substantially associated to purchase intention (β=.221(.043), t (5.193), p=.000), verifying hypothesis 8.

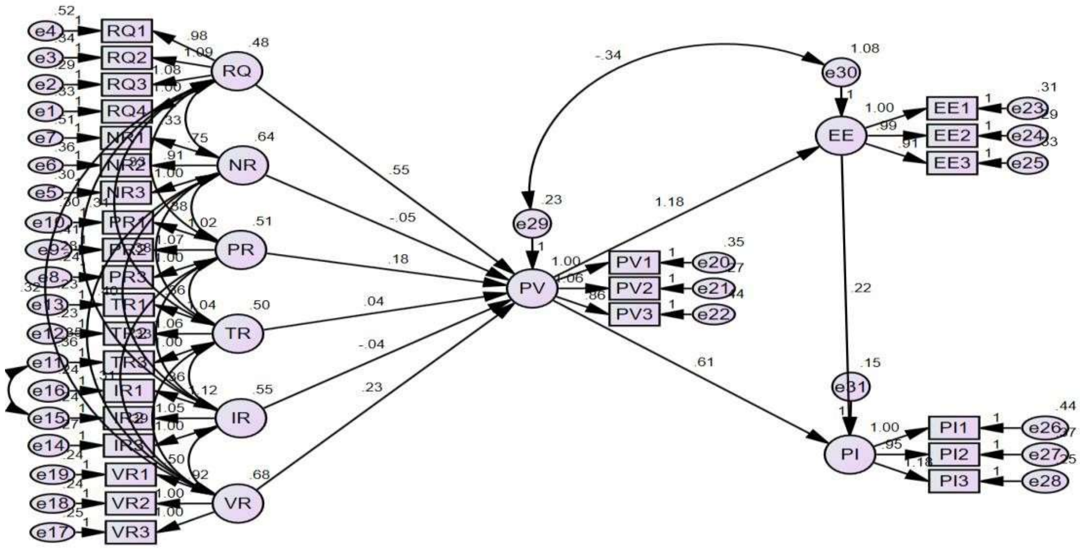

Figure 5.1 Final Output of SEM using AMOS

5.2 Research Study 2

5.2.1 Word Frequency analysis

To analyze the occurrence of commonly used words in the reviews the frequency of top 10 words is plotted separately for positive and negative reviews as follows:

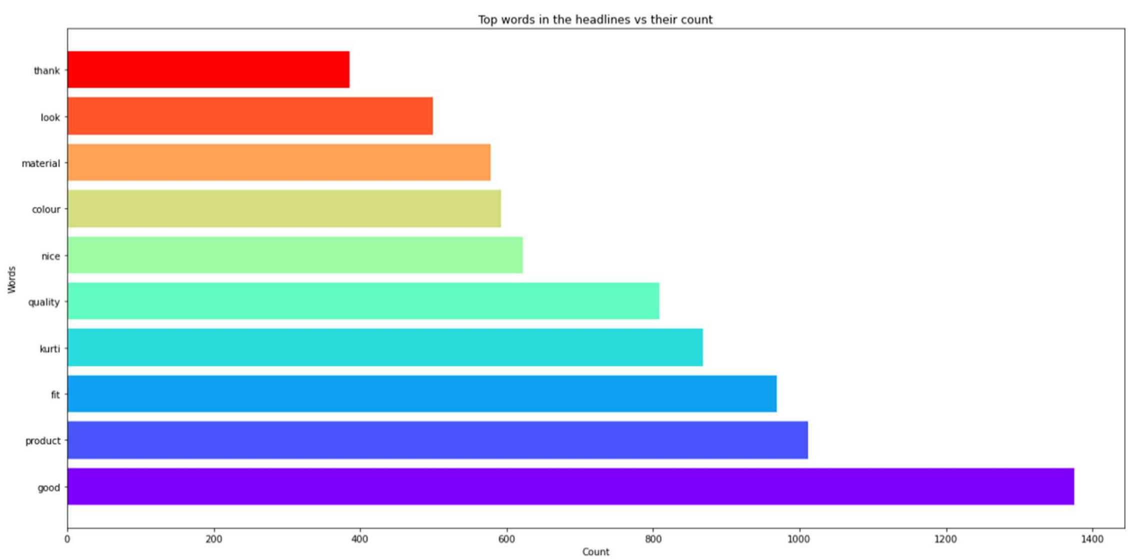

Figure 5.2 Top words in the headlines vs their count (Positive Class for Kurtis price under 2000 category)

Top 10 frequently used words in Positive Class for Kurtis price under 2000 category by referring Figure 5.2: The most common word is good, to appreciate the dress. Commonly used words include, product, fit, kurti, quality, thank, nice.

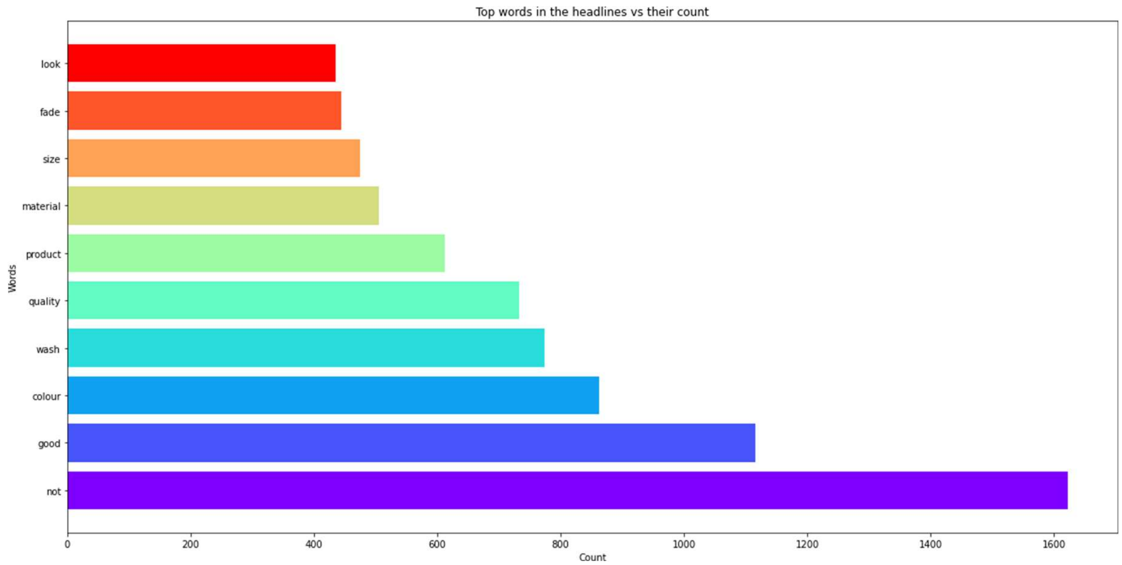

Figure 5.3 Top words in the headlines vs their count (Negative Class for Kurtis price under 2000 category)

Top 10 frequently used words in Negative Class for Kurtis price under 2000 category by referring Figure 5.3: The most common word used in classification is not. The presence of positive words good indicates that mostly reviews are the negation of common words. Other describing words are wash, size, fade.

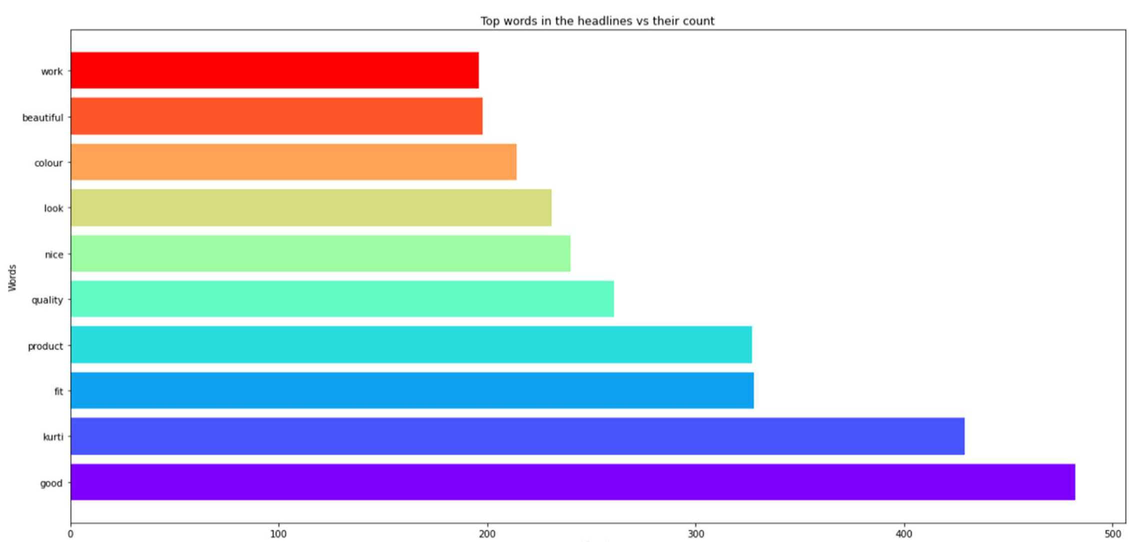

Figure 5.4 Top words in the headlines vs their count (Positive Class for Kurtis price above 2000 category)

Top 10 frequently used words in Positive Class for Kurtis price above 2000 category by referring 5.4: The most common word is good, to appreciate the dress. Commonly used words include, good, kurti, fit, product, quality, nice, look.

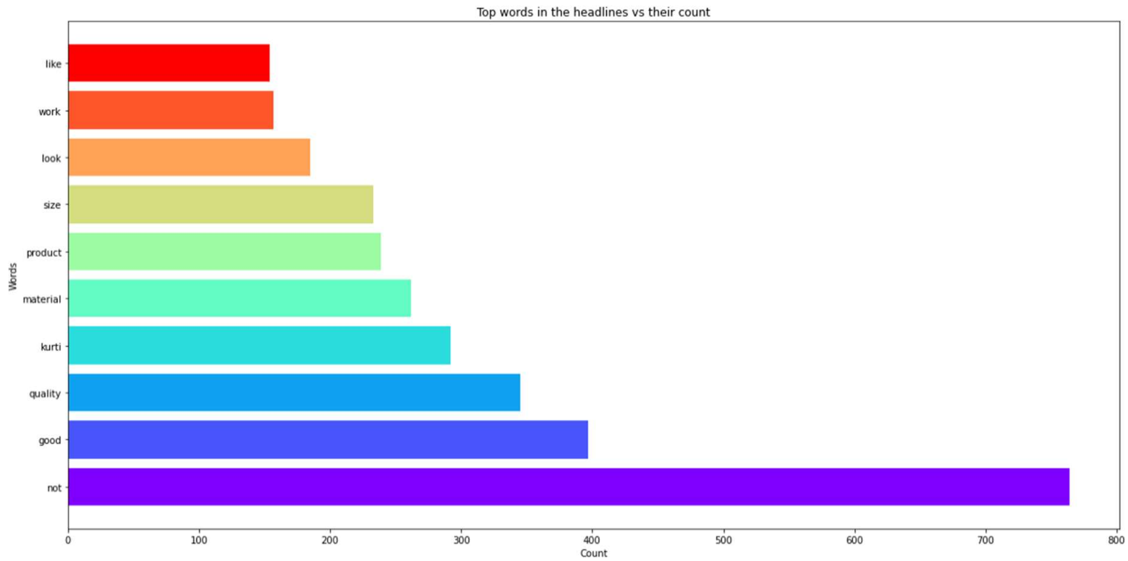

Figure 5.5 Top words in the headlines vs their count (Negative Class for Kurtis price above 2000 category)

Top 10 frequently used words in Negative Class for Kurtis price above 2000 category by referring Figure 5.5: The most common word used in classification is not. The presence of positive words good indicates that mostly reviews are the negation of common words. Other describing words are quality, material, size, look.

5.2.2 Word Cloud Analysis

To understand the common adjectives and phrases that define the positive and negative reviews, irrelevant words and nouns have been removed.

Figure 5.6 Word cloud (Positive Class for Kurtis price under 2000 category)

Word Cloud for Positive Class for Kurtis price under 2000 category by referring Figure 5.6: While reviewing, the most commonly used adjectives to describe the Kurti are, **nice, awesome, love, beautiful, good, super.** The customers have mostly appreciated the **product, colour, Fitting, Comfort, Fabric material, Look, Quality of kurti**.

Figure 5.7 Word cloud (Negative Class for Kurtis price under 2000 category)

Word Cloud for Negative Class for Kurtis price under 2000 category by referring Figure 5.7: While reviewing, the most commonly used adjectives to describe the Kurtis are, **bad, poor, fade, not good, worst, waste.** The users have mostly resorted to negation of positive adjectives to express.

The customers have most often criticized the **Colour and Quality of the Kurti after wash**.

Figure 5.8 Word cloud (Positive Class for Kurtis price above 2000 category)

Word Cloud for Positive Class for Kurtis price above 2000 category by referring Figure 5.8: While reviewing, the most commonly used adjectives to describe the kurti are, **nice, beautiful, awesome, love, good, perfect.**

The customers have mostly **appreciated the Quality, colour, Fitting, Comfort, Fabric material, Look.**

Figure 5.9 Word cloud (Negative Class for Kurtis price above 2000 category)

Word Cloud for Negative Class for Kurtis price above 2000 category by referring Figure 5.9: While reviewing, the most commonly used adjectives to describe the Kurti are, **bad, disappoint, transparent, poor, cheap.** The users have mostly resorted to negation of positive adjectives to express.

The customers have most often criticized the **Colour, Material and Quality of the Kurti**.

5.2.3 Emotion Analysis

Emotion analysis for each review is performed using the library file, text2emotion. Upon the analysis, the function returns scores for each of the emotions, angry, sad, happy, surprise, and fear. It is observed that for certain entries, all the fields are observed to be 0, so it is labeled as neutral.

Word Cloud Emotion Distribution for Kurtis price under 2000 category:

By referring Figure 5.10 below, the most common emotion amongst all reviews is ‘Happy’. From the above word cloud, it is observed that ‘Happy’ is mainly associated with overall satisfaction from the product.

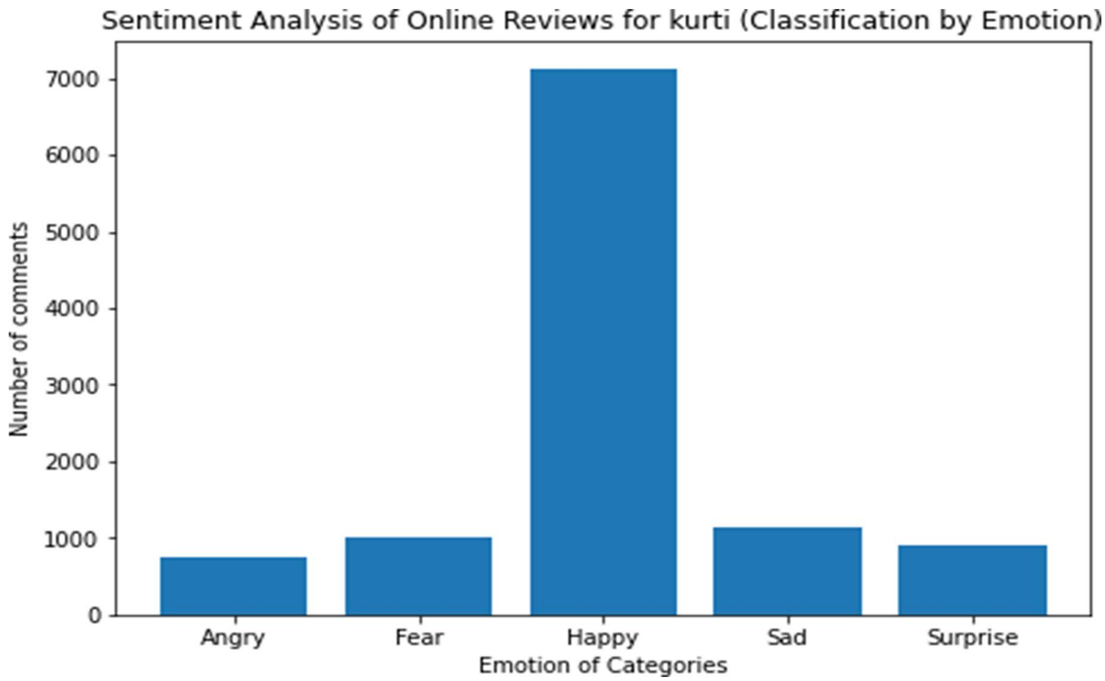

Figure 5.10 Relative Emotion Distribution for Kurtis price under 2000 category

The second most common emotion is 'Sad'. It is associated with quality of the product.

Word Cloud Emotion Distribution for Kurtis price above 2000 category:

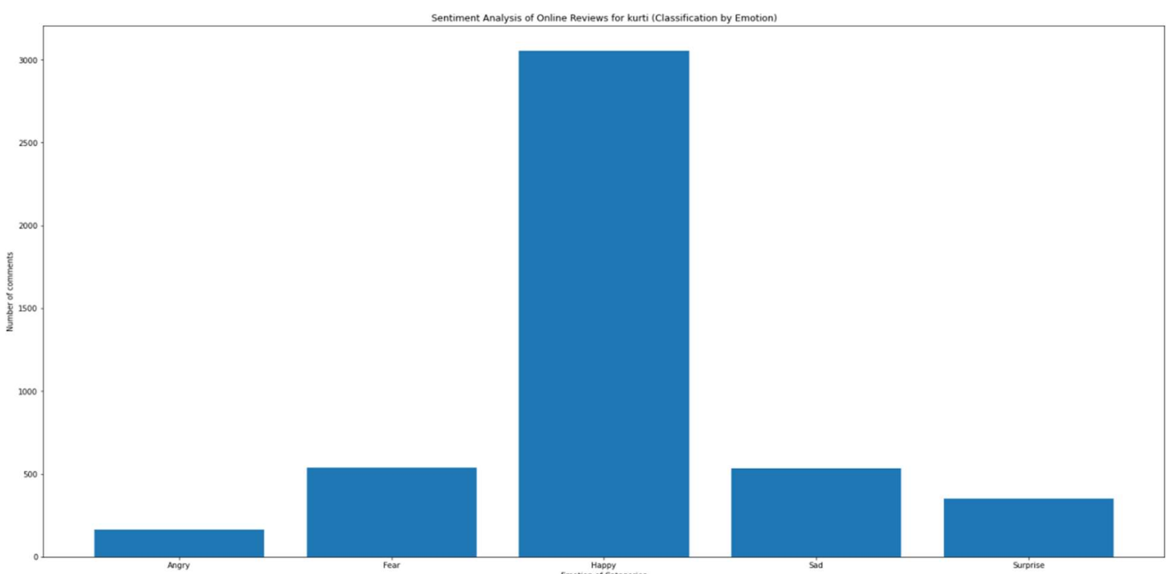

Figure 5.11 Relative Emotion Distribution for Kurtis price above 2000 category

By referring Figure 5.11, the most common emotion amongst all reviews is **‘Happy’**. From the above word cloud, it is observed that ‘Happy’ is mainly associated with **overall satisfaction from the product**.

The second most common emotion is **‘Fear’**. It is associated with **quality of the product**.

5.2.4 Sentiment Analysis

Sentiment analysis for Kurtis price under 2000 category:

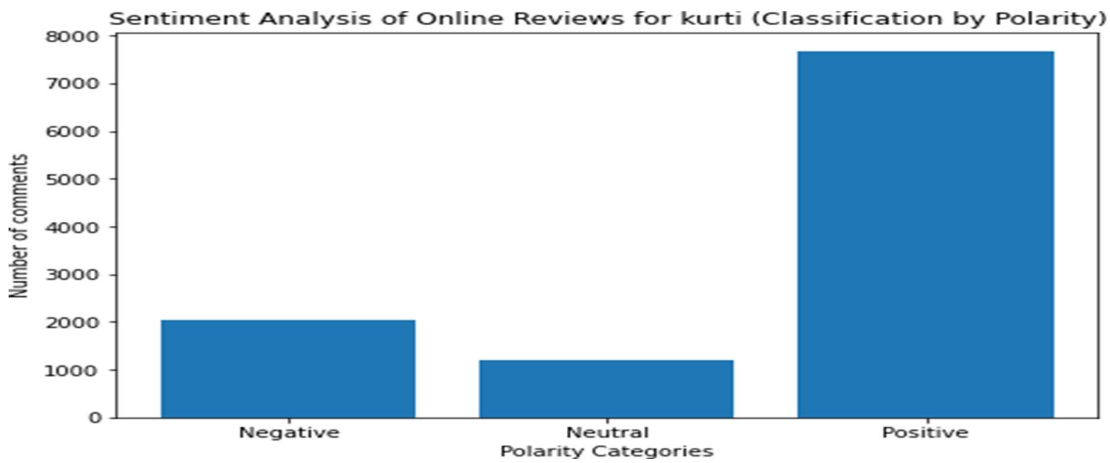

Figure 5.12 Sentiment analysis for Kurtis price under 2000 category

Sentiment analysis for each review is performed using the library file, Vader. Upon the analysis, the function returns compound scores for each of the reviews. If compound score is greater than 0, then it is positive statement. If compound score is less than 0, then it is negative statement. If compound score is equal to 0, then it is neutral statement. From Figure 5.12, it is observed that total 7689 reviews are positive, 2029 reviews are negative, 1212 reviews are neutral.

Sentiment analysis for Kurtis price above 2000 category:

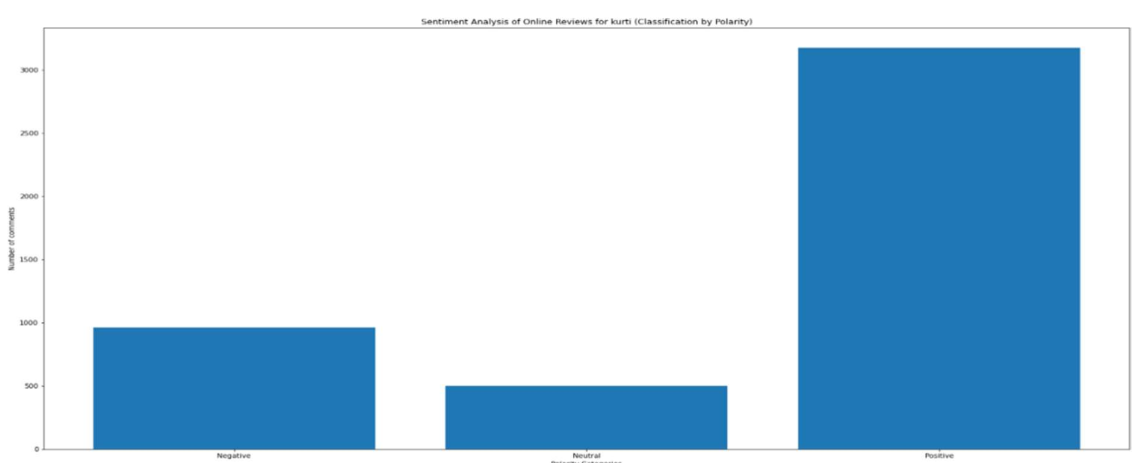

Figure 5.13 Sentiment analysis for Kurtis price above 2000 category

Sentiment analysis for each review is performed using the library file, Vader. Upon the analysis, the function returns compound scores for each of the reviews. If compound score is greater than 0, then it is positive statement. If compound score is less than 0, then it is negative statement. If compound score is equal to 0, then it is neutral statement. From Figure 5.13, it is observed that total 3174 reviews are positive, 963 reviews are negative, 501 reviews are neutral.

5.2.5 Text Classification Model for Recommendation

Take the two classes Recommender (Class 1) and Not-Recommended (Class 2) and take unigram, bigram, and trigram features for text classification model. Accuracy, F1-score, sensitivity, and specificity are the performance metrics used in this study. All of this is used to determine the performance of our model.

<u>For Kurtis price under 2000 category:</u>

<u>Part A. For Unigram</u>

For Unigram features use the following machine learning models with 10-fold cross validation

1. Lasso Logistic Regression
2. Decision Tree
3. Random Forest
4. Naive Bayes Classifier
5. Multi-Layer Perceptron
6. Support Vector Machine
7. Deep neural networks

Following results were obtained:

Table 5.5 Text Classification Model for unigram for price under 2000 category

Classifier	Accuracy Train	Accuracy Test	F1-score	Sensitivity	Specificity
Lasso Logistic Regression	0.8913242009132419	0.8715068493150685	0.8732806224505121	0.8568146450602482	0.8862153924693544
Decision Tree	0.990177574835109	0.9402739726027398	0.9367696699597499	0.9955726024776492	0.8849855076458187

Random Forest	0.9901674277016742	0.960730593607306	0.9594196145718049	0.9949947797219275	0.9265528134849685
Naive Bayes Classifier	0.8741248097412481	0.8561643835616438	0.8572220823145461	0.8484195696703832	0.8640305899382567
Multi-Layer Perceptron	0.5012683916793506	0.48858447488584467	0.3282125602785749	0.5	0.5
Support Vector Machine	0.961324200913242	0.9268493150684932	0.9268789090822788	0.927227604684045	0.9264297692877207
XG Boost	0.8553424657534248	0.8423744292237444	0.8434138482222526	0.8356572252796959	0.8492030454382089

By referring Table 5.5, the accuracy train value for Decision tree model was highest and lowest for multi-Layer perceptron model. The accuracy test value for Random Forest model was highest and lowest for multi-Layer perceptron model. The F1-score value for Random Forest model was highest and lowest for multi-Layer perceptron model. The sensitive value for Decision tree model was highest and lowest for multi-Layer perceptron model. The specificity value for Random Forest model was highest and lowest for multi-Layer perceptron model.

<u>Part B. For Bigram</u>

For Bigram features use the following machine leaning models with 10-fold cross validation

1. Lasso Logistic Regression
2. Decision Tree
3. Random Forest
4. Naive Bayes Classifier
5. Multi-Layer Perceptron
6. Support Vector Machine
7. Deep neural networks

Following results were obtained:

By referring Table 5.6, the accuracy train value for Decision tree and Random Forest model was highest and lowest for XG Boost model. The accuracy test value for Random Forest model

Table 5.6 Text Classification Model for bigram for price under 2000 category

Classifier	**Accuracy Train**	**Accuracy Test**	**F1-score**	**Sensitivity**	**Specificity**
Lasso Logistic Regression	0.931111111111111	0.9079452054794519	0.9095405869296685	0.8904380887351326	0.9256151349262186
Decision Tree	0.9695078640284119	0.9357077625570775	0.9345676610535719	0.9516904028001413	0.9195170495071853
Random Forest	0.9695078640284119	0.9463013698630137	0.9461249348466554	0.9502076520774276	0.9423494249618368
Naive Bayes Classifier	0.9093150684931507	0.8923287671232878	0.8934660912435831	0.8803873226373542	0.9055896995615047
Multi-Layer Perceptron	0.9188330796549975	0.8884931506849316	0.838104668757359	0.948183904740838	0.8292483894088096
Support Vector Machine	0.9648858447488585	0.9439269406392694	0.9447701587469145	0.9292411900361142	0.9585497319636582
XG Boost	0.739583967529173	0.7274885844748857	0.6544100004121897	0.938696380539539	0.5163881051550434

was highest and lowest for XG Boost model. The F1-score value for Random Forest model was highest and lowest for XG Boost model. The sensitive value for Decision tree model was highest and lowest for Naive Bayes model. The specificity value for Support Vector Machine model was highest and lowest for XG Boost model.

Part C. For Trigram

For Trigram features use the following machine learning models with 10-fold cross validation

1. Lasso Logistic Regression
2. Decision Tree
3. Random Forest
4. Naive Bayes Classifier
5. Multi-Layer Perceptron

6. Support Vector Machine
7. Deep neural networks

Following results were obtained:

Table 5.7 Text Classification Model for trigram for price under 2000 category

Classifier	**Accuracy Train**	**Accuracy Test**	**F1-score**	**Sensitivity**	**Specificity**
Lasso Logistic Regression	0.8788330796549975	0.8659360730593608	0.8781605513560446	0.7652490283388095	0.9666384907517424
Decision Tree	0.8865347539320142	0.8752511415525113	0.8861020353049749	0.7794821865343001	0.9709859606412777
Random Forest	0.8865347539320142	0.8758904109589041	0.8869170529802789	0.7780151193418805	0.9737354527955018
Naive Bayes Classifier	0.7776661593099949	0.7466666666666667	0.7055817054790745	0.8039646123122749	0.6982257288798266
Multi-Layer Perceptron	0.7684119736174531	0.7484018264840183	0.695199057129182	0.7171407496702379	0.7807755035132965
Support Vector Machine	0.8866666666666667	0.8480365296803654	0.8594203868626047	0.7669400094957409	0.9291220202709248
XG Boost	0.6124809741248098	0.5980821917808219	0.7113145406302404	0.20539274813189717	0.9908555249100202

By referring Table 5.7, the accuracy train value for Support Vector Machine model was highest and lowest for XG Boost model. The accuracy test value for Random Forest model was highest and lowest for XG Boost model. The F1-score value for Random Forest model was highest and lowest for Multi-Layer Perceptron model. The sensitive value for Naive Bayes model was highest and lowest for XG Boost model. The specificity value for XG Boost model was highest and lowest for Naive Bayes model.

For Kurtis price above 2000 category:

Part A. For Unigram

For Unigram features use the following machine learning models with 10-fold cross validation

1. Lasso Logistic Regression
2. Decision Tree
3. Random Forest
4. Naive Bayes Classifier
5. Multi-Layer Perceptron
6. Support Vector Machine
7. Deep neural networks

Following results were obtained:

Table 5.8 Text Classification Model for unigram for price above 2000 category

Classifier	**Accuracy Train**	**Accuracy Test**	**F1-score**	**Sensitivity**	**Specificity**
Lasso Logistic Regression	0.9085573424306155	0.8811978662396666	0.8799697142738993	0.8905163488089579	0.8716070883103889
Decision Tree	0.9910162310740283	0.9230324160274075	0.9176718957124933	0.9880773647748894	0.858625848474575
Random Forest	0.9910162310740283	0.951488139569524	0.9497308601183878	0.9849100101479131	0.9180138515963414
Naive Bayes Classifier	0.8964111623423016	0.8702046250093097	0.8680604659758757	0.8866517510082709	0.8537296034533632
Multi-Layer Perceptron	0.9776962318774046	0.918283123557012	0.9129782248646208	0.9756921590451577	0.8610792555578124
Support Vector Machine	0.969574985151881	0.9420007261488049	0.9415661607619379	0.9472454378642828	0.936526555305948
XG Boost	0.8717838286053672	0.8544653496685782	0.8521869921955114	0.867937861159435	0.8403926354893345

By referring Table 5.8, the accuracy train value for Decision tree and Random Forest model was highest and lowest for XG Boost model. The accuracy test value for Random Forest model was highest and lowest for XG Boost model. The F1-score value for Random Forest model was highest and lowest for XG Boost model. The sensitive value for Decision tree model was highest and lowest for Naive Bayes model. The specificity value for Support Vector Machine model was highest and lowest for XG Boost model.

<u>Part B. For Bigram</u>

For Bigram features use the following machine leaning models with 10-fold cross validation

1. Lasso Logistic Regression
2. Decision Tree
3. Random Forest
4. Naive Bayes Classifier
5. Multi-Layer Perceptron
6. Support Vector Machine
7. Deep neural networks

Following results were obtained:

Table 5.9 Text Classification Model for bigram for price above 2000 category

Classifier	Accuracy Train	Accuracy Test	F1-score	Sensitivity	Specificity
Lasso Logistic Regression	0.9448996668856825	0.9152626238176808	0.9168745025854882	0.8953873705272963	0.9351218721392305
Decision Tree	0.9653346608173209	0.9318644336039326	0.9320898378369634	0.9274131502705376	0.9363198242990605
Random Forest	0.9653346608173209	0.9307845199970208	0.9312240904920932	0.9235805522938474	0.9379970073442282
Naive Bayes Classifier	0.9332086799089889	0.9085778654948984	0.9068706022672487	0.927605865480631	0.8919414147442234
Multi-Layer Perceptron	0.8929254437937733	0.8535139085424891	0.8036287434635476	0.8804447023852543	0.8146844640881243

Support Vector Machine	0.9630348177626539	0.9437234676398303	0.9457241720428561	0.9081496196279264	0.9789944187092946
XG Boost	0.7138851056870448	0.67831561406122	0.5843653949771996	0.8908726421675037	0.4742249702409298

By referring Table 5.9, the accuracy train value for Decision tree and Random Forest model was highest and lowest for XG Boost model. The accuracy test value for Support Vector Machine model was highest and lowest for XG Boost model. The F1-score value for Support Vector Machine model was highest and lowest for XG Boost model. The sensitive value for Naive Bayes model was highest and lowest for Multi-Layer Perceptron model. The specificity value for Support Vector Machine model was highest and lowest for XG Boost model.

Part C. For Trigram

For Trigram features use the following machine learning models with 10-fold cross validation

1. Lasso Logistic Regression
2. Decision Tree
3. Random Forest
4. Naive Bayes Classifier
5. Multi-Layer Perceptron
6. Support Vector Machine
7. Deep neural networks

Following results were obtained:

Table 5.10 Text Classification Model for trigram for price above 2000 category

Classifier	Accuracy Train	Accuracy Test	F1-score	Sensitivity	Specificity
Lasso Logistic Regression	0.9056346014248456	0.8904674350189916	0.9000033139883739	0.7927969990188221	0.9878302753910131
Decision Tree	0.9081500535106116	0.8943486072838309	0.9030192796508946	0.8018129725887124	0.9863588629960347

Random Forest	0.9081500535106116	0.8949956244879719	0.903783330456364	0.801362522138262	0.9882314458134382
Naive Bayes Classifier	0.8307210648181357	0.8020760408132865	0.7729971826614092	0.9045231788984476	0.7105347856338009
Multi-Layer Perceptron	0.8078483282596283	0.7739824607134878	0.7799988009282652	0.6711280396032991	0.88209503651978
Support Vector Machine	0.9080781914847833	0.895642641692113	0.9050131270588253	0.7944228910018175	0.9963748417757706
XG Boost	0.6600065532566873	0.6078028412899383	0.7168372424405061	0.22084441609344613	0.9948795368150085

By referring Table 5.10, the accuracy train value for Decision tree and Random Forest model was highest and lowest for XG Boost model. The accuracy test value for support Vector Machine model was highest and lowest for XG Boost model. The F1-score value for Support Vector Machine model was highest and lowest for XG Boost model. The sensitive value for Naive Bayes model was highest and lowest for XG Boost model. The specificity value for Support Vector Machine model was highest and lowest for Naive Bayes model.

5.2.6 Topic Modelling

The data corpus is modeled into the tf-idf model and Latent Dirichlet allocation was done on the tf-idf matrix using the library file *genism.* Through this unsupervised learning technique, a list of common topics was extracted, which have been commonly addressed in the reviews.

To pre-process, common adjectives like good, bad, poor, awesome, which were common for the description (of these topics which are to be inferred and are addressed in the reviews) were removed from the corpus, to ensure that these do not overpower the topics.

The optimum number of topics have been selected by comparing the Coherence score.

For Kurtis price under 2000 category:

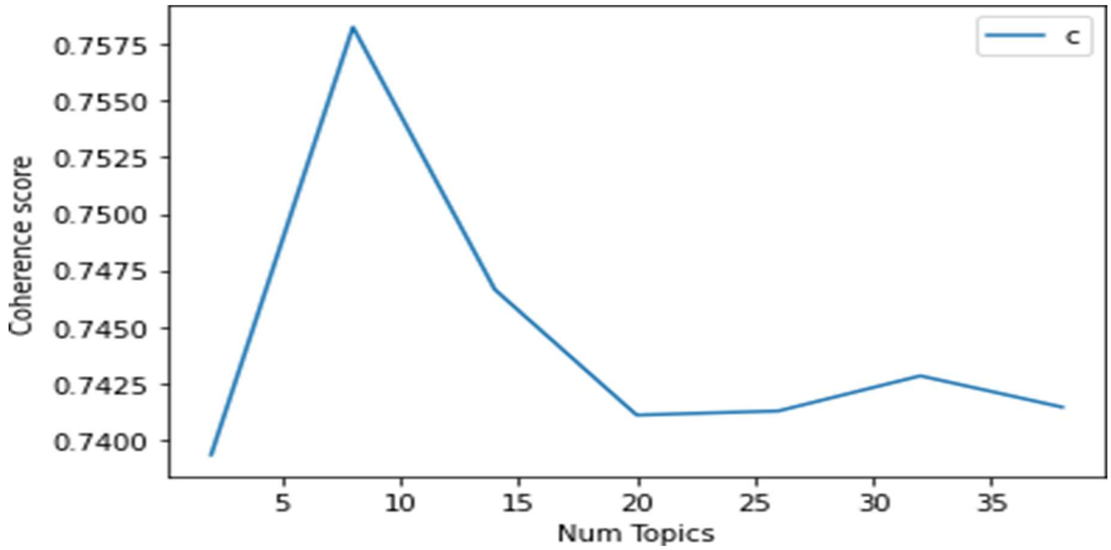

Figure 5.14 Coherence score for different topics for Kurtis price under 2000 category

From the Figure 5.14 we find that the maximum Coherence value is observed as 0.7575, when there are 10 topics.

Table 5.11 Topic Modelling for price under 2000 category

Topic	Word	Topic label
1.	0.001×"lovers" + 0.001×"match" + 0.001×"suggest" + 0.001×"like" + 0.001×"compy" + 0.001×"lools" + 0.001×"soft" + 0.001×"royal" + 0.001×"chip" + 0.001×"stick"	Comfort ness of the product
2.	0.001×"top" + 0.001×"translucent" + 0.001×"scatter" + 0.001×"hu" + 0.001×"buy" + 0.001×"margins" + 0.001×"stylist" + 0.001×"info" + 0.001×"summary" + 0.001×"display"	Labelling
3.	0.001×"xxxl" + 0.001×"cover" + 0.000×"umbrella" + 0.000×"anyone" + 0.000×"curve" + 0.000×"uneven" + 0.000×"vibrancy" + 0.000×"lift" + 0.000×"peice" + 0.000×"inspite"	Shape of the product
4.	0.001×"jewellery" + 0.001×"prblm" + 0.000×"allergitic" + 0.000×"except" + 0.000×"small" + 0.000×"kgs" + 0.000×"packet" + 0.000×"style" + 0.000×"stun" + 0.000×"us"	Packaging of the product
5.	0.001×"comfort" + 0.001×"every" + 0.001×"pure" + 0.000×"thread" + 0.000×"supervisor" + 0.000×"window" + 0.000×"due" + 0.000×"hips" + 0.000×"jansya" + 0.000×"bias"	Material

6.	0.001×"ridiculous" + 0.001×"avergae" + 0.001×"fitment" + 0.001×"meet" + 0.000×"odd" + 0.000×"fine" + 0.000×"skinny" + 0.000×"ill" + 0.000×"osom" + 0.000×"behalf"	Fittings
7.	0.001×"muchnice" + 0.001×"unique" + 0.001×"become" + 0.001×"everywhere" + 0.001×"demage" + 0.001×"fitgood" + 0.001×"paisa" + 0.001×"fabic" + 0.000×"allergitic" + 0.000×"extremely"	Damaged fabric
8	0.001×"stout" + 0.001×"qualitysoft" + 0.001×"fade" + 0.001×"nicedress" + 0.000×"home" + 0.000×"chage" + 0.000×"embrodiery" + 0.000×"reliable" + 0.000×"girlfriend" + 0.000×"better"	Quality
9	0.001×"whilst" + 0.001×"tnxs" + 0.001×"rs" + 0.001×"prosuct" + 0.001×"vary" + 0.001×"non" + 0.001×"capital" + 0.001×"tht" + 0.001×"hangout" + 0.001×"goodybagor"	Price of product
10	0.001×"wash" + 0.001×"tassels" + 0.001×"less" + 0.001×"unable" + 0.001×"description" + 0.000×"lighten" + 0.000×"post" + 0.000×"speed" + 0.000×"accept" + 0.000×"uncomfortable"	Uncomfortable after wash

From Table 5.11, the topics discovered for price under 2000 category are, Comfort ness of the product, Labelling, Shape of the product, Packaging of the product, Material, Fittings, Damaged fabric, Quality, Price of product, Uncomfortable after wash.

For Kurtis price above 2000 category:

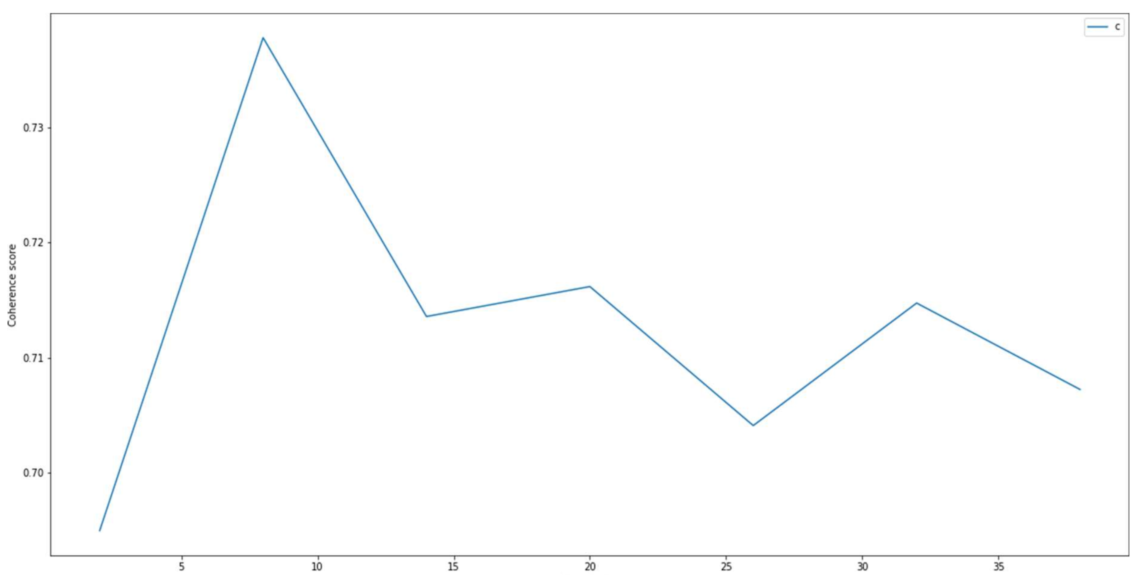

Figure 5.15 Coherence score for different topics for Kurtis price above 2000 category

From the figure 5.15 we find that the maximum Coherence value is observed as 0.75, when there are 10 topics.

Table 5.12 Topic Modelling for price above 2000 category

Topic	Word	Topic label
1.	0.001×"rainy" + 0.001×"blow" + 0.001×"fat" + 0.001×"match" + 0.001×"feed" + 0.001×"comfort" + 0.001×"plz" + 0.001×"unprofessional" + 0.001×"irritate" + 0.001×"lossing"	Uncomfortable product
2.	0.001×"initiate" + 0.001×"quality" + 0.001×"casual" + 0.001×"negative" + 0.001×"hopeless" + 0.001×"never" + 0.001×"detect" + 0.001×"colleges" + 0.001×"candid" + 0.001×"fr"	Unexpected poor quality
3.	0.001×"roadside" + 0.001×"members" + 0.001×"sew" + 0.001×"filpkart" + 0.001×"break" + 0.001×"negligible" + 0.001×"sarees" + 0.001×"thnxx" + 0.001×"pair" + 0.001×"then"	Comparison of product in market
4.	0.001×"almost" + 0.001×"prefer" + 0.001×"support" + 0.001×"prominent" + 0.001×"glad" + 0.001×"legs" + 0.001×"low" + 0.001×"experience" + 0.001×"true" + 0.001×"initially"	Online support through review
5.	0.001×"german" + 0.001×"warst" + 0.001×"replace" + 0.001×"many" + 0.001×"fell" + 0.001×"fist" + 0.001×"mouse" + 0.001×"appropriate" + 0.001×"oblige" + 0.001×"desolate"	Replacement of product
6.	0.001×"th" + 0.001×"reliable" + 0.001×"attract" + 0.001×"tear" + 0.001×"wheatish" + 0.001×"attach" + 0.001×"neet" + 0.001×"suspect" + 0.001×"start" + 0.001×"sell"	Reliable products
7.	0.001×"easy" + 0.001×"clearly" + 0.001×"fibre" + 0.001×"wali" + 0.001×"chest" + 0.001×"towards" + 0.001×"conform" + 0.001×"classy" + 0.001×"money" + 0.001×"events"	Price and worth
8	0.001×"w" + 0.001×"l" + 0.001×"steal" + 0.001×"beautifully" + 0.001×"exceed" + 0.001×"large" + 0.001×"unlike" + 0.001×"quay" + 0.001×"case" + 0.001×"view"	Design of the product
9	0.001×"search" + 0.001×"underarms" + 0.001×"husband" + 0.001×"nince" + 0.001×"store" + 0.001×"wrinkle" + 0.001×"idea" + 0.001×"ethnic" + 0.001×"reject" + 0.001×"loos"	Rejected ethnic product
10	0.001×"return" + 0.001×"best" + 0.001×"lengthy" + 0.001×"open" + 0.001×"abt" + 0.001×"keep" + 0.001×"grant" + 0.001×"travel" + 0.001×"inbuilt" + 0.001×"saggy"	Returning of product

From Table 5.12, the topics discovered for price under 2000 category are, uncomfortable product, unexpected poor quality, comparison of product in market, online support through review, replacement of product, reliable products, price and worth, design of the product, rejected ethnic product, returning of product.

5.3 Summary

In this chapter, Phase 1 analysed the data from the primary survey. Demographic background, correlation analysis, reliability analysis, validity analysis, and hypothesis testing were all carried out. Phase 2 looked at online reviews from three e-commerce sites: Amazon, Flipkart, and Snapdeal. Following that, word frequency analysis, word cloud analysis, emotion analysis, sentiment analysis, text categorization model, and topic modelling were carried out. The results discussion and managerial implications will be examined in further detail in the following chapters, beginning with Chapter 6.

CHAPTER 6

DISCUSSION AND IMPLICATIONS

6.1 Discussion

The conclusions of this investigation are extremely unusual. Negative reviews, textual reviews, and image reviews are all key contributors to the formation of online buy intents, according to many previous studies. However, none of these criteria had a substantial impact on perceived value in the current study, according to the findings. The study's scope does not include research into why these characteristics are not substantial enough for Indian e-shoppers. However, one might assume that individuals nowadays are considerably more informed before purchasing a product. The happiness or dissatisfaction with a product is determined by customer feedback. Every e-commerce platform is attempting to boost the number of video reviews for a product. People no longer depend on text-based reviews. People increasingly depend on dynamic reviews (i.e., video reviews) rather than text or image reviews. People can't tell the actual size, colour, or quality of a thing from a word evaluation. As a result, individuals no longer depend on text reviews. Although, through picture reviews, customers may see the actual product image and tell the difference between it and the image provided by the e-commerce platform. Video reviews, on the other hand, are more dynamic than image reviews. As a result, video reviews are preferred over text or image reviews. People will trust video reviews more than other types of reviews because they deliver the exact message that the company wants to send to its customers. Reading might lead to data misunderstanding in several cases. Some words, when read in a different way, send a distinct message. It is more entertaining and easier to follow. Videos that make viewers laugh, weep, or pay attention to them will undoubtedly entertain them. If a viewer finds the video engaging, they are more likely to watch it all the way through. A customer will typically watch a video review of a product or service that has already piqued their interest; the video review's main goal is to maintain that interest and pique their curiosity. For example, if a buyer watches a dress review, the consumer will be able to see the product in person, giving them the correct product to buy as well as some recommendations on how to use it properly and, of course, the finished result. A three-second film can have a lot of historical and current information. If people employ the right visual effect and put in extra effort to make high-quality movies, they will be able to effectively educate purchasers. Unlike other types of reviews, which take hours to complete before you can gain critical information, the video may deliver the message in seconds. People with a short attention span will benefit most from video reviews. Mobile users will find a video to be incredibly accessible and easy. Mobile phones and videos have taken over our lives since they are easy to view through them. Videos are both fashionable and interactive. Because it is easier to communicate and engage with customers, they are one of the most successful ways to reach out to them. People are eager to obtain accurate information, but they also want it quickly. They would prefer to watch a three-minute video than read a longer piece of text. Videos also assist firms in quickly relaying crucial information to their clients. Thus, the buyer's decision-making process is also influenced by video.

The satisfaction or dissatisfaction of a product can be known through reviews. Through word frequency analysis and word cloud analysis, we can know the most frequent word used in the reviews. Then, the emotions of the reviews can be known, which helps the companies know people's reactions about the product, whether they are happy, sad, angry, fearful, or surprised. Then through sentiment analysis, companies know that people are giving more positive reviews or not. If they see more negative reviews are there, they definitely try to improve their product through customer feedback. Then, using different features like unigram, bigram, and trigram, the text classification model is recommended. It is shown that Support Vector Machine and Random Forest model are very good models and XG Boost and Multi-Layer Perceptron are not a good models. Through topic modelling, we can know the topics which can be important while improving the product.

6.2 Implications

The study's implications for online businesses are that they should focus on creating a positive purchasing experience for their customers. Companies should focus more on video reviews in order to improve the online purchasing experience for customers. Despite the fact that picture reviews were determined to be inconsequential, giving reviews in image form on an e-commerce site is still recommended. It provides more details about the product. Then, by analysing online reviews, companies can know the satisfaction or dissatisfaction of the product through sentiment and emotional analysis. Through topic modelling also, we can extract ten important topics from reviews that are affecting the purchase of a product. By taking all the feedback from customers, companies can modify their products and launch a new product according to user’s requirements.

6.3 Summary

This chapters talks about the factors which are coming insignificant and the possible reason for these factors coming as insignificant. Then, the customers satisfaction/dissatisfaction about a product using emotional and sentiment analysis. Then, the managerial implications from the study, how it helps the businesses to improve their marketing. In Chapter 7, the conclusion from the given study and future research is given.

CHAPTER 7

CONCLUSION AND FUTURE RESEARCH

7.1 Conclusion

The primary goal of the study was to determine the factors that affects e-WOM engagement and purchase intention of Indian consumers. From all the factors, only five were considered to be of greater importance. Review quality, positive reviews, video reviews, perceived value, and e-WOM engagement were found to be important factors whereas factors like negative reviews, textual reviews, and image reviews found to be insignificant. The study highlights the importance of e-WOM towards the formation of intentions for online purchase. These findings are vital for the online shopping sites to help them make customers buy products from their websites. In addition, people satisfaction/dissatisfaction about a particular product analysed through online reviews. Through Sentiment and emotional analysis, it is known that people are happier and giving more positive reviews to a product. Still, we can't ignore the negative reviews provider and those customers who provide sad/angry/fear as emotions. Companies should take there queries very seriously and resolve their issues. Companies should focus more on customer feedback and the trend, then changes in there product according to the customers requirement.

7.2 Future Research

This study only focuses on the Kurtis from all Indian ethnic dresses. So, there is a scope to study on other Indian ethnic dresses. Factors like negative reviews, textual reviews and image reviews comes insignificant but previous studies says that these are the most important factor. So, there is a scope to analyse these factors, why it is coming as insignificant. Other limitations may be, as the sample size is only restricted to 250 due to time constraint, the factors might not come as significant. So, by increasing the sample size, further analysis can be done. In this study, only textual reviews are analysed. So, there is further scope to analyse image or video reviews. The image data that is collected from the reviews can be treated for computer vision methods wherein an image comparison analysis is performed between the images depicted by the retailer and the actual product received.

7.3 Summary

In this chapter, we conclude that five factors i.e., Review quality, positive reviews, video reviews, perceived value, and e-WOM engagement were found to be significant. Then, people satisfaction/dissatisfaction about the product analysed by emotional and sentimental analysis. Further, the scope for the future research is discussed. Apart from Kurtis, other Indian traditional clothing can be researched. Computer vision can also be used to perform image reviews.

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Appendix I

Survey Questionnaire

Dear Madam/Sir,

I am Deepak Samal, pursuing my Post Graduate Studies at National Institute of Technology Calicut (II Year M.Tech. in Industrial Engineering and Management, Department of Mechanical Engineering, NIT Calicut).

As a part of my M.Tech. Thesis, I am conducting a survey on the topic "Understanding the impact of online reviews on the purchase behaviour of e-commerce store customers who buy Kurtis online".

For this survey I had chosen you as one of the respondents. The survey will take only a few minutes of your time to complete. I assure you that your survey responses will be strictly confidential and data from this research will be reported in aggregate. The data collected will only be used for academic purposes.

We request your participation in the survey. Thank you very much for your time and support. Let's start with the survey now!!!

Part 1: Socio-Demographic Profile

Instruction: Please select (√) your category for each question that best describes you.

1. Age?
   - ☐ 16-24 Years
   - ☐ 25-34 Years
   - ☐ 35-44 Years
   - ☐ 45-54 Years
2. Gender?
   - ☐ Male
   - ☐ Female
   - ☐ Other
3. Education?
   - ☐ Less than or equal to higher secondary (10+2) education
   - ☐ Bachelor degree
   - ☐ Master degree
   - ☐ Professional degree
4. Annual income (INR)?
   - ☐ Less than 5 Lakh
   - ☐ 5-10 Lakh
   - ☐ 10-15 Lakh
   - ☐ 15-20 Lakh
   - ☐ More than 20 Lakh
5. Nature of employment?
   - ☐ Student
   - ☐ Service
   - ☐ Business
   - ☐ Freelance worker
   - ☐ Unemployed/Retired
   - ☐ Housewife
6. Internet experience?
   - ☐ Less than 2 Years
   - ☐ 2-4 Years
   - ☐ 4-6 Years
   - ☐ 6-8 Years

- ☐ More than 8 Years
- ☐ Last 4-6 Years

7. Online Kurtis purchase experience
   - ☐ Last 2 Years
   - ☐ Last 2-4 Years
   - ☐ Last 6-8 Years
   - ☐ More than 8 years

Part 2: Questions related to factors influencing online purchase of Kurtis

Based on your experiences of online purchasing of ethnic wear Kurtis, select (√) your level of agreement for each item, using a scale of 1=strongly disagree/very high to 5=strongly agree/very low

1. **Perceived value**

1.1. If I buy a Kurtis in e-commerce portals, I feel I would be getting my money worth.

Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5
○	○	○	○	○

1.2. If I buy a Kurtis in e-commerce portals, I think I would be getting good value for the money I spend.

Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5
○	○	○	○	○

1.3. I get a lot of pleasure knowing that I have saved money while purchasing a Kurtis online.

Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5
○	○	○	○	○

2. **Review quality**

2.1. Most reviews in e-commerce portals where Kurtis is listed have sufficient reasons supporting the opinions

Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5
○	○	○	○	○

2.2. Most reviews in e-commerce portals where Kurtis is listed are objective.

Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5
○	○	○	○	○

2.3. Most reviews in e-commerce portals where Kurtis is listed are credible.

Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5
○	○	○	○	○

2.4. In general, the quality of most reviews in ecommerce portal where Kurtis is listed is high.

Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5
○	○	○	○	○

3. Negative reviews

3.1. There are too many negative reviews on online store

Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5
○	○	○	○	○

3.2. Negative reviews are worth trusting

Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5
○	○	○	○	○

3.3. Negative reviews are worth reading/watching

Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5
○	○	○	○	○

4. Positive reviews

4.1. There are too many positive reviews on online store

Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5
○	○	○	○	○

4.2. Positive reviews are worth trusting

Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5
○	○	○	○	○

4.3. Positive reviews are worth reading/watching.

Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5
○	○	○	○	○

5. Textual reviews

5.1. Customer product review in text form make it easier for me in purchase decision

Strongly disagree	Disagree	Neutral	Agree	Strongly Agree

1	2	3	4	5
○	○	○	○	○

5.2. Customer review in text form enhances my effectiveness in making purchase decisions

Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5
○	○	○	○	○

5.3. Customer product review in text form motivates me in making a purchase decision

Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5
○	○	○	○	○

6. Image reviews

6.1. Customer product review in image form make it easier for me in purchase decision

Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5
○	○	○	○	○

6.2. Customer review in image form enhances my effectiveness in making purchase decisions

Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5
○	○	○	○	○

6.3. Customer product review in image form motivates me in making a purchase decision

Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5
○	○	○	○	○

7. Video reviews

7.1. Customer product review in video form make it easier for me in purchase decision

Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5
○	○	○	○	○

7.2. Customer review in video form enhances my effectiveness in making purchase decisions

Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5
○	○	○	○	○

7.3. Customer product review in video form motivates me in making a purchase decision

Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5
○	○	○	○	○

8. eWOM engagement

8.1. Most of the time, I am pleased to read on e-commerce portals about the experiences other people have had with the product that interest me.

Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5
○	○	○	○	○

8.2. I tend to share my consumption experiences on e-commerce portals after using a new product.

Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5
○	○	○	○	○

8.3. When I receive information on e-commerce portals about product, I tend to express my opinion

Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5
○	○	○	○	○

9. Purchase Intention

9.1. I intend to continue to purchase Kurtis from online store in the future.

Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5
○	○	○	○	○

9.2. I say positive things about the online Kurtis store to other people.

Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5
○	○	○	○	○

9.3. I encourage friends and relatives to purchase Kurtis online.

Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5
○	○	○	○	○