Shopping Assistant: A Fashion Suggesting Intelligent System using Natural Language Processing: An Aspect Based Opinion Mining Approach

R. Keerthiga

2021

Shopping Assistant: A Fashion Suggesting Intelligent System using Natural Language Processing: An Aspect Based Opinion Mining Approach

A dissertation submitted for the Degree of Master of Computer Science

R. Keerthiga

University of Colombo School of Computing

2021

DECLARATION

I hereby declare that the thesis is my original work, and it has been written by me in its entirety. I have duly acknowledged all the sources of information which have been used in the thesis. This thesis has also not been submitted for any degree in any university previously.

Student Name: R. Keerthiga

Registration Number: 2018/ MCS/ 046

Index Number: 18440466

29/11/2021

Signature of the Student & Date

This is to certify that this thesis is based on the work of Ms. Keerthiga Rajenthiram under my supervision. The thesis has been prepared according to the format stipulated and is of acceptable standard.

Certified by,

Supervisor Name: Dr. M.G.N.A.S Fernando

Signature of the Supervisor & Date 29-11-2021

I would like to dedicate this thesis to my parents for their endless love, support and encouragement given throughout my life.

ACKNOWLEDGEMENTS

I have completed the thesis successfully with great confidence and passion with the assistance of several people who have been extremely supportive in various ways. First of all, I would like to offer my humble gratitude to my supervisor Dr. M.G.N.A.S Fernando, Senior Lecturer at the University of Colombo School of Computing (UCSC) for his tremendous encouragement, support and guidance given throughout this research. Without your support, I could not have completed this research with success.

I would like to sincerely thank all the lecturers and staff members at the University of Colombo School of Computing and a special thanks to Dr. B.H.R Pushpananda, the course coordinator of Master of Computer Science Research Projects for his valuable support and guidance at various stages of this research.

I am also grateful to the examiners and reviewers who given their feedbacks and comments during various stages of the research that helped to correct the error and go in the research flow.

I would like to thank all my well-wishers and friends who were there supporting me with their encouragement. Last but not least, I should express my heartfelt thanks towards my family for their support and encouragement throughout my research study and for staying late nights with me to make this research a success.

ABSTRACT

In the 21st century, the usage of Web 2.0 shows a vast increase in its growth with highly attracting more users each year by allowing them to carry out most of the activities online. After the impact of Covid19, most of the fashion cloth and textiles industries transferred from the physical to the digital world. When it comes specifically to clothing and accessories shopping, people always look for new styles, fashions, and brands in the market. However, it is challenging to find high-quality products which meet the exact needs in an online scenario. The customer reviews and ratings play a vital role in helping customers find quality items that best match the need. With the advancement of social media, opinionated information and reviews available on the web are vast. Therefore, it is hard to manually go through and compare every review, and it is a time and energy-consuming task. The lack of personalized suggestions given to the users depending on customer opinions, user preferences, and their factors makes them difficult to choose from various items. Getting to know about own customers and their behaviours is very important for a success of a business. Only having the customer details and their purchased details would not yield a clear insight. Without knowing the targeted groups of customers and the product's strengths and weaknesses, the retailers cannot improve their sales. In addition, there is no option for the users to try on clothes and accessories in online scenarios before they make the purchase. The customers must take the body measurements manually and decide on a size that would fit their body. This paper presents a 'Fashion Suggesting Intelligent System' which addresses the current problems the customers and retailers facing in the online fashion retailing industry using Opinion Mining, Aspect-Based Sentiment Analysis, Personalized Suggestions and Augmented reality. The research proposes a hybrid approach that combines unsupervised and supervised learning to enhance sentiment analysis. The results from the sentiment analysis are used in providing personalized suggestions to customers and intelligent insight to merchants. The proposed system aims to assist customers and retailers while shopping and selling online by providing an intelligent system that can analyze customer's opinions at an aspect level and provide personalized suggestions, deep customer insight and targeted groups to of customers. In addition, the system combines augmented reality in a traditional online shopping context to virtually fit on clothes before making a purchase.

Keywords: Sentiment Analysis, Opinion Mining, Aspect Level, Personalized Suggestion, Augmented Reality

LIST OF PUBLICATIONS

Conference Publication

Keerthiga, R., Fernando, M.G.N.A.S., 2021. Shopping Assistant: A Fashion Suggesting Intelligent System using Natural Language Processing (NLP): An Aspect Based Opinion Mining Approach, Colombo ACM SIGCHI.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

1.1 Introduction

The research work aims to develop and evaluate a feasible solution to an aspect-based opinion classification task, which consists of an intelligent system to provide personalized suggestions on fashionable clothes and assist customers while shopping online. In addition, the research expects to include an Augmented Reality (AR) feature which allows the user to outfit clothes virtually. Along with the online customers, the merchants would also benefit from the research work by getting intelligent customer insight and targeted personalized advertising.

The research work addresses four research areas for the above purposes: aspect-based opinion mining on textual reviews, personalized recommendations, AR in virtual dressing, and intelligence in customer insight with targeted advertising.

In this chapter, Section 1.1 outlines the domain of the problem, and Section 1.2 discusses the primary motivation with the relevance and the challenges in the selected research fields. Next, in Section 1.3, the research problem is discussed in more detail, and the rest of the sections highlight the aim, objectives, scope, and contribution of the proposed research work. Finally, in Section 1.7, the structure of the thesis is given, summarizing the contents.

1.2 Problem Domain

In the 21st century, the usage of Web 2.0 shows a vast increase in its growth with highly attracting more users each year by allowing them to carry out most of the activities online. After the impact of Covid19, most of the fashion cloth and textiles industries transferred from the physical to the digital world. There is a considerable increment in people who do shopping online in the past few years because of social distancing. This fact brought up the concept 'E-Commerce' a very popular all around the world.

Clothes are the basic need of a human being, giving more benefit to companies, including small businesses selling clothes and accessories. Scientists psychologically proved that shopping could reduce stress and depression more effectively by improving the buyer's mood, called 'Retail Therapy'. Hence, the number of people who do shopping online and offline keeps increasing over the years.

When it comes specifically to clothing and accessories shopping, people always look for new styles, fashions, and brands in the market. In the past, the users ask their families, friends, and neighbours before buying any item to get their opinions. In the case of merchants, they use polls, surveys, and feedback forms to get back their customer's views and reviews. Since all the industries are moving into the digital era, the amount of information consumed also increased.

According to the Fashion Ecommerce report[1] produced by Statista in 2021, there is noticeable substantial growth in fashion sectors including apparel, footwear and accessories. Figure 1 shows the penetration rate change in the fashion market as the year progress.

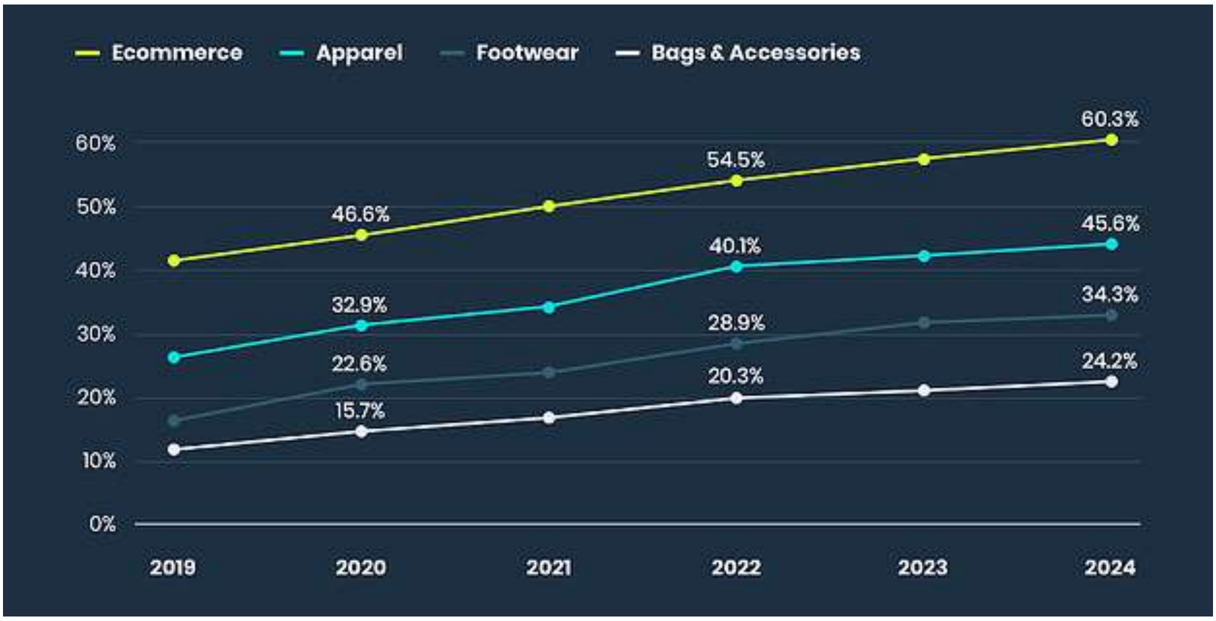


Figure 1: Penetration Rate Change in Fashion Market

Social media has taken an essential role in impacting the usage of e-commerce by sharing opinionated information with others. Customer opinions are publicly available nowadays as reviews and ratings in several sources (e.g., Online reviews, blogs, forums, Facebook, Tweets). For example, the big companies in e-commerce, Amazon, Myntra, Cnet, Trip Advisor, Yelp, Reteiltall, Epinions, and Ciao UK, have already collected their customer's opinions.

The customer reviews and ratings help the user in decision-making, find the strengths and weaknesses of any product and buy high-quality products. On the other hand, it helps the merchants to understand their customers better and release desired products. However, the high volume of opinionated information makes it both the customers and merchants challenging to make decisions.

[1] https://www.statista.com/study/38340/ecommerce-report-fashion/

When buying clothes and accessories, the other concern is how to make sure the item will best fit the user. The unavailability of a fit-on option while making online purchases discourages customers and might make them buy clothes and accessories that do not suit user body measurements at the end.

Even though there is huge customer demand in the online cloth retail domain, there are problems in the current context which need to be addressed to improve the overall online shopping experience and customer merchant satisfaction.

1.3 Motivation

In the digital era, people are so familiar with buying and selling products online with the help of the internet. The new normal after Covid19 further encouraged the people more to shop online rather than physically visiting an outlet. People always love to buy new clothes and fashionable accessories despite the time. Hence, there is a considerable demand for the online fashion retailing industry, which benefits online merchants.

Most retailers got forced to shut their outlets during the pandemic and go for an online selling business model. The need for e-commerce stores to handle the demands of consumers during the lockdown period is continually growing. According to the report[2] submitted by just-style, 36% of total fashion sales are expected by 2022 in the global fashion online market.

With the rapid development in online shopping, the opinionated information available on the web also got increased. The blogs, forums, Facebook, Twitter, YouTube, and all other social media paved the way for customers to share their opinions about the purchased items as reviews and ratings (Gupta and Joshi, 2020). The customer reviews help customers compare the strengths and weaknesses of an item in making buying decisions and help merchants market their products and identify new opportunities.

According to Spiegel news website[3], about 95% of customers read reviews before buying any product. This fact shows the impact of customer opinions in the field of online shopping. The statistics reported by Heinz Marketing[4] says 92% of buyers are more likely to buy an item after reading a trusted review. Therefore, it is essential to understand the customer opinions semantically to assist users in decision-making.

[2] https://www.juststyle.com
[3] https://www.spiegel.de/international/
[4] https://www.heinzmarketing.com/

The customer reviews are usually in a text format which requires to be carefully read and understood. Manually analysing many text reviews and comparing the product's positive and negative points is a difficult task. The abundance of reviews available on the web needs a mechanism to automatically extract the opinions expressed from the reviews and summarize helpful information to the users and the retailers. A popular NLP technique to apply on such cases is Sentiment Analysis and Opinion Mining.

One of the primary motivations for mining opinions in reviews is that they represent positive and negative sentiments. The numbers would not completely give an idea about the user sentiments towards an item in rating systems frameworks. As indicated by (Pang and Lee, 2008), it is tough to adjust different user's scales appropriately.

The Aspect-Based Opinion Mining (ABOM) is a sub-research area that evaluates the opinions about the aspects of an entity, for example, examining the feature, attribute, or characteristics. Analysing the sentiment at aspect levels gives more fine-grained opinions towards each aspect (Bauman et al., 2017). The overall rating gives a general opinion towards the particular product, but critically analysing the review word by word gives a deep insight into how customers react to each aspect and what sentiment they have towards it.

ABOM can be used in online fashion retailing to extract the aspects of the items and examine the customer's opinions and sentiments towards each aspect. The aspect level opinion mining can benefit customers and retailers in many ways. The customers can get a summarized knowledge of other's opinions towards a product and its aspects. That makes the traditional way of searching for products more time and energy-efficient. By providing this knowledge in e-commerce stores, the users can easily compare and buy items.

In addition, the recommender systems can utilize opinions about aspects to provide personalized suggestions. Traditional recommender systems generally use customer's purchase details and behaviour in the past. However, this knowledge about the past is not much effective in the modern scenario of online shopping. They do not reflect the user's interest and sentiment towards the products and their aspects. Therefore, incorporating aspect-based sentiment analysis in recommender systems conduces to provide personalized suggestions to the customer and enhance the overall performance.

On the other hand, the customer opinions in the textual reviews are assets for a business. The opinions can signify the strengths and weaknesses of each product from the merchants' point of view. The aspect-based opinion mining can point out the aspects which have customer's positive opinions and negative opinions. The positive opinions allow identifying the excellent products and important aspects. On the other hand, negative opinion helps to determine the defects in a product and its aspects. Identifying different customers and their sentiments towards products promotes personalized market advertising on a targeted group of customers.

Customer reviews have a strong impact on sales profit because they can influence a user's buying decision. It has been proved in the previous studies that the customer is willing to pay 20% to 90% more for products with a 5-star rating compared to other products (Pang and Lee, 2008). The retailers can gain advantages from aspect-based opinion mining by having an intelligent customer insight to support business tasks, develop new products, and perform quality control.

Another motivation factor for this research work is incorporating Augmented Reality (AR) technology in the online shopping context. Even though the rate of online cloth sales shows continual growth, there is a high return rate on online cloth purchases for the past five years.

In the survey carried out by Barclaycard UK[5], it is reported that £7 billion of purchases are returning by shoppers in the UK. According to the global web index 2019 report, the most frequently returned product category is Clothing.

The lack of a standardized system in finding the correct size and fit clothes is the major reason for the returns. Since there is no fixed standard for measurements, the cloth size varies depending on the brand and country. The demand for this motivates the research work to adopt Augmented Reality (AR) in the online shopping model to have a virtual dressing room.

The rate of return affects the online retailers also. The Barclaycard survey[4] also showed that 57% of retailers face a negative impact on their business because of purchase returns and the cost of returned products causes loss to their profits since they accept free returns most of the time.

Even though multiple problems need to be addressed, there is a huge demand for online cloth shopping and retailing. With all the motivation discussed above, the research study investigates the importance of opinions in online shopping and how personalized suggestions and intelligent customer insight can help users and merchants improve the effectiveness of traditional online shopping. In addition, the research focuses on providing an augmented reality experience to the users while shopping for clothes and accessories online.

[5] https://www.barclaycard.co.uk/

1.4 Statement of the problem

Online fashion retailing is a highly demanded industry in the current world. It helps to interconnect the global customers and merchants all around the world in a single market. Since the number of online shoppers is rapidly increasing, the amount of digital information flowing through is also high.

In modern society, people are always concerned about fashion clothing and styling, increasing their web usage in searching and buying trending clothes and accessories that match their personal needs. Even though online shopping makes all the processes easy and faster, making the correct buying decision is always difficult for customers.

It is challenging to find high-quality products which meet the exact needs in an online scenario. The customer reviews and ratings play a vital role in helping customers find quality items that best match the need. With the advancement of social media, opinionated information, and reviews available on the web are vast. Therefore, it is hard to manually go through and compare every review, and it is a time and energy-consuming task.

The customer's reviews are mostly textual, unstructured, and written in the natural language, for example, in the English language. There are possibilities that these textual reviews may be unstructured, unclear, and ambiguous opinions expressed by the customers. There is no guarantee that all the customers would write a genuine opinion in an understandable form.

The rating and reviews alone would not help the customers //reference. The reviews can only give an idea about the strengths and weaknesses of an item. Even though the user decides to buy an item, simply querying the search engines or checking the merchant would give a huge list of available items. It is again a time-consuming task to manually go through the items listed and check which matches the user preferences.

The lack of personalized suggestions given to the users depending on customer opinions, user preferences, and their factors makes them difficult to choose from various items. It is difficult to compare the colour, size, style, price, and so on and choose the desired product. It may result in making ineffective decisions and buying items that are not suitable and least liked.

Getting to know about own customers and their behaviours is very important for a success of a business. Only having the customer details and their purchased details would not yield a clear insight. Even though the feedbacks are collected through surveys, the results are more general. Manually reading and understanding customer reviews is not practical if there is a huge amount of information available. Without knowing the targeted groups of customers and the product's strengths and weaknesses, the retailers cannot improve their sales.

There is no option for the users to try on clothes and accessories in online scenarios before they make the purchase. The customers must take the body measurements manually and decide on a size that would fit their body. The only way possible is to try on items after they got delivered to their hands. There is a high possibility that the purchased item may not fit as expected, especially the cloth items. After making payment and purchasing, it is too late to change the size, and the exchange process again takes a lot of time and effort.

1.5 Research Aims and Objectives

1.5.1 Aim

The research aims to critically review the current technologies and approaches used in aspect extraction, opinion extraction and classification, recommendation system, intelligent customer insight with targeted advertising, and augmented reality. The objective of the research study is to assist customers and retailers while shopping and selling online by providing an intelligent system that can analyse customer's opinions at an aspect level and provide personalized suggestions, deep customer insight and targeted groups of customers.

In addition, the proposed study focuses on how to combine augmented reality with a traditional online shopping context. Thus, a problem definition is given to describe and compare applicable works in the relevant research areas. The research also aims to identify which current methodologies are the best and significant for further exploration.

1.5.2 Objectives

The main objectives of the proposed research work are given below.

- To investigate the user opinions about aspects and form aspect-opinion pairs to improve the shopping experience in buying clothes and accessories.
- To provide personalized suggestions based on aspect-opinions pairs, user preferences, and personal factors.
- To provide customer insight to merchants by tracking user's preferences and interests to increase sales revenue.
- To build an Augmented Reality feature model to allow the user to fit on clothes and accessories virtually.

1.6 Scope

In the current context of the online fashion retailing industry, finding and buying the desired item is a challenging task for the customers. Even though the reviews are available to assist users, the vast number of opinionated information makes it difficult to read and analyze manually. The lack of personalized suggestions discourages online buyers and result in buying the least likely items. From in merchant's point of view, poor customer insight causes producing least selling items and fewer sales revenue.

The proposed system would address these current problems the customers and retailers facing in the online fashion retailing industry using Opinion Mining, Aspect-Based Personalized Suggestions and Augmented reality. The scope of the project is bounded to merchants who sell fashionable clothes and accessories online. The research area of the proposed study is Opinion Mining and Personalized Recommendation, which uses Natural Language Processing (NLP) and content-based filtering and collaborative filtering techniques.

There are four main research components in the proposed work: aspect-opinion extraction, aspect-based personalized suggestions, intelligent customer insight with targeted advertising, and augmented reality for virtual dressing. The proposed approach investigates the opinions related to the aspects of the items to provide suggestions to the customers. To personalize these suggestions, the user preferences (interest and favourite) and their personal factors like age, gender, salary, culture, etc., gets combined along with the aspect-opinion pairs.

The results from the first two components are utilized to produce intelligent customer insight. The products' opinions towards aspects of the products are used to examine the strengths and weaknesses of the products, and different clusters of customers based on their personal factors, preferences, interest and their past opinions resulting from the personalized suggestion component are used to target users to market personalized advertising.

The proposed system extracts all the aspects in the fashion clothing and accessories domain and extracts the opinions related to those aspects using investigating the customer reviews and finding opinion polarities whether the opinion expressed is positive, negative, or neutral. The results form aspect-opinions pairs that can provide suggestions concerning other parameters such as the user's personal factors, preferences, interests, and past opinions.

Opinion mining can be carried out in three levels. (At document level or sentence level or at aspect level). The proposed system carious out opinion extraction at aspect level, which extracts an item’s aspects, such as cloth material, fabric or design, price, etc., and finds customer opinions towards each aspect.

The personalized suggestions are produced using extracted aspect-opinion pairs with content-based, collaborative filtering and hybrid aspect-based recommendation techniques. Content-based filtering is used to get the user personal interest and favourites. In contrast, collaborative filtering is used to get the preferences of like-minded people to predict the items the user would like. The aspect-based recommendation gives more fine-grained results based on the user’s opinions on each aspect. The proposed system gives personalized suggestions depending on opinion, user preferences and personal factors.

The proposed system also utilizes Augmented Reality (AR) technology to enable users to virtually outfit clothes and accessories. The user can select clothes or accessories they want to buy and can outfit virtually. The proposed system uses AR technology to model the user and show 3D outfit over-processed user model in real-time. The user can also try a combination of clothes and accessories, which enables the user to see the full outlook.

As the proposed framework creates clusters of online users with similar interests and shopping behaviours and has some personal factors in common, the merchants get a clear classification of their customers and more detailed customer insight. The merchant can use this useful information to promote their products and send personalized promotional offers.

As product deliverables, the final implementation of a web application is developed. The customers can use the web application to search for items, virtually outfit and purchase online. Online or local clothing retail stores will use the web application to register their store and upload available products and items which they sell. The web application can be accessed by using any web browser.

1.7 Contribution

The proposed research contributes to novel techniques to extract aspects and opinions from customer reviews, classify opinion polarities, and provide personalized suggestions through aspect-based opinion mining, natural language processing, content-based filtering, and collaborative filtering techniques.

The research literature review shows the existing approaches on aspect-based mining, personalized recommendation, and virtual fit using Augmented Reality Techniques. This helps to evaluate and combine the existing methods and approaches in implementing an aspect-based personalized suggestion system.

The research results show that the suggestions in account with the opinionated information, user preferences and personal factors improve the effectiveness of the overall online shopping experience. In addition, the proposed framework shows how an augmented reality feature model can be implemented to fit items virtually.

The research also contributes to extract all the aspects and opinions related and to form clusters of likely minded people, which give more customer insight to merchants to send personalized promotions and increase sales revenue.

1.8 Structure of the Thesis

The thesis document consists of five chapters and is structured as follows.

- Chapter 2 presents the previous related works on aspect-based opinion mining, personalized recommendation system, and virtual fit using Augmented reality, approaches, and limitations. The chapter also discusses how the previous works related to the proposed research.
- Chapter 3 outlines the methodology of the proposed research work. The data collection, pre-processing, design, and methods for opinion mining, aspect-based personalized suggesting and AR virtual fit have been discussed.
- Chapter 4 analyses the results of the experiments conducted to evaluate the developed methods and system.
- Chapter 5 concludes the research work and presents some areas which can be further improved in future.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

In chapter one, an outline of the research problem and an overview of the background is presented. In this chapter, the foundation on the explored research areas and technologies identified are given. This research intends to explore and examine the technologies for aspect-based opinion mining, provide personalized recommendations with sentiment analysis, provide customer insight to the merchants, targeted advertising and build virtual fit using augmented reality.

In addition, the chapter presents related definitions and terms, explores various existing methods and applications identified with aspect-based opinion mining, personalized recommendation, augmented reality and customer insight generation. Giving an overall outline on such areas and topics, the chapter aims to permit the reader to acquire a simpler and better understanding of the research work proposed.

2.2 Background and Context

For example, most current web content, web indexes, question answering frameworks, and text mining techniques work with numerical data. Online users express their opinions and feelings on nearly anything at review sites, forums, blogs, articles, etc. This important data is freely accessible for all Internet users. The pattern those online users browse reviews on websites prior to buy clothes, accessories, and fashionable items, motivates researchers to analyse this important web-based information, i.e., reviews. In a common situation, customers record their own opinions and rate items with numerical scores (Gallagher et al., 2019).

The web contains a large volume of opinionated information. Nevertheless, the large amount of opinions on the web makes it exceptionally hard to get valuable data easily and quickly (Nawaz et al., 2020). Manually go through all reviews to make a decision is tedious work. In addition, understanding potentially different and conflicting opinions written by various customers may make other customers and merchants more confused.

In spite of the fact that online users can understand how the reviewer feels about a particular item, however, the general rating score is not just enough. Without fine-grained investigation, we cannot tell whether the customer expresses different opinions on what aspects because everything is added to the overall rating scores (Xue, 2017). Then again, people generally do not have the tolerance for reading all the reviews.

These requirements have motivated a new research area on mining opinionated information at the aspect level, which is called Aspect-Based Opinion Mining (ABOM). Sentiment Analysis or Opinion Mining is the field of study that process and examines the opinions, sentiment or feelings of the customers using written texts (Liu, 2012). The aspect-based sentiment analysis provides a good solution to analyse these at a fine-grained level.

Recognizing the entity aspects and learning more useful opinions of each aspect is an attractive topic in opinion mining. It assists online buyers with informative facts about each aspect of an item. Recommendation systems can use this knowledge to provide personalized suggestions to online buyers.

Opinion mining is exceptionally valuable for customers to understand the different customer's opinions before they purchase an item (Abbasi Moghaddam, 2013), yet additionally significant for merchants to understand their own items, services and customers (Liu, 2007).

While item particulars are clearly significant, tracking down the reasons for low profit requires analysing their customer's own perspectives on such aspects (Pang and Lee, 2008). AOBM is an excellent way for carrying out numerous business tasks and sales management, marketing and advertising. In addition, organizations can perform forecasting to predict patterns in sales by analysing opinions.

In addition, the businesses aim to increase sales by providing their customers with personalized suggestions. The opinions, preferences, interests, and personal factors such as age, gender, culture, educational background and etc., differs from person to person. This difference in society causes a need for an intelligent system to filter the items and display the results in a more personalized manner (Göker and Thompson, 2000).

Thus, merchants can use machine learning algorithms to predict the customer shopping behaviour and make recommendations with more personalized items based on their preferences, personal factors, interests and past shopping history (Al-Safadi, 2010). This way of marketing helps users to easily find and purchase items, as well as merchants to understand their own customers.

Online advertisements are an excellent way to attract customers and earn more profit in a web-based business (Proios et al., 2015). The clusters of customers resulted from aspect-based opinion mining and recommendation tasks can be used to target personalized advertising and promotional offers. This benefits customers to receive promotions that are relevant and best match their needs or criteria.

In the cloth retailing industry, the amount of returns that occur annually is approximately $62 million, and above 70% of that causes because incorrect size and fitting issues (Lee and Xu, 2020). There are many researchers carried out studies over the past years on providing a system to correctly measure body size online and virtually outfit. With the development of technology, there are mechanisms to have a virtual fitting room. Using augmented reality, a customer can virtually try clothes on themselves and check fit without visiting a physical outlet (Erra et al., 2018).

The related works on each interesting research area of this study are discussed below sections in more detail.

2.3 Sentiment Analysis and Opinion Mining

The interest in sentiment analysis has increased drastically with the development of web-based services like review websites, blogs, articles, social media networks, and forums (Kumar et al., 2020). In the current business context, online reviews are a great value for organizations to advertise items, find market opportunities and enhance reputations (Gallagher et al., 2019). Numerous organizations are presently utilizing opinion mining techniques to analyze their customer feedbacks and respond appropriately.

Recently one of the articles posted on the search engine journal[6] website published some statistics on online reviews as follows.

- According to a report by PowerReviews in 2016, 82% of customers explicitly search out negative reviews.
- BrightLocal's neighbourhood customer study shows that among 18 to 34 aged buyers, 91% of people believe in online reviews.
- On whole, people accept a product's rating only after it has at least 40 reviews.
- A study on Harvard Business Review showed that a business increases its income by 5-9% for each increment in star rating.
- Research by the Spiegel Research Centre uncovers that the probability of an item getting bought increments by 270% when it gets five reviews.

[6] https://www.searchenginejournal.com

(Pang and Lee, 2008) additionally, report the results of two surveys on American grown-ups, which show solid demand for opinions. The overview of the discoveries is listed below.

- Among the online shoppers, 81% of people have done product research at least once.
- 20% of people perform consistent product research online.
- The number of buyers who get impacted by reviews is between 73% to 87%.
- People are willing to pay more for a 5-star rated item than lower-rated items.
- 30% of the respondents have written an online review on an item or service.

(Dave et al., 2003) has introduced the term "opinion mining" for the very first time.

The term "opinion mining" was firstly introduced by (Dave et al., 2003). Dave proposed some approaches and classified opinions as positive or negative. An opinion is a person's personal appraisals, decisions and thoughts with respect to a specific product/subject/topic.

Figure 2: Normal Distribution of Opinions on a Scale from 1-5

Figure 2 (Al-Matarneh, 2018) shows the distribution of opinions on a scale from 1 to 5. Green, blue and red represents positive, negative, and neutral opinions, respectively. The ratings 2 and 4 are considered neutral, even though they fall on the red and green regions where only 1 and 5 are considered purely negative and positive.

Opinion mining is an active research area that automatically extracts and classify opinions from texts about the entities such as individuals, events, topics, products, or organization and their aspects. An opinion is usually represented as combining four factors: entity, holder, claim, and sentiment.

The opinions of others can affect and offer direction for governments, social networks, people and associations during the decision-making process (Tuzhilin, 2012). While thinking about others' opinions, individuals need brief, precise and timely data so they may make the right and fast choices. Opinions make individuals integrate various experiences, approaches, information and intelligence of several groups of people when deciding. It is general that people express their perspectives and opinions when participating in conversations (Abbasi Moghaddam, 2013).

2.3.1 Definitions and Terminology

In this part, the essential wordings and terms currently utilized in the opinion mining research area are characterized.

Opinion phrase: An opinion phrase is consists of two terms (head h and modifier m) (Lu et al., 2009). The head term is the aspect and modifiers holds the sentiment towards the aspect, e.g., <price, expensive>, <material, too silky>, etc.

Sentiment: a semantic word that refers to an idea or opinion that is interpreted (Liu, 2007). Sentiments might be expressed as opinions, thoughts or as feelings (Boiy et al., 2007). Lu says opinions are emotional indications that show individuals' sentiments, ideas, or feelings (Lu, 2010).

Opinion: An opinion is a conviction about things normally viewed as subjective and is the result of feeling or understanding of realities.

Opinion Orientation: An opinion can be grouped on a scale of n-level. Opinion orientation is a representation of user opinion as a mathematical value.

Polarity: Polarity is a directed scale of two values; positive or negative.

Rating: Rating is a number from 1 to 5 scale that represents an evaluation on a particular aspect.

Overall Rating: Overall assessment of the quality of the particular item given by users.

Review: A written text that contains opinion bearing words regard to a particular item. This text may be complete sentences or with only short remarks.

Aspect: Item characteristic or feature that gets remarked by the users. If an aspect is expressed directly in a review, it is known as an explicit aspect else implicit aspect. Most of the research works focus on extracting explicit aspects while some strategies are proposed to recognize implicit aspects (Liu, 2007).

Explicit Aspects: Aspects that are directly referenced as nouns or noun phrases in a sentence, e.g., In the sentence here "The design quality of this saree is great, the explicit aspect is design quality.

Implicit Aspects: Aspects that are not directly referenced in a sentence, e.g., price in the sentence "The red frock is very costly" is an implicit aspect.

2.3.2 Opinion Mining Tasks and Sentiment Calculation

In this section, the existing related works carried out on opinion mining tasks and sentiment calculation proposed in early and recent days are critically discussed.

Comprehensively, sentiment analysis can automatically identify an individual's opinions and towards an entity and classify them (Liu, 2012). An entity can be an item, an individual, an occasion or an organization.

Sentiment analysis is performed directly on written texts and verbal speech. However, it can also be used in different structures, for example, facial emotion recognition. Consequently, sentiment analysis may include the utilization of natural language processing (NLP) techniques, text analysis, computational linguistics, and biometrics methods.

Sentiment analysis is also known as opinion mining where sentiment analysis refers to the inside feeling an individual has towards an item or entity. However, opinion mining separates the individual's opinion on an entity. The two ideas are utilized in most of the related words, yet it must be noticed that an individual may or may not have expressed an opinion fully.

Pang and Lee classify the stages of opinion mining into three classes: sentiment polarity identification, subjectivity identification, and topic-sentiment analysis (Pang and Lee, 2008). Liu likewise characterizes three mining tasks in his book (Liu, 2007). He further broadens this as classification of sentiment and subjectivity, aspect-level opinion mining, analysis of sentiments in comparative sentences, search and retrieval of opinions, and spam detection. Finally, in his latest book (Liu, 2012), opinion mining is characterized at three levels: document-level, sentence-level, and phrase-level.

2.3.3 Opinion Definition

An opinion bearing phrases or sentences consists of 5-tuple (Liu, 2012),

$$(e, a, s, h, t)$$

where each symbol denotes entity, aspect, sentiment on the aspect, opinion holder, and posting time respectively.

A review of The Lawnmower Man from (Wang et al., 2012) is shown in Figure 3. In the review given, the entity is The Lawnmower Man, and the review is posted on August 12th, 2007. The review talks about four aspects whose sentiments are mostly positive apart from the last one.

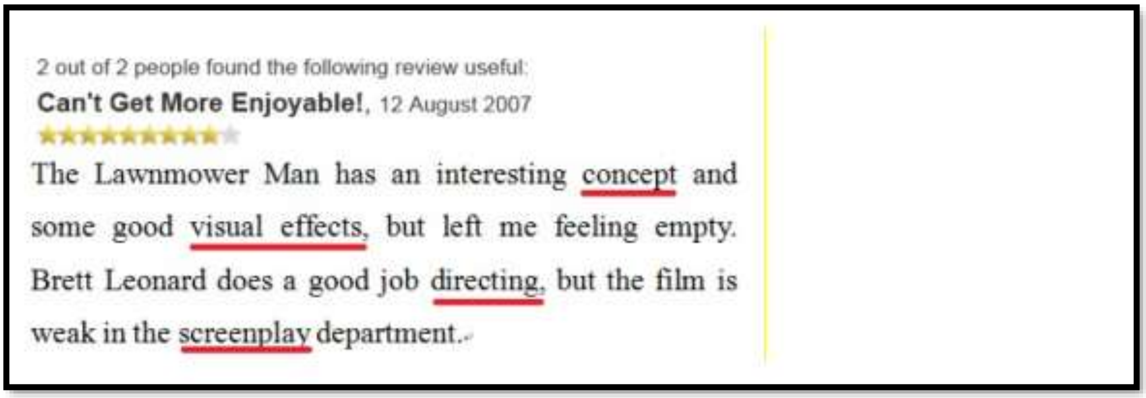


Figure 3: A review on The Lawnmower Man (Wan et al., 2012)

2.3.4 Opinion Tuples Extraction

In the opinion mining task, the first phase is to extract the five opinion tuples from written reviews. There may be situations where all the tuple components may not be expressed fully, or the opinions are expressed towards implicit aspects.

As examined in (Liu, 2012), there can be found different types of opinions which are not following the given five-tuple structure. For example, when classifying opinions in comparative sentences, the user contrasts a common aspect between two entities.

In addition, the given definition for opinion tuples assumes that the text communicates opinion about a single entity. A general opinion can be further divided into two types; direct and indirect opinions. In direct opinions, the objective of the sentence is the main entity where the objective is another entity in indirect opinions.

2.3.5 Opinion Extraction and Sentiment Classification

As of now referenced, sentiment analysis intends to separate and break down the five components of the opinion tuple. Generally, information like entity, opinion holder, and posting time is simple to get since they are expressed explicitly in the metadata. Therefore, it is necessary to focus on extracting the opinions and their sentiment polarities.

Classifying sentiments and opinion mining on texts is a tedious task (Pang et al., 2002; Turney, 2002), and it can be carried out in three levels: document level, sentence level, and aspect level (Pang and Lee, 2008). In the early days, researchers focused mainly on mining at document and sentence levels.

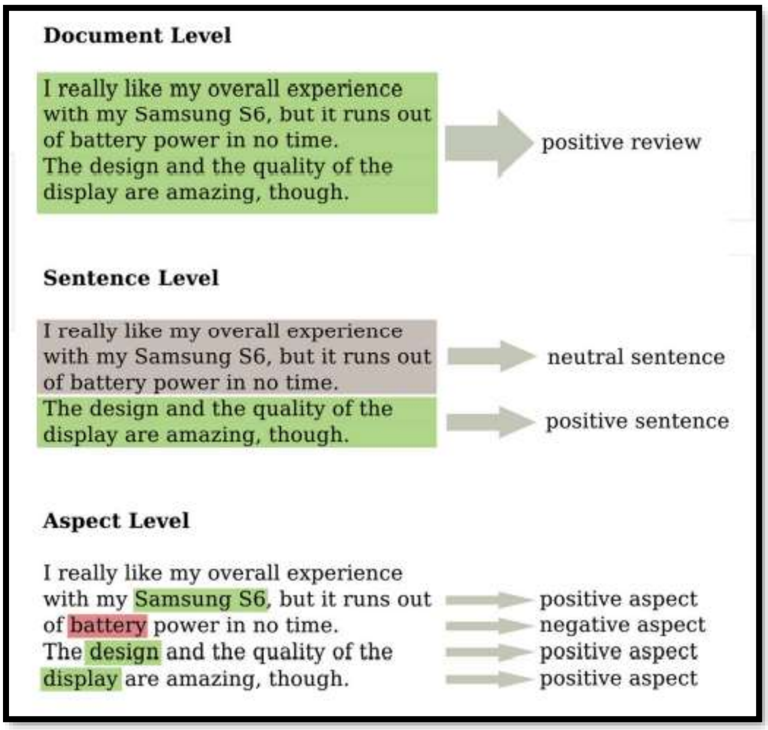


Figure 4: Granularity Levels in Opinion Mining

- **Document-level**

At the document level, the classification is carried out considering the opinion (positive, negative, or neutral) conveyed in the whole document. It is assumed that the entire document contains an overall opinion about an individual entity.

- **Sentence level**

Each sentence in the text is classified independently based on the sentiment orientation. Only the subjective sentences are selected for examination.

- **Aspect level**

Each aspect of an entity in the text is considered and classified depending on their opinion polarities. Aspect based opinion mining extracts various aspects and derives conclusions which aspects make the customers favour an item.

Figure 4 (Arboleda et al., 2017) shows a customer review where opinion mining at three levels is clearly shown. Mining reviews as a whole at document or sentence level and classifying as positive and negative opinions would not give deep insight about how customer prefer each aspect of the products.

2.3.6 Opinion Polarity Classification

In ABOM, the very much considered task is polarity classification. Generally, this is viewed as binary classification where it considered two classes: positive and negative. The objective here is to decide the overall tone of a given text is whether positive, negative or neutral. Clearly, a critical point is a manner by which to characterize the two poles of sentiment.

Early commitments by (Turney, 2002) and (Pang et al., 2002), examined various methodologies for recognizing the polarity of item and film reviews separately. On account of film/item reviews, rating systems with stars or expressions are utilized frequently as in (Turney, 2002) and (Pang et al., 2002).

A document's polarity can also be examined on different scales, which was tried by (Pang and Lee, 2005) and (Snyder and Barzilay, 2007), among others. In these early developments, Pang and Lee expanded the methodology of classifying as positive and negative to consider the star ratings also while Snyder analysed reviews by predicting rating for different aspects.

Practically speaking, a neutral opinion is not considered as an opinion (Liu, 2010). In most statistical and computational methods, the neutral class is overlooked. Different specialists have recommended that three classifications should be associated with each polarity problem. Likewise, it is shown that particular classifiers like the Max Entropy and Support Vector Machines (SVMs) can be enhanced by the taking neutral class into consideration and improve the overall performance rate (Schler, 2005).

Several examinations (Hu and Liu, 2004; Qiu et al., 2011) have experimented and showed that opinion is mainly communicated using adjectives words along with other verbs and compound expressions. This is the main perception where sentiments are developed dependent on the adjective words found in the textual reviews.

As portrayed by (Khan et al., 2014), lexicons play a significant role in sentiment evaluation. Opinion words are keys to opinion mining. These opinion lexicons include two types of opinion words: positive polar words that confer positive meanings and negative polar words that give unfortunate negative meanings.

The presence of the adjective words was viewed as a solid sign of the opinion orientation. In any case, considering just adjective words is not sufficient and has a low precision while analysing opinion polarities in text-based information.

2.3.7 Emotion classification

The sentiment polarity classification can be further refined by doing emotion classification on texts. The objective here is to arrange a text according to the predefined set of emotions. Sentiment polarity generally classifies positive versus negative while emotion classification attempts to recognize more fine-grained information.

The early work on emotion classification (Ekman et al., 1987) outlines six fundamental emotions. Those six emotions are anger, disgust, fear, happiness, sadness, and surprise. These are used labels to denote different classes. Other than getting a categorization of emotions, class labels may likewise be specially used in applications.

2.3.8 Source detection

The source detection intends to recognize the individual, organization, or entity that is the source of emotional data. The sentiment source can also be called an “opinion holder” or “opinion source” in the literature. In numerous application situations (e.g., review mining), the opinion holder is just the content creator. However, the issue might be more complex, including more than one opinion holder (Wiebe et al., 2005).

Rather than the previous referenced classification issues, deciding opinion sources is viewed as a data extraction task. It includes sub-tasks like recognizing named entities and extracting relationships.

The methodology proposed by (Lu, 2010) created a bigger number of results than those referenced in (Seki et al., 2008) with the same information. This research work showed that it is feasible to recognize opinion holders by verbs and targets by opinion bearing words with a dependency parser for Chinese news.

2.3.9 Aspect-Based Opinion Mining

The document level or sentence-level opinion mining is helpful much of the time. In any case, these levels are not adequate for decision making. In many situations, document-level mining is excessively coarse-grained and does not give the ideal data. This just assists with data about the number of customers who are fulfilled or unsatisfied. In view of these numbers where the patterns in the customers' impression of an item can be found, however, the specific explanations behind cannot be realized.

To acquire such data, we need to go to a better degree of granularity. Aspect level opinion mining performs a better-grained investigation and straightforwardly takes a look at the opinion (Liu, 2012). As referenced previously, aspect-based sentiment analysis aims to find all the aspects expressed in reviews and categorize them according to the user's opinion.

Aspect-based opinion mining examines the customer's sentiments with respect to each item aspect. This includes the joined investigation of two measurements: find all important item aspects and the connected sentiment. As opposed to reviewing classification, aspect-level opinion mining is better in changing the unstructured data of a review text into an organized summary.

In the previous decade, countless techniques have been proposed for aspect-level opinion mining. The works showed various strategies to extract aspects and analyse its opinions from reviews. Some of these works utilized full content documents, while others took benefits of organized short comments. Different algorithms and frameworks have additionally been introduced for distinguishing the rating of aspects. Aspect based opinion mining data gives more points by detailed information to buyers to take decisions and merchants to understand their customers.

2.3.10 Aspect Extraction Techniques

The sentiment analysis involves two major stages: aspect extraction, aspect sentiment classification. Accordingly, there is a need to use techniques that consequently removes the most applicable set of item aspects. Ways to deal with aspect extraction can be partitioned into four fundamental classes: frequency-based, relation-based, supervised learning and unsupervised learning (topic modelling).

Figure 5 shows how the aspect extraction techniques can be based on the algorithm and the data usage.

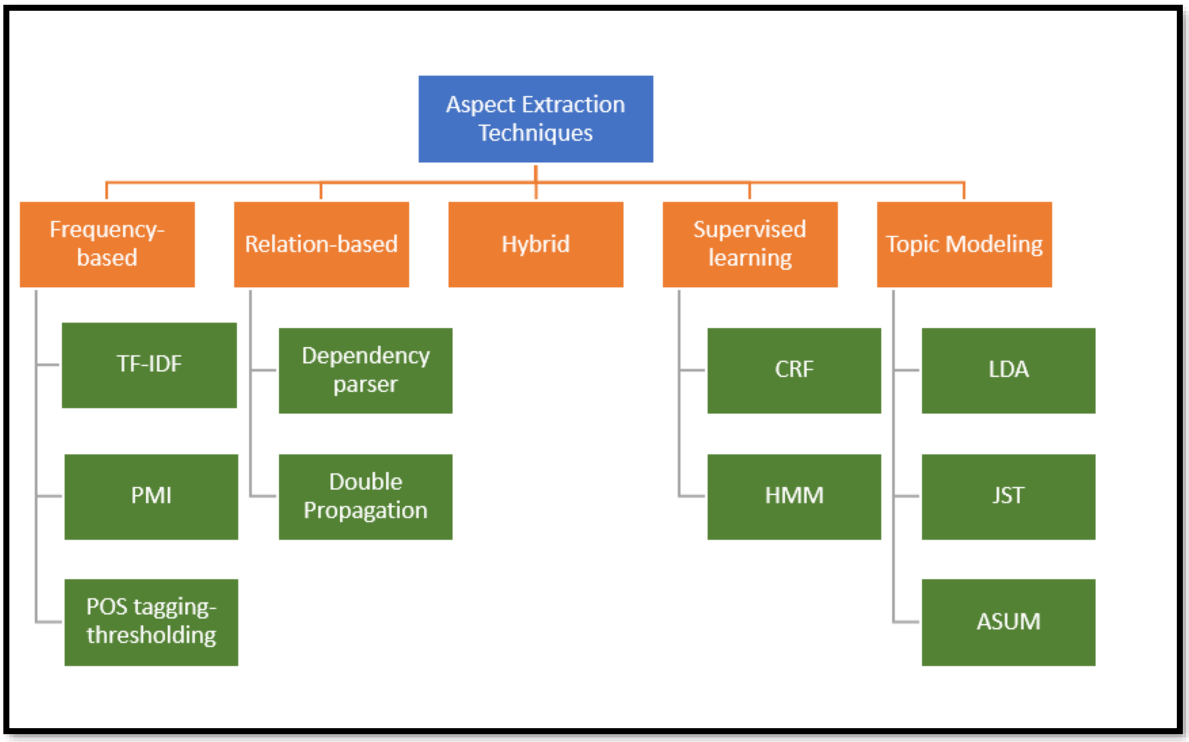


Figure 5: Aspect Extraction Techniques

- **Frequency-based Approach**

Most of the early works are based on frequency-based methodologies. This is the first methodology proposed to identify item aspects by counting the frequencies of words in a certain area (Scaffidi et al., 2007). The candidates to be aspects are selected based on the nouns and noun phrases with high proportions of existence. A strategy dependent on frequencies has been utilized by considering the appearance of the words in the text distribution (Caputo et al., 2017).

In reviews, individuals are bound to discuss relevant aspects, which recommends that aspects ought to be frequent nouns. These techniques are simple, and they are very powerful. Many organizations are utilizing these strategies for investigating their customer feedback. These techniques will, in general, deliver an excessive number of aspects that are not actually aspects and miss actual aspects with low frequency. Moreover, the frequency based approach expects to tune the parameters manually that makes portability difficult.

- **Relation-based techniques**

While frequency-based techniques are very powerful, they miss aspects with less frequency distribution. To beat this shortcoming, relation-based methods are proposed. These NLP methods discover connections among aspects and related sentiments. Even though the shortcoming of the frequency-based techniques can be defeated, the relation-based approach produces numerous non-aspects.

- **Hybrid Approach**

At last, researchers adopted the benefits of the two strategies and proposed a hybrid solution that does filtering of the words with high frequency using NLP. The exactness of hybrid method techniques is more accurate enough than the past strategies. Nonetheless, like the past approaches, hybrid methods need manual settings of parameters which causes portability issues.

In the hybrid-based method, the number of non-aspects is more restricted compared to frequency- and relation-based approaches since they apply frequency threshold and relation pattern. However, the hybrid solution also fails to overcome the missingness of love frequency words.

- **Supervised Learning**

To overcome the issue of manual tuning of parameters, supervised learning methods are investigated to make the model learn the parameters automatically. The past research works have shown that supervised learning can be applied to aspect-based opinion mining to identify aspects and their opinions in text reviews.

In the past, numerous algorithms are proposed based on supervised learning to extract data. Some of the renowned techniques proposed are sequential learning strategies like Hidden Markov Models (HMM) proposed in (Rabiner, 1989) and Conditional Random Fields (CRF) (Lafferty et al., 2001).

These methods do word labelling depending on the hidden state sequence. In the task of extracting aspects, the words or the expressions in the review are considered as tokens whereas the hidden states are the phrases containing the opinions. During training, the target token and opinion pairs are generated that enable the aspect-sentiment classification. The limitation with these techniques is manually labelled data is needed for training.

- **Unsupervised Learning (Topic modelling)**

While supervised learning overcomes the shortcomings of the past methods, it needs a dataset that is manually labelled for training purposes. The researchers have examined an unsupervised learning technique particularly topic modelling to overcome this problem.

The topic modelling gets a document and recognizes all the topics in the documents. These topics are typically a group of words, and the distribution of the topics along the document gives an idea about the proportion of that particular topic. In the context of aspect extraction, the documents are the reviews, and the aspects are treated as the topics.

Most of the topic modelling approaches are depend on Latent Dirichlet Allocation (LDA) that is proposed in (Blei et al., 2003) and Probabilistic Latent Semantic Indexing (PLSI) proposed by (Hofmann et al., 2001), which identifies the word occurrences inside documents and word dispersion to induce topic clusters.

In a specific domain, the reviews about items may contain sentiments towards a defined set of aspects, and in this manner, their topic distributions might be basically the same. Consequently, topic models also help to identify global topic models and discover more appropriate aspects.

Both the aspects and sentiments need to be extracted separately in aspect-based opinion mining. This can be accomplished by using the LDA and PLSI topic models (Liu, 2012).

In unsupervised learning, there is no requirement for labelling data manually. In addition, these techniques can perform both aspect extraction and topic clustering at the same time. However, topic modelling typically requires an enormous number of unlabelled data for training purposes.

2.3.11 Aspect sentiment classification Techniques

Aspect extraction alone would not make any sense in applications, yet additionally, the sentiments/opinions communicated about such aspects also need to be addressed. We can recognize two principal approaches for sentiment classification: lexicon-based sentiment classification approaches and machine learning for sentiment classification.

Figure 6 shows the two major techniques used in sentiment analysis and their different approaches.

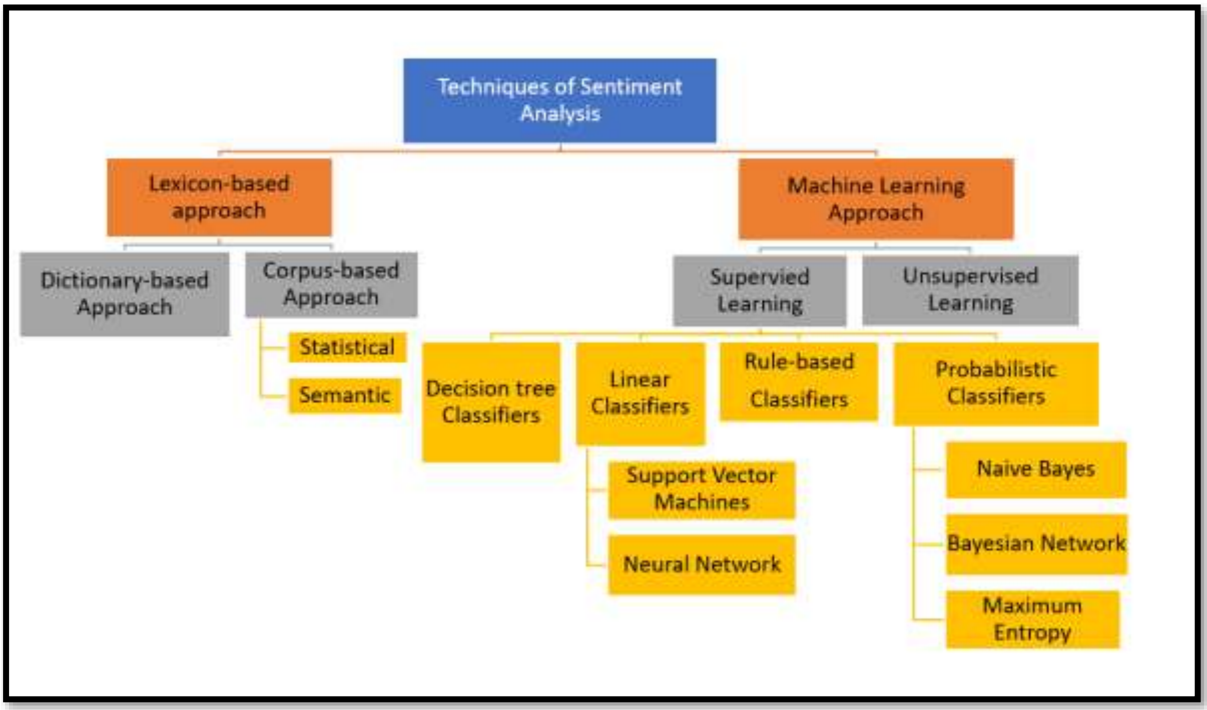


Figure 6: Sentiment Analysis Techniques

- **Lexicon-based Approach**

In this approach, the sentiment lexicons are used to find the orientation for a given statement. This methodology is capable of solving the limitations shown by supervised learning. Since these techniques are mostly followed an unsupervised approach, there is no requirement for labelled data for training. Therefore, it is proved that lexicon-based approaches perform well in several domains (Liu, 2012).

It is possible to perform a lexicon-based approach in two different ways. In the first place, the large corpora are used to find the co-events of a list of small seed words to identify different words with different opinions as in (Hatzivassiloglou and McKeown, 1997) and (Turney, 2002). The second strategy utilizes sentiment dictionaries, like WordNet or General Inquirer, to gather the word sentiment polarity.

A famous research trend (Miller, 1995) incorporated the use of a lexical database called ‘WordNet’. It groups the words based on the synonyms called ‘Synsets’ and semantic connections. Research work on measuring the semantic orientation of adjectives (Kamps et al., 2004) utilized WordNet to check the number of synonyms from the investigated adjective to the seed words.

(Sebastiani et al., 2006) extended the methodology by adopting a manually constructed words set utilizing the WordNet synonym and antonym connections of adjectives. This early work prompted the development of SentiWordNet where the positive, negative and target scores can be found. One of the downsides of this lexicon is the certain words could take various scores.

Along these lines, an intensive POS examination is expected to precisely use these lexical databases. A few investigations have prompted the development of universally useful lexicons. For example, Sentiment Lexicon (Hu and Liu, 2004) and SentiWordNet (Sebastiani et al., 2006) are openly accessible,

The lexicon-based methodology additionally has its own deficiencies: it is difficult to use to discover sentiments dependent on the domain or context. As such, the sentiment orientation of the words is identified regardless of the domain of the context (Liu, 2012).

- **Machine learning for sentiment classification**

In terms of supervised learning techniques, the methods used to classify sentiment at the sentence level can be used to classify at the aspect level. The primary shortcoming here is for every domain requires labelled training data and the model built will purely rely on the data given for training.

Therefore, the built model for the particular domain is ineffective to use in another domain. Though, as the investigation has begun on this method, this innovation is still a long way from development (Liu, 2012). In addition, this method requires a great deal of data for training to build a very accurate model.

2.3.12 Challenges in Opinion Mining

The are many challenges while attempting to find opinion phrases in texts written in natural language and to decide the sentiment polarity. Especially, the following difficulties need to be addressed when separating aspects from the text reviews of the customers.

- **Implicit sentiment**

A serious issue in extracting aspects is the presence of implicit expressions. For example, “expected to stand by two hours to check-in”, the negative opinion of the check-in process is not expressed directly.

- **Contextual Polarity**

An expression can convey different sentiments depending on the context.

The sentiment polarity of an expression might be dependent on the context. Sentiment or valence shifters are the words or phrases that influence the slant sentiment polarity. (Wilson, 2008) directed a point-by-point investigation of context-oriented polarity.

- **Target-Specific Polarity**

Sometimes, the polarity of words or expressions may depend on the altered target. In most of the lexical databases, this is not get considered.

- **Relations Among Aspects**

The aspects of the items are regularly related to each other. Depending upon the application, these various levelled relations should have been made explicit, another relationship that can be seen is similarity. The comparable aspects can be grouped together and can recognize synonyms. In ontology learning (Maedche, 2002), grouping aspects automatically and deciding the relations between them is an issue.

- **Comparative Reviews**

Up to this point, the assumption will be that a review always refers to an individual item. It is not valid in every case. A user may assess an item by contrasting it with other similar items. If so, the diverse item entities referenced in the content should have been resolved.

2.3.13 Summary of Recent Literature on Sentiment Analysis and Opinion Mining

Table 1: Summary Review Table of Recent Literature on Sentiment Analysis

Year	*Research*	*Domain/ Dataset*	*Technique*	*Results/ Limitation*	*Best Accuracy*
2021	Adversarial Training for Aspect-Based Sentiment Analysis with BERT (Karimi et al., 2021)	Laptop and Restaurant Dataset	Bidirectional Encoder Representations from Transformers (BERT)	Showed that the performance of BERT can be enhanced by utilizing adversarial training.	Laptop – 79.4% Restaurant – 86%
2020	Enhanced Twitter Sentiment Analysis Using Hybrid Approach and by Accounting Local Contextual Semantic (Gupta and Joshi, 2020)	SemEval-2013 dataset	SentiWordNet (SWN) feature vector with Support Vector Machine (SVM)	Proved that a hybrid approach of combining lexicon and machine learning gives better results.	Precision for positive – 84% Negative – 55%
2020	Big data and Sentiment Analysis considering reviews from e-commerce platforms to predict consumer behaviour	BigData/ Ecommerce reviews from Amazon and other platforms	Machine learning (ML) algorithms compared with Convolutional Neural Network (CNN) or Long Short Term Memory (LSTM).	A combination of ML techniques offers the best results.	Accuracy is compared among techniques.

Table 1. continued

2020	Weakly Supervised Framework for Aspect-Based Sentiment Analysis on Students' Reviews of MOOC (Kastrati et al., 2020)	Coursera Student Reviews	TF-IDF to extract aspects. CNN and FastText	Adopted weak supervision strategy to improve the effectiveness of ABOM.	Aspect Extraction F1 score is 86% and 82% for sentiment classification
2020	Aspect Based Sentimental Analysis of Hotel Reviews: A Comparative Study (Abro et al., 2020)	SemEval-2016 public dataset	N-gram with TF-IDF with supervised learning algorithms	Feature engineering techniques are compared with machine learning algorithms and showed word2vec with SVM gives better results.	SVM with Word2Vec – 71%
2019	The Application of Sentiment Analysis and Text Analytics to Customer Experience Reviews to Understand What Customers Are Really Saying (Gallagher et al., 2019)	Mobile phone reviews from Amazon	TextBlob with Multinomial Naïve Bayes	The results show that sentiment analysis can help businesses to understand their customers.	Accuracy of 74%
2019	Predictive aspect-based sentiment classification of online tourist reviews (Afzaal et al., 2019)	Tourist reviews from TripAdvisor and OpenTable	Semantic Relation Based with Supervised Learning algorithms.	Aimed at explicit and coreferential aspects. Domain-Specific.	Naïve Bayes – 89.34%

Table 1. continued

2018	Analysis on Opinion Mining Using Combining Lexicon-Based Method and Multinomial Naive Bayes (Isabelle et al., 2018)	Movie Review Dataset	Adverb + Adjective and Adverb + Verb (AAAVC) algorithm with Lexicon Based Approach	The adoption of the AAAVC algorithm increased the accuracy of supervised learning and the lexicon method.	Multinomial Naive Bayes – 62% Lexicon based – 70%
2017	A Hybrid Approach for Sentiment Analysis Applied to Paper Reviews (Keith et al., 2017)	Reviews of the papers were sent to an international Spanish Conference.	Naïve Bayes (NB) and Support Vector Machine (SVM) with POS tagging and scoring algorithm	Increased the performance by combing the scoring algorithm with supervised learning. Not tested for deep learning methods because of the smaller dataset.	NB – 68% SVM – 70% With scoring – 81%
2017	Lexicon-enhanced sentiment analysis framework using rule-based classification scheme (Asghar et al., 2017)	Drug review dataset (public dataset)	Rule-based classification	Sentiment classification is performed using a rules-based framework. The results showed the proposed model is applicable to cross domains.	Accuracy of 74%
2017	A Proposal for Brand Analysis with Opinion Mining (Arboleda et al., 2017)	Product reviews from different brands.	Logistic Regression and SVM supervised learning.	The importance of opinion mining in the brand analysis is evaluated. Proposed a model as a visual representation.	-

Table 1. concluded

30

2.4 Recommendation System

Recommendation systems can be considered as data filtering frameworks that consider user preferences such as their need, tastes, interests and personal factors to choose the most relevant and appropriate items for the user. The recommendation systems are useful when there are enormous accessible items to such an extent that they confuse the user to make a decision.

While a user searches for a specific item, either by categorical filtering or by typing keyword queries, the user will be given an outcome list that may contain even many things. At that point, the user needs to investigate the whole results and select the most preferable item. This leads to waste an excessive amount of energy and time to find appropriate items relevant to the need.

Recommender systems help to overcome such situations by having the most likely to be preferred items at the start of the results list. The important step here is to filter and sort the items list frequently based on the user's preference. The business domain of E-commerce has improved the sales and revenue income by having recommender systems, submitting customized and personalized suggestions.

The main challenge in the recommender system is to provide suggestions that are more personalized to each customer. In the age of Web 2.0, people are not expecting items in common, repeating the same number of items in the list. This forces the recommender systems to have more user-based information, their personal preferences and interests.

2.4.1 Personalized Recommendation Systems

The necessities of a personalized recommendation system raise different difficulties, as precisely finding the customer behaviour patterns in online shopping and suggesting products and services by considering user preferences. In suggestion/recommendation systems, the personalized suggestion results can be improved by considering sentiment polarities of reviews at a fine-grained level (Pang and Lee, 2008).

The results from sentiment analysis and opinion mining can be utilized in other systems, like recommendation system (to give clarifications to suggestions), advertising and marketing framework (to put the promotion of an item with similar comparative aspects), and numerous business tasks with involves the customer relation, sales management and marketing.

2.4.2 Types of Recommendation Systems

Depending on the algorithms and the data used to build and filter the items for suggestions, there are different kinds of recommendation systems. There are three main models and an additional hybrid approach of recommending items. All four types of recommendation systems are discussed below.

- **Content-based Recommendation System (CB)**

The users and items are addressed through content features in Content-Based (CB) recommender systems. The assumption here is, a user will tend to give a rating higher for the items that are similar to the items that are like by the user in the past.

The content features of an item are normally addressed as vectors that have related weights. Among the strategies to process such weights, TF-IDF (Term Frequency-Inverse Document Frequency) is the most famous one. The weights of the items liked by the user previously are get summed up to find weight. A user profile is get generated by combining the items profiles that were evaluated previously.

- **Collaborative filtering (CF)**

Unlike CB systems, the preferences of like-minded individuals are considered in the collaborative filtering systems to estimate the ratings collaboratively. This strategy uses accessible data about other user's ratings collaboratively rather than just utilizing the particular user's ratings.

In CF, it is assumed that if there are two users with similar preferences on specific items, there is a higher probability that they will have a similar preference on different items. CF systems only require information about the user, items and ratings since they do not consider any content features. This permits to use of this technique in different domains and contexts.

CF strategies can be additionally separated into two more categories: memory-based and model-based techniques.

- **Memory-based collaborative filtering**

Memory-based filtering is also known as k nearest neighbours (kNN) or heuristic technique. In this approach a specific number of neighbours who are similar is get focused and based on their ratings the suggestions are given. This is known as user-based collaborative filtering

(Shardanand and Maes, 1995). Item-based collaborative filtering also can be performed by comparing predetermined items similarly rated.

User-based collaborative filtering suggests items that are highly rated by similar-minded people where as item-based collaborative filtering suggests items that are very much similar to the highly-rated items.

- **Model-based collaborative filtering**

The kNN method is based on heuristic equations where the parameters need to be set manually, for example, the number of neighbours. Model-based CF limits estimation errors since it makes rating prediction models where the parameters for it is giving during the training stage. In recent times, Matrix Factorization is considered as the best and generally utilized model-based method. This accepts that the preferences of the users are based on various unseen factors.

Collaborative filtering also has specific advantages and disadvantages. CF can give variety on the item suggestion lists. However, for situations with new users and items, CF experiences a cold start problem. If any user has not rated a particular item, then it is never going to be suggested in CF. Another significant weakness of CF is the items with the most popular will get suggested more.

- **Hybrid recommender systems**

As discussed previously, CB and CF approaches have their own advantages and disadvantages. Therefore, a hybrid solution by joining CB and CF techniques is introduced to have the benefits of both methods.

There are different ways to build hybrid recommendation systems; some of them are:

- Joining the results through a weighted normal from CB and CF after running them independently.
- Select content data as CF latent vector features.
- Incorporate CB with collaborative rating-based features.

Hybrid recommendation systems demonstrated a high performance than the other two approaches. Many real-time applications such as Netflix, YouTube and etc., use the hybrid technique for suggestions (Gomez-Uribe and Hunt, 2016).

- **Aspect-Based Recommendation Systems**

The greater part of the techniques that have been discussed above considers the general item's rating only, disregarding the user opinions towards various aspects. Aspect-Based Recommendation Systems (ABRS) takes various opinions into consideration to improve suggestions. The overall ratings can be predicted by using aspect opinions in various ways.

In any case, those sentiments from reviewers that disagree at the aspect level (since they esteem various features) should not be considered as neighbourhoods in any event. ABRS might be seen as an advancement of the Multi-Criteria Recommendation System (MCRS). In here, the users expressly imposed a few limitations about attributes of the items, similar to filtering systems. However, in ABSR, the past sentiment on aspects are considered to understand the fine-grained data and improve suggestions without setting any filtering.

ABRS shares numerous components with Context-Aware Recommendation System (CARS) since they consider additional data that can influence the suggestions along with ratings. The information regarding the contexts like time of day, weather, season and etc. are get incorporated in CARS. This is because depending on the various contexts user ratings might change.

The significant difference in ABRS is that the context is shared across items though the aspects are domain-specific. This makes the systems to be very different, and ABRS and CARS procedures are not built or utilized together.

2.4.3 Summary of Recent Literature on Recommendations with Sentiment Analysis

Table 2: Review Table of Recent Literature on Recommendations with Sentiment Analysis

Year	*Research*	*Domain/ Dataset*	*Technique*	*Results/ Limitation*	*Accuracy/ Precision*
2020	Movie Recommendation System Using Sentiment Analysis From Microblogging Data (Kumar et al., 2020)	Two datasets have been used: user-rated movie database and user tweets from Twitter	Valence-aware dictionary and sentiment reasoner (VADER)	Used weighted score to enhance the recommendations with sentiment analysis.	Precision is 4.97
2020	A Recommendation Mechanism for Under-Emphasized Tourist Spots Using Topic Modeling and Sentiment Analysis (Shafqat and Byun, 2020)	Reviews from blogs	Topic Modeling Using Latent Dirichlet Allocation (LDA)	Incorporated cross-mapping matrices along with LDA.	Accuracy of 94%
2020	Product's behaviour recommendations using free text: an aspect-based sentiment analysis approach (Nawaz et al., 2020)	Car and Hotel Reviews from TripAdvisor	Distance-based approach with Visuword for aspect reduction.	The proposed method showed higher performance than the relational classifier. Non-supportive for real-time scenarios.	Car – 72.65% Hotel – 80.5%

Table 2. concluded

2019	A comparative analysis of recommender systems based on item aspect opinions extracted from user reviews (Hernández-Rubio et al., 2019)	Yelp and Amazon Datasets	Vocabulary Based Method with Double Propagation	Showed that the aspects extracted using LDA are more appropriate and effective. Also discussed deep learning methods can enhance aspect-based recommendations.	Yelp – 90% but showed 50% for Amazon.
2017	Aspect Based Recommendations: Recommending Items with the Most Valuable Aspects Based on User Reviews (Bauman et al., 2017)	Restaurant, Hotel and Beauty & Spa reviews from Yelp	Sentiment Utility Logistic Model	Recommends items along with the positive aspects of that and extracts the most important aspects for the future.	Restaurant - 65.1% Hotel – 58% Beauty & Spa – 71.2%
2017	Integrating Collaborative Filtering and Sentiment Analysis: A Rating Inference Approach (Leung et al., 2017)	IMDb Movie Reviews	Collaborative Filtering with Rating inference	Collaborative filtering with rating prediction to enable sentiment analysis.	-

Table 2. concluded

2.5 Virtual Dressing Room

In a clothing department, the queue for the dressing room is longer than the billing queue. Usually, people want to make sure the clothes are fit well their body and look good on them. However, waiting in a queue for a long time would make the user lose interest in buying. In the context of online purchases, users do not have a fit-on option at all.

The statistics reported by Narvar Consumer Study[7] showed that the main reason for the online orders is because the size, form or colour is incorrect. Figure 7 shows the percentage of returns to Amazon and non-Amazon retailer stores. In both cases, the reason behind the returns is the size and fit problem.

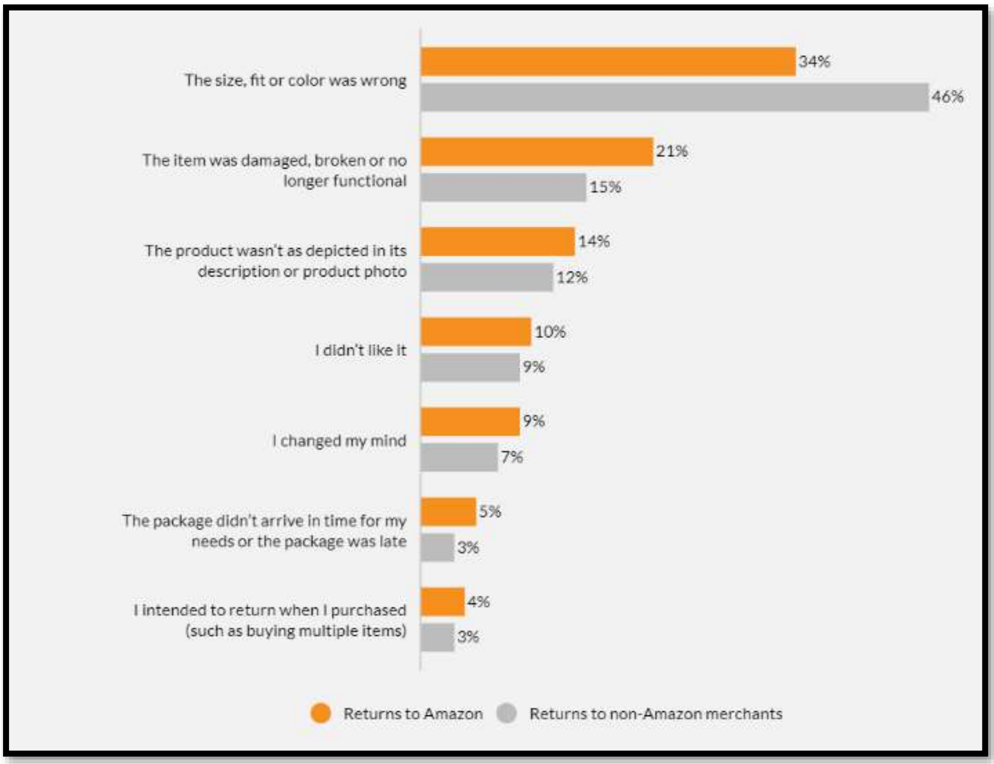


Figure 7: Statistics on Reasons behind the Returns reported by Narvar

In the latest report published by the Narvar Consumer Study[5] showed the increase in people does bracketing. Buying multiple types of the same item at once and try them at home and return the items which did not fit is called 'Bracketing'. Figure 8 shows the huge increment in shoppers who do bracketing in the last year compares to the past three years.

[7] https://see.narvar.com

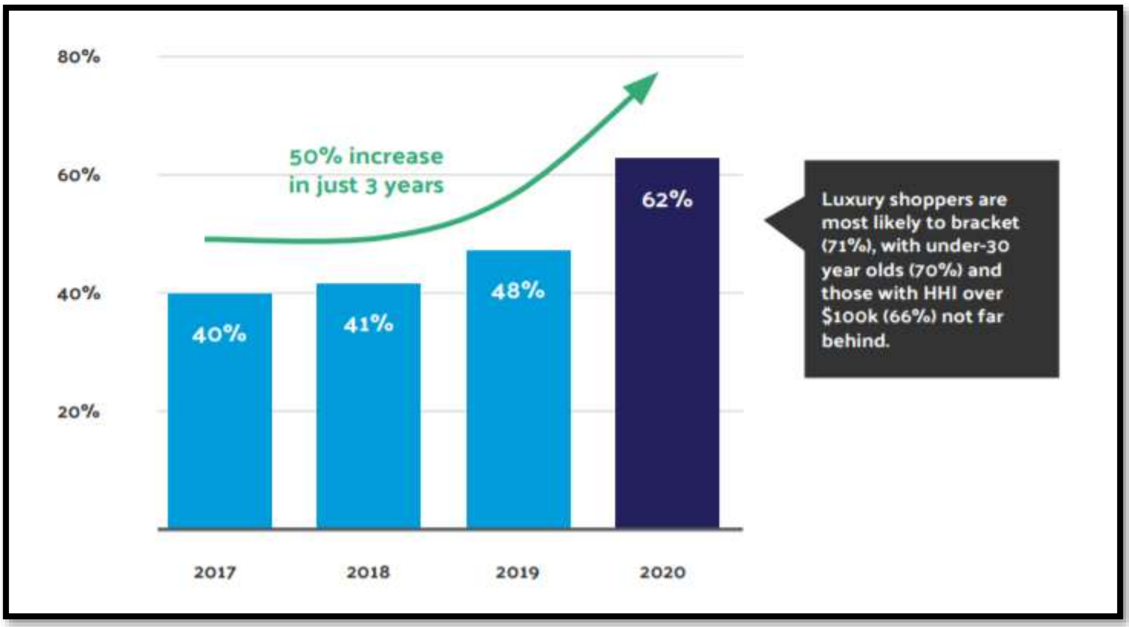


Figure 8: Bracketing Behavior of Customers in last 4 years

The solution to these problems may be solved by providing a virtual dressing room where customers can try on clothes virtually on their bodies without waiting in a long queue. A virtual dressing room is a real-time interactive platform that provides facilities to fit on clothes virtually (Boonbrahm et al., 2015).

The virtual dressing rooms allows the customers to try 2D/ 3D models of items on their 3D avatar before they make a decision to buy (Holte et al., 2015). There were various research works carried for quite some time on the virtual dressing room. The developed frameworks range from the online virtual dressing room to the run of mobile phones.

2.5.1 Technologies in Virtual Dressing

The virtual dressing room is an interesting research topic, and many researchers have proposed their solutions and new technologies during the past years. The following technologies are used in building a virtual dressing room to detect the user body, build 2D/ 3D models of items and overlap the user's body with the virtual cloth items.

- **3D Body Scanner**

3D body scanner uses a scanning system to captures the dimensions of the user's body three-dimensionally (3D). Thea separate scanning booths are allocated in this approach to scanning the full body of the user (Lee and Xu, 2020). The main limitation of this approach is the customer needs to a physical store where a booth exists to get scanned. This approach is completely not applicable in a situation where a customer is from another country and making an online purchase.

- **3D Avatar**

In this approach, a 3D avatar is modelled, which is a close representation of the user's size and shape (Erra et al., 2018). The virtual dressing works like the 3D scanning of the cloth items are get modelled of the customer's avatar. Virtual dressing room using 3D avatar gives customers a gaming experience by allowing users to create a 3D avatar of themselves by manually entering few body measurements (Lee and Xu, 2020). Since the body measurements are inputted manually and only a few, the accuracy of this approach is relatively low.

- **Photo Accurate 3D Customer Model**

The 3D model of the customers is created using body metrics and photos. This approach provides more accuracy than the previous technique (Schwind et.al., 2017). The products are also modelled using the same technique with photos and product information. Since the technique simulates the real model of the customer, it enhances the user experience.

- **Virtual Reality**

Another popular technique in this field is Virtual Reality (VR) which provides virtual dressing online. VR used a computer-generated 3D model to represent customers to enable virtual dressing. The VR may be personalized or non-personalized. If the VR utilizes a standard set of avatar options provided, the customer has no options to personalize. However, they can select options to more personalize and better represent their appearance (Yaoyuneyong et al., 2014). VR makes traditional shopping more efficient and time-consuming (Erra et al., 2018).

- **Augmented Reality**

Using Augmented Reality (AR), the customers can try on augmented items on their augmented model on a web browser or kiosks. AR superimposes the products over the captured user model via camera-based technology (Lee & Leonas, 2018). This way of processing gives a more realistic experience to the users. The benefit of having AR over other methods is the customers do not need to travel somewhere to get scanned or virtually try-on. They can use the AR feature from anywhere and anytime.

2.5.2 Augmented Reality in Virtual Dressing

Augmented Reality technology is changing the traditional way of shopping completely into a new face. The ease of access to AR from home computers, mobile devices or kiosks in stores encourages the customers to make buying decisions correctly. The technologies and devices behind AR applications are affordable and cheap (Erra et al., 2018). This is the reason why many researchers are exploiting their studies in this area.

AR uses a web camera to represent the actual customer and imposes the outfit or cloth they want to fit on virtually in real-time (Yaoyuneyong et al., 2014). To have a perfect virtual model using VR is expensive in implementation. On the other hand, video reflections using AR is convenient, interactive and less expensive.

The AR uses a camera-based device to capture the motion and take body measurements. AR incorporates 3D virtual simulation technology to offer a mixed reality and imposes the 3D models of the products over the augmented customer model within the live video (Lee and Xu, 2020).

In addition, AR technology can be used online and in physical stores, unlike the other proposed methods. In recent years many brands have adopted AR dressing room in their marketplace. For example, Burberry, Rebecca Minkoff, and Atelier provided a magic mirror for their customers in the physical stores and launched an AR app called Zeekit App to use in online shopping.

2.6 Research Gap

Sentiment Analysis also called opinion mining, is one of the most interesting research areas explored by many researchers in the field. Many studies were carried out focusing on extracting opinions at the document level and sentence level. It has been reviewed in the literature that mining documents and sentences as a whole would not yield deep insight into what customers actually thinks and feels about a product.

It has been proved by many experiments that aspect-based opinion mining can yield better results in extracting actual customer's sentiments towards each aspect of the products. Even though a considerable amount of work is carried out over time, the proposed solutions still lack to provide higher accuracy in predicting customer's opinions.

As discussed in the literature, the two main tasks in aspect-based opinion mining are aspect extraction and opinion extraction and classification. Most of the proposed methods over the past decades adopted only one approach in achieving the end results. However, to obtain high accuracy results, there is a need for a method that combines the best approaches adopted for the two main tasks.

The opinions a user has about a product not only depends on the product alone. The personal factors, preferences, interests and background also affects the user’s sentiment towards a product. The research studies missed out to take these into consideration when mining customer’s opinions in reviews.

The recommender systems developed over time use filtering methods such as collaborative filtering, content-based filtering and context-aware filtering to provide suggestions to customers. Having only a filtering option based on the algorithm and the data provides a set of suggestions that are common to all.

In the context of shopping for clothes online, people have different tastes, interests, preferences and beliefs when buying an item. The past opinions about the products and their aspects also play a major role here. There is a need for a personalized recommendation system that considers aspect level opinions along with customer’s personal factors, preferences and interests.

It can be concluded that from the literature that there is no system developed which combines all four research components: aspect-based opinion mining, personalized recommendation, intelligent customer insight with personalized advertising and AR virtual dressing room. Many studies have proved the importance of having targeted groups and advertising can increase profit. Classifying the targeted groups not only based on their past purchase details, grouping them based on opinions and interests is an interesting area that needs to be addressed.

In a recommendation system, customers are provided with a list of items to choose from. Even though the suggestions are personalized and give an easy way to make the buying decision, the size and fit issue is a major problem in the online cloth retailing industry. Therefore, the recommender should not stand alone just by providing suggestions. A way to overcome the cloth fitting issues also be incorporated with the recommendation systems.

2.7 Summary

In this chapter, a review of the related works associated with aspect-based opinion mining, personalized recommendation systems, intelligent customer insight with advertising and AR virtual dressing room is viewed in a broader context. In particular, different approaches to aspect extraction, opinion extraction and classification, collaborative filtering, content-based filtering, targeted advertising, augmented reality technologies are discussed. In addition to reviewing the accuracy metrics of each approach, the evaluation strategies are also focused on in this chapter. The proposed approach of this research work and its methodologies are illustrated and described in the following chapter.

CHAPTER 3

METHODOLOGY

3.1 Introduction

A critical review of literature in Aspect-Based Opinion Mining, Recommender System with, Personalized Advertising with Sentiment Analysis, Intelligent Customer Insight, and Augmented Reality to Virtual Outfit is presented in Chapter 2. This chapter describes the proposed approach and the techniques and methodologies adopted to solve the research problem.

The chapter illustrates and discusses the proposed model for aspect extraction, aspect-sentiment analysis, personalized recommendation tasks, augmented reality in virtual dressing and intelligent customer insight generation.

3.2 Representation of the Problem

As the opinionated information about fashionable clothes and accessories is getting to increase on the web every second, this makes the analysing of these opinion sources and getting the desired result very difficult. Most of the time, these opinions are hidden in customer reviews, forums posts, comments, and blogs. It is not a simple task for a human mind to read each and every piece of data and process it manually. This requires an automated, intelligent way to extract important information, summarize and organize them into a form that is useful in the decision-making process to buy clothes and accessories.

In the online cloth shopping context, the reviews of customers play a vital role. People always look for other's opinions and reviews before they buy a cloth or accessories. Reading a huge list of reviews of items is not practical, and it is a time and energy-consuming task. People need a mechanism to easily compare the products get a summary of other's opinions. However, having a way to just analyse the reviews as a whole would not give a deep insight. Usually, humans have opinions towards each and every aspect of products. So, the need to analyse the reviews and mine important information at an aspect level becomes compulsory here.

In addition to reading reviews, online buyers need to go through all the list of items available to decide which items best suit their preferences and interest. Even though there are filter options in the current systems yet yields a huge list of items that may be not relevant to the user. These difficulties put the customer in trouble and make them confused to take a decision. If there is a recommendation system that provides more personalized suggestions to users based on their preferences, interests, personal factors and past opinions, this could take up the traditional online shopping experience to the next stage.

Another biggest issue in online cloth shopping is the size and fit problem. Online customers often return the bought items if they find the cloth is very tight, small, large or loose. Since there is no standard system for apparel sizing worldwide, the sizes differ from brand to brand and country to country. This makes the user give a wrong measurement when they are buying online. At last, customers end up paying for the items which did not suit their bodies.

As there are a lot of problems from the point of online customers, there are another set of problems from the perspective of merchants who sells their items online. Due to the lack of systems that predict the buying behaviour and customer’s opinions towards item’s aspects, organizations could not understand their customers fully and assess their own products completely. This results in low-profit sales, customer dissatisfaction, high manufacturing cost and a bad reputation in the market. This requires a new system to produce intelligent customer insight and personalized advertising campaigns.

It is clearly seen that there is a heavy demand for an intelligent system to assist both customers and merchants to analyses customer reviews, summarize different opinions of customers towards items and their aspects, assess a product’s strengths and weaknesses, provide personalized suggestions, understand customer buying patterns to have intelligent customer insight and market targeted groups with personalized advertising. It also requires an easily affordable solution to have a virtual dressing option over an online platform. All the above-mentioned problems needed to be addressed concerning both the online customers and merchants.

3.3 Research Methodology

In conducting this research, a constructive research methodology is used. It is aimed to produce novel solutions with research potential both practically and theoretically. The theoretical evaluation and practical implementations are the valuable outcomes of this constructive based approach. The main phases in the research methodology followed is given below in Figure 9.

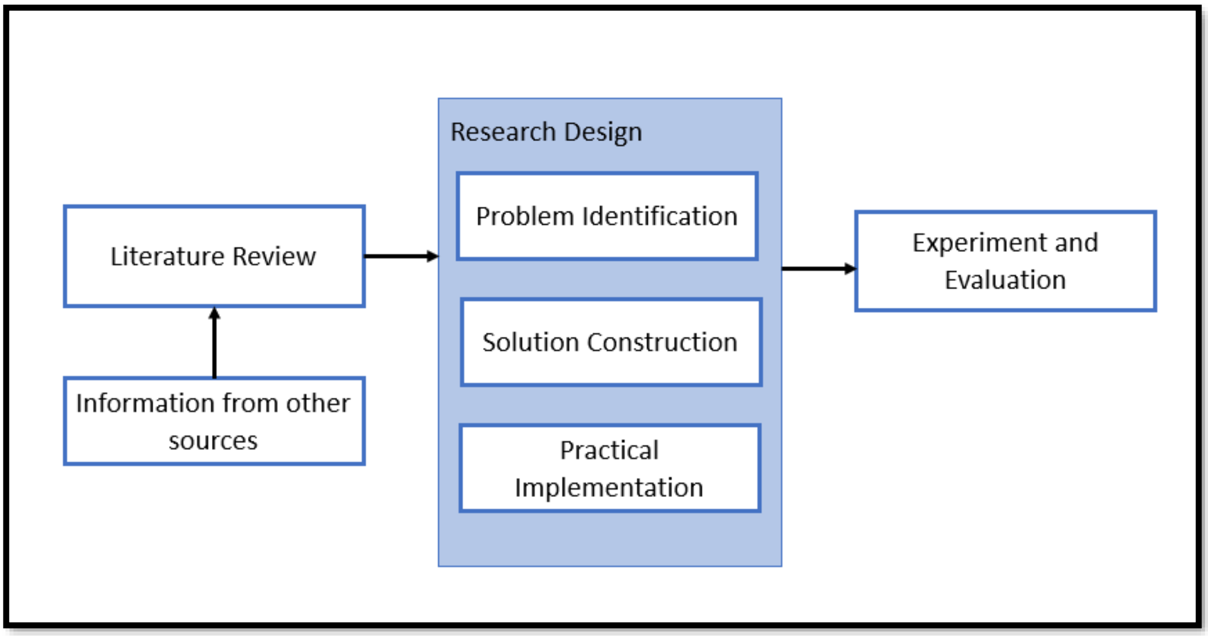


Figure 9: Constructive Research Methodology

3.4 Possible Solutions and Justification

The research problem outlines in the previous section highlights the need for a system to perform opinion mining on text reviews, provide personalized suggestions concerning user's personal factors, preferences, interests and their opinions about aspects, generate intelligent customer insight to market personalized advertising on targeted groups and at last a mechanism to provide a virtual dressing room in an online platform.

To solve the research problem identified, there are many technologies and approaches identified in the literature review conducted. The possible pathways to achieve the solution and solve the research problem and the reasons for the methods selected are justified in the following sections.

3.4.1 Opinion Mining on Text Reviews

The methods identified in the research literature to perform opinion mining are related to pre-processing, data extraction, natural language processing techniques and machine learning models. The opinion mining can be performed in three levels: document level, sentence level and aspect level.

As discussed in the literature review, mining review at document and sentence level results in an overall sentiment the user has about the product, which is more coarse-grained. In order to get more fine-grained information like opinions about each aspect, aspect-based opinion mining is the optimum solution.

Aspect-based opinion mining comprises two main tasks aspect extraction and opinion extraction and classification. There are different approaches proposed by researchers to perform these two tasks. Initially, the aspects need to be extracted from the text to find opinions towards them. There are four main approaches, namely frequency-based, relation-based, supervised learning and unsupervised learning (topic modelling).

The frequency-based approach is the first methodology proposed, yet powerful. This technique is very simple and based on the word frequencies in the text. However, the frequency-based approach does not count the low-frequency aspects. To overcome this problem, a relation-based technique can be used.

The best approach to perform aspect extraction is by combining a frequency-based approach and a relation-based approach. This hybrid approach would take the power of both the techniques and yield high accuracy results.

Supervised learning would not be a good approach in this research work since it needs manually labelled data for training and which is very domain-specific. Since the topic modelling works best at document-level and sentence level opinion mining, the hybrid approach is selected to perform the aspect-extraction task.

The second main task in aspect-based opinion mining is opinion extraction and classification. There are mainly two approaches: lexicon-based and machine learning approaches. As strengths and weaknesses are critically reviewed in the literature study, the solution which combines both approaches gives a more accurate opinion mining. The results from the lexicon-based approach can be combined with supervised learning to build the model.

3.4.2 Personalized Recommendation

There are different types of recommender systems available, namely, content-based, collaborative filtering, and hybrid recommendation systems. All these recommendation systems consider the rating of the products only, not taking into count the opinions of the users. The customer’s sentiment towards items and their aspects is very important in providing the personalized recommendation. Therefore, proposing an aspect-based recommendation system is the ideal solution.

3.4.3 Intelligent Customer Insight with Personalized Advertising

The customer insight can be retrieved from past purchase details and customer general details. This is the type of insight practised by many businesses for over a long time. The customer insight needs to be intelligent enough to form different clusters based on their personal factors, interests, background and past opinions. This information gives some knowledge to understand the customers better and target groups to market and provide personalized advertising.

The results of the aspect-based opinion mining and the personalized recommendation system can be utilized in this component to find important aspects, product's strengths and weaknesses, high selling products, target groups of customers and strongly recommended products.

3.4.4 Virtual Dressing Room

The virtual dressing room can be developed using many technologies such as 3D body scanners, avatar models, virtual simulation, virtual reality, augmented reality and etc. From the literature review, it has been concluded that adopting augmented reality is a very feasible, effective and cheap solution. There is no need for expensive devices on the customer side as well as the retailer side. In addition, augmented reality can provide virtual dressing rooms in both online and physical store contexts.

3.5 Proposed Approach

The proposed approach transforms the textual customer reviews in the natural language to a more meaningful summary of aspect-opinion comprehension using aspect-based opinion mining. The knowledge output from the mining process which is the aspect-sentiment pairs are used by the recommendation system to provide personalized suggestions to customers along with considerations on their preferences, personal factors, interest and their past opinions.

Figure 10 shows the proposed model to solve the identified research problem.

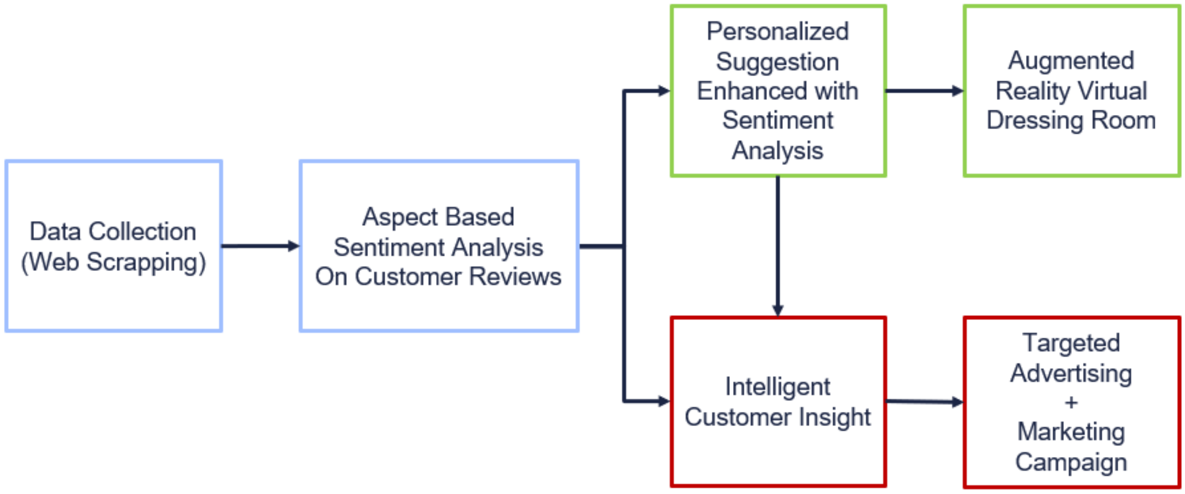


Figure 10: Proposed Model

The mined opinion information about the items and their aspects is used by the merchants to identify their product's strengths and weaknesses. The aspect level opinion mining not only helps in recommending items but also helps the merchants to understand their customer buying behaviours and provide personalized advertising campaigns and seek intelligent customer insight.

Along with that, the clusters of similar-minded users modelled based on their past opinions, personal factors and interests are used to promote marketing campaigns to targeted groups and send personalized advertising.

The proposed approach also overcomes the issue of incorrect size and fitting. The proposed system incorporates the Augmented Reality feature to provide a virtual dressing room for online users. The more detailed information about each component of the proposed system and its architecture is explained in the following sections.

3.6 Design assumptions

In the research, the design proposed there are few design assumptions are concerned before its actual implementations since the study is involved with natural language processing. The study is only scoped to text reviews written in English thus training and evaluation is carried out in the English language only.

The context and the point of time of the reviewer and the reader are assumed to be independent observations. Any sentences with sarcasm are not considered as part of this implementation as it directly influences the opinion of a user. All the sentences used for training and testing are assumed to be subjective sentences opinionated positively, negatively or neutrally. With all the design assumptions said the architecture of the research problem is designed.

3.7 Research Design of the Proposed Model

Figure 11 shows how the proposed model is achieved at an abstract level.

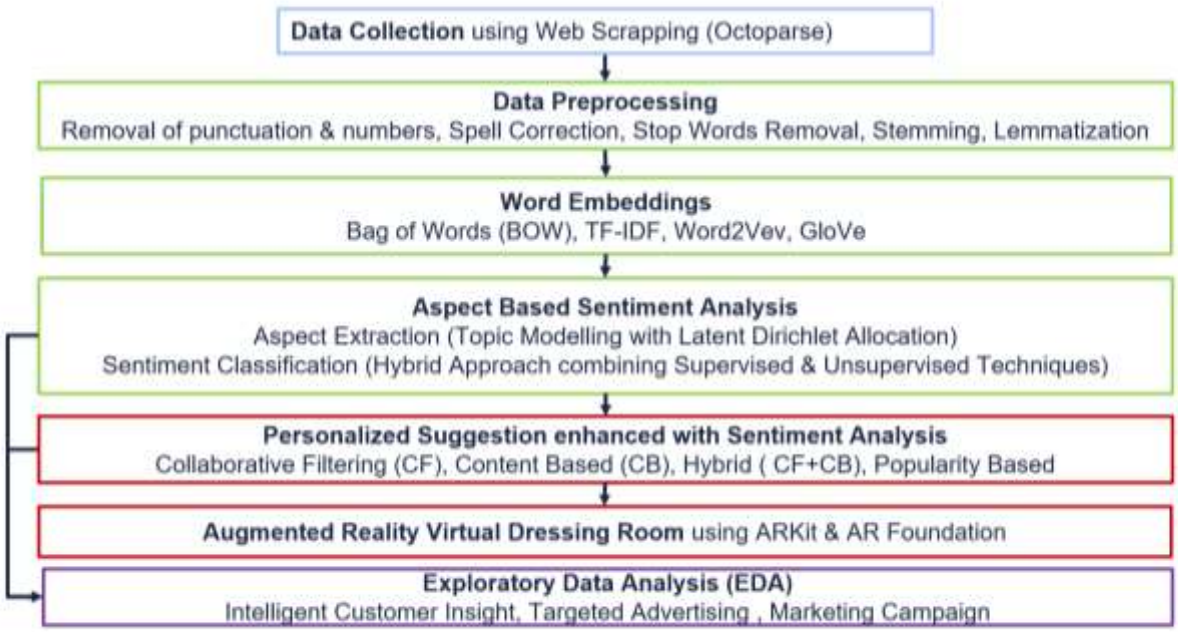


Figure 11: Methodology of the Proposed Solution

After data collection, the raw data needs to be pre-processed to remove unnecessary information and be converted to a form appropriate for the analysis. After word embedding should be done to convert into a vector form because the machines cannot understand the texts. Different word embedding techniques have been used in this research work to evaluate the accuracy and performance.

After that aspect-based sentiment analysis is carried out in two steps. First, the relevant aspects are extracted using an unsupervised approach since the collected dataset is unlabelled. and the sentiment is classified towards extracted aspects by combining unsupervised and supervised techniques.

After getting the sentiment analysis results, they are incorporated with the recommender system to produce a list of suggestions based on a hybrid approach combining collaborative filtering and content-based filtering. In addition, a popularity recommender engine was also built to give insights on popular products based on specific aspects.

The products suggested can be virtually tried on by using the augmented reality virtual dressing room developed using ARKit and AR Foundation.
Finally, the results from the sentiment analysis and personalized suggestions can be used to perform exploratory data analysis to produce intelligent customer insight, targeted advertising, and marketing campaigns.

3.8 Proposed System Architecture

To solve the research problem, a shopping assistant system is proposed which can suggest personalized fashionable clothes and accessories based on aspect-level opinion mining. The system also benefits online retailers by providing intelligent customer insight with targeted advertising. In addition, an augmented reality model enhances customer attractiveness by allowing a virtual dressing room.

The detailed architecture of the model is shown in Figure 12.

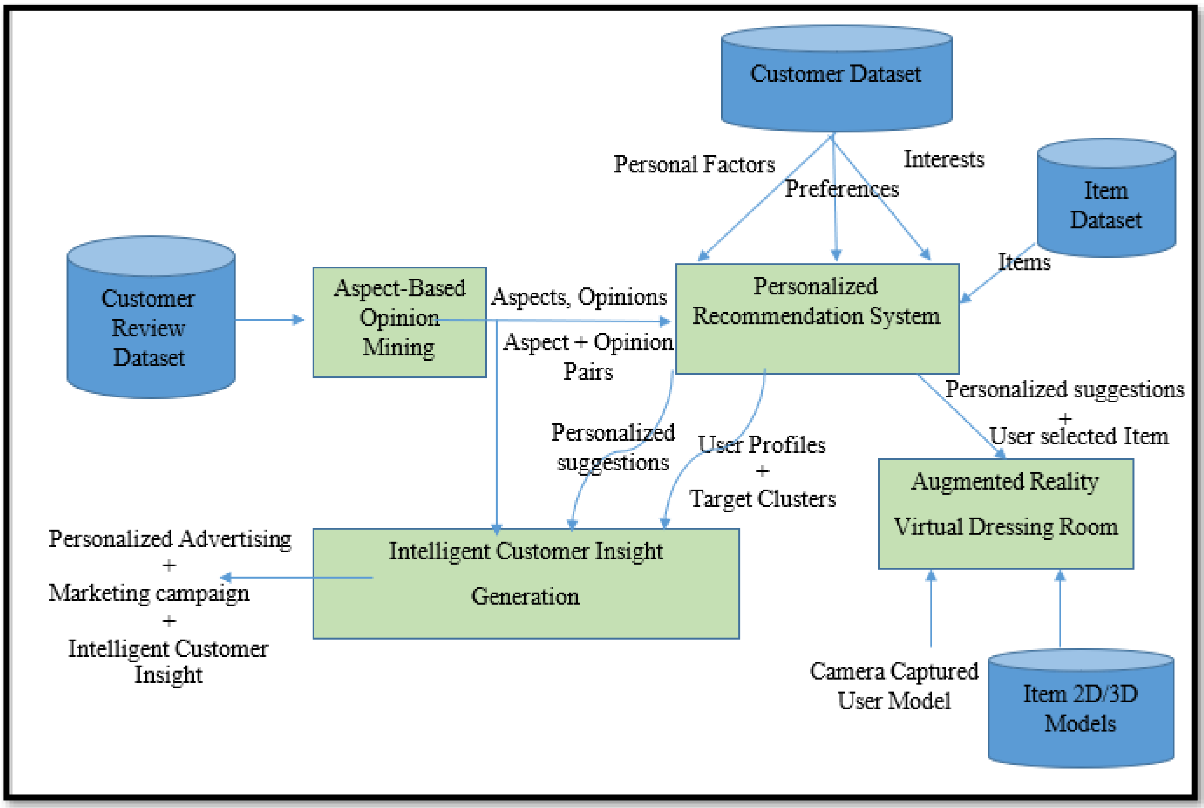


Figure 12: Detailed Model Architecture

The proposed architecture comprises four components: Aspect-Based Opinion Mining, Personalized Recommendation System, Augmented Reality Virtual Dressing Room and Intelligent Customer Insight Generation. The following sections discuss the four components of the architecture in more detail.

3.8.1 Data Collection

The data relevant for the research study is collected from the web using a web scraping tool called ‘Octoparse’. It is a web data extraction software that is used to extract information from websites.

Manually copying and pasting the content from the web is extremely a difficult task. The web scraping tools make it easy and time-efficient to extract required content from the web.

3.8.2 Dataset Description

The data of a reputed online woman cloth retailing company is collected for the research along with safeguarding the protection and the usage of the data. The dataset consists of information related to 22 categories of clothing for women. Each category consists of 100 items nearly.

Table 3: Number of Reviews per Item Categories and Subcategories

Category	*Subcategory*	*No. of Items*	*No. of Reviews*
Clothing	Gowns	511	9563
	Party	344	5693
	Night Out	348	5632
	Wedding	747	5963
	Work	298	4886
	Active wear	111	2036
	Jumpsuits	546	9568
	Rompers	184	2963
	Tops	685	13132
Jackets and Coats	Blazer	337	5214
	Jackets	588	9632
	Wool Coats	225	3256
Bottoms	Pants	1060	20365
	Skirts	656	15489

Table 3 below shows the details about the categories, sub-categories, items and reviews collected for each subcategory. The dataset includes information as follows.

- Item Dataset- item name, brand, price, description, style notes and size.
- Item 2D/3D Models – 2D images and 3D models of the items
- Customer Dataset – Name, age, height, weight, body type and size, interests, preferences
- Customer Reviews – Author, date, topic, text review, rating

3.8.3 Aspect-Based Opinion Mining

This section presents a novel approach to mine the opinions on the text reviews written by the customers. The approach identifies the different aspects, opinions and classifies and opinion on each aspect as positive, negative and neutral based on the polarities. The aspect-based opinion mining is carried out in several steps. Figure 13 shows the overview of the aspect-based opinion mining component.

Analysing the text reviews written by the users is often a challenge in the opinion mining process. Table 4 shows a few samples of actual customer's feedbacks. There may be reviews that are very short, incomplete and maybe with mistakes in the spellings, grammar, shortcuts, abbreviations etc. These kinds of informal reviews are considered noisy and unstructured data. This causes difficulty in extracting the aspects and the opinions accurately.

Table 4: Sample Customer Text Reviews

Customer	*Item*	*Review Title*	*Review Sentence*
Silvia	Green Off Shoulder Sweater Dress	More interesting than I expected.	Warm enough for a late winter day without being bulky.
Justine	Purple Mock Neck Dress	Really cute dress, odd fit	I ordered this dress in two sizes, the fabric on both sizes is quite billowy on top. This dress was super cute!
Stephanie	Zeyboard Top	Versatile Blouse	Beautiful loose blouse.
Karla	Vitala Skirt	Gorgeous	Very well made. I love the simple line and the slight flair.
Annie	Black Faux Suede Sheath	Loved this	cute fall dress that works for everyday and work.

Figure 13 shows how the aspect and opinion extraction process is carried out along with utilizing the opinion lexicon to find the opinion value.

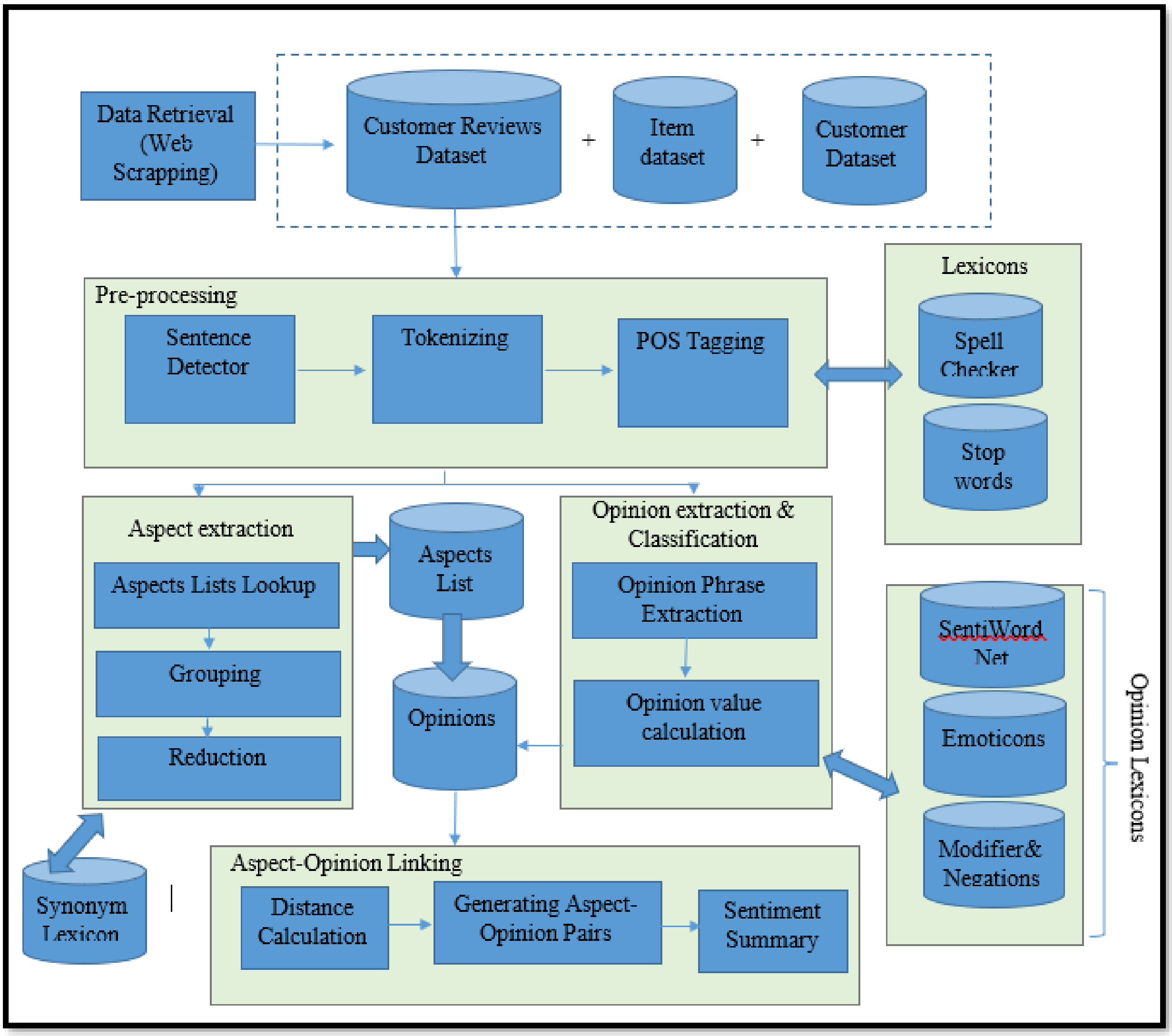


Figure 13: Aspect Based Opinion Mining Component

The very first step is to pre-process the data. Afterwards, the aspects in the woman clothing domain are get extracted. Following that, the opinion bearing phrases are detected and classified. An opinion lexicon for the English language, i.e., SentiWordNet, is used to classify the phrases into positive, negative and neutral expressions. Finally, these opinion bearing phrases are linked with the associated aspect to form aspect-sentiment pairs.

- **Pre-processing**

i. Removing unnecessary annotations (Cleaning)

Eliminating all human annotations alongside all symbols, for example, {,}, :), :(, ##, ..., [, etc. For these reasons, regular expressions are being utilized.

ii. Sentence Detection

After cleaning, the dataset is divided into sentences utilizing NLP sentence splitter tools. The Apache OpenNLP2 Sentence Detector is used to isolate the sentences.

iii. Tokenizing

Afterwards, the Apache OpenNLP Tokenizer is applied to separate words.

iv. POS Tagging

The Apache OpenNLP Part-Of-Speech Tagger is used to assign the POS-tags to each word correctly.

- **Aspects and opinion extraction**

The second step after the pre-processing stage is to extract aspects and opinions. This step consists of parts:

1. Aspect Extraction
2. Opinion Extraction and Classification

The aspect and opinion extraction start by finding the aspects and then identify the corresponding opinions. It is assumed that the item aspects and their associated opinions are written within a sentence. Therefore, the aspects and the opinions are extracted from each sentence. All the sentences identified in the first stage must be considered in order to extract all the aspects and their opinions expressed by the customer. The proposed approach to extract aspects and opinions is shown below.

- **Aspects Extraction**

As the clothing domain is chosen for this research work, the entities and the aspects related to this domain have to be extracted from the text reviews.

The aim of this step is to find the aspects which have the opinions of the users. The aspects are usually nouning or noun phrases.

The aspect extraction model is created in a semi-automated way. In the initial step of the model, the entities and the aspects are collected in a base list. Then, the list is get extended using the community-generated synonym lexicon OpenThesaurus and WordNet dictionary. In the last step, the list is normalized by lemmatizing all words.

The extraction of the aspects is done as a simple search. A few aspects range over more words. In those cases, the longest possible phrase is taken. Inside the extraction of the aspects from the reviews, the same lemmatizer used to generate the list is getting applied.

- **Aspects grouping**

The next following task is gathering aspects dependent on frequency and synonyms words. Users can state their opinions for similar aspects in various words and phrases. In this manner, to get accurate results, comparable words and phrases should be grouped. Moreover, two words are synonyms in one domain, and it is important to group them under the same aspect name.

In the extraction process, all potential aspects are recognized. However, the grouping of aspects is necessary because of the large number of possible synonyms. There are two principal issues here.

Many words are not synonyms in various dictionaries even though they refer to the same aspect. Another issue is with domain synonyms. The synonyms refer to the same aspect on one domain but work differently in any other domain.

- **Aspect reduction**

In addition to the above procedure, VisuwordsTM is also used to purify the aspects (reduce aspects). It is an online graphical dictionary tool used to find meanings of the words and their associations with other words.

The refined aspects list can be used to produce aspect-opinion pairs after extracting opinion phrases and classifying them.

- **Opinion words extraction and sentiment classification**

Opinion extraction and classification is the second task of the extraction method. The main objective of this step is to extract the relating opinion words used for each item aspect and classify them into relevant sentiment classes (strong positive, strong negative or neutral) using an opinion lexicon.

Aspect sentiment classification depends on a set of sentiment expressions, called as sentiment lexicon, to decide whether the text in the review is positive or negative about an aspect. It is assumed that customers use adjectives to communicate or express their opinion about an item and its aspects. Therefore, opinion words generally come in the form of adjectives.

The lemmatizing of the phrases is necessary to get the opinion value from the opinion lexicon because that all words in the lexicon are lemmatized. Therefore, some minor changes must be applied to lemmatize all words correctly, and specifically for comparative and superlative forms to suppress.

Once the opinion words have been located in the sentence and from that point, the corresponding aspects are looked through the sentence in reverse first for the nearest aspect. If not found, then the search goes forward.

In the proposed method, the opinion lexicon is used to find opinion words and their relevant opinion orientation value. The opinion lexicon incorporates opinion values for both single opinions bearing words and phrases with a length of up to five words. It is possible to get an opinion value for a given opinion phrase which is extracted from the reviews directly by using the opinion lexicon.

If the extracted phrase consists of just one word, it is not possible to find an opinion value. If the phrase comprises more than one word, the phrase is get shortened by a single word, and another lookup is performed in the opinion lexicon. The opinion value is taken in all situations if the shortened phrase is found in the list.

It is important to note that the shortening of the phrases should not cut off the negation words. for instance, the phrase 'very very good' can occur but is not in the opinion lexicon list, so the phrase is get shortened to 'very good.

On the other hand, if the phrase 'not exceptionally good' is found and its opinion value cannot retrieve from the opinion lexicon, it will not be shortened as omitting the negation word would change the tonality definitely.

In the end, every opinion phrase is classified as positive, negative and neutral. Both the positive and negative classes can be divided again into subclasses addressing strong and weak. If the opinion value is greater than 0.67, the opinion phrase is classified as strongly positive, and any value less than -67 is considered as a strong negative.

- **Distance-Based Linking**

Opinion words are usually positioned in the sentence close to aspects. Opinion words are put as the nearest adjective to the aspects. As the final step, the classified opinions should be connected to the associate aspects. A distance-based approach is used to link the opinion phrases with the relevant aspects at the sentence level.

All strong positive or negative opinion phrases are connected to the following aspect found in a sentence as per the word position.

3.8.4 Personalized Recommendation System

In this section, the personalized recommendation architecture is discussed. The research work proposes a hybrid personalized recommendation system that comprises the traditional content-based and collaborative filtering methods along with the aspect-based sentiment analysis. Figure 14 shows a detailed overview of the proposed personalized recommendation system.

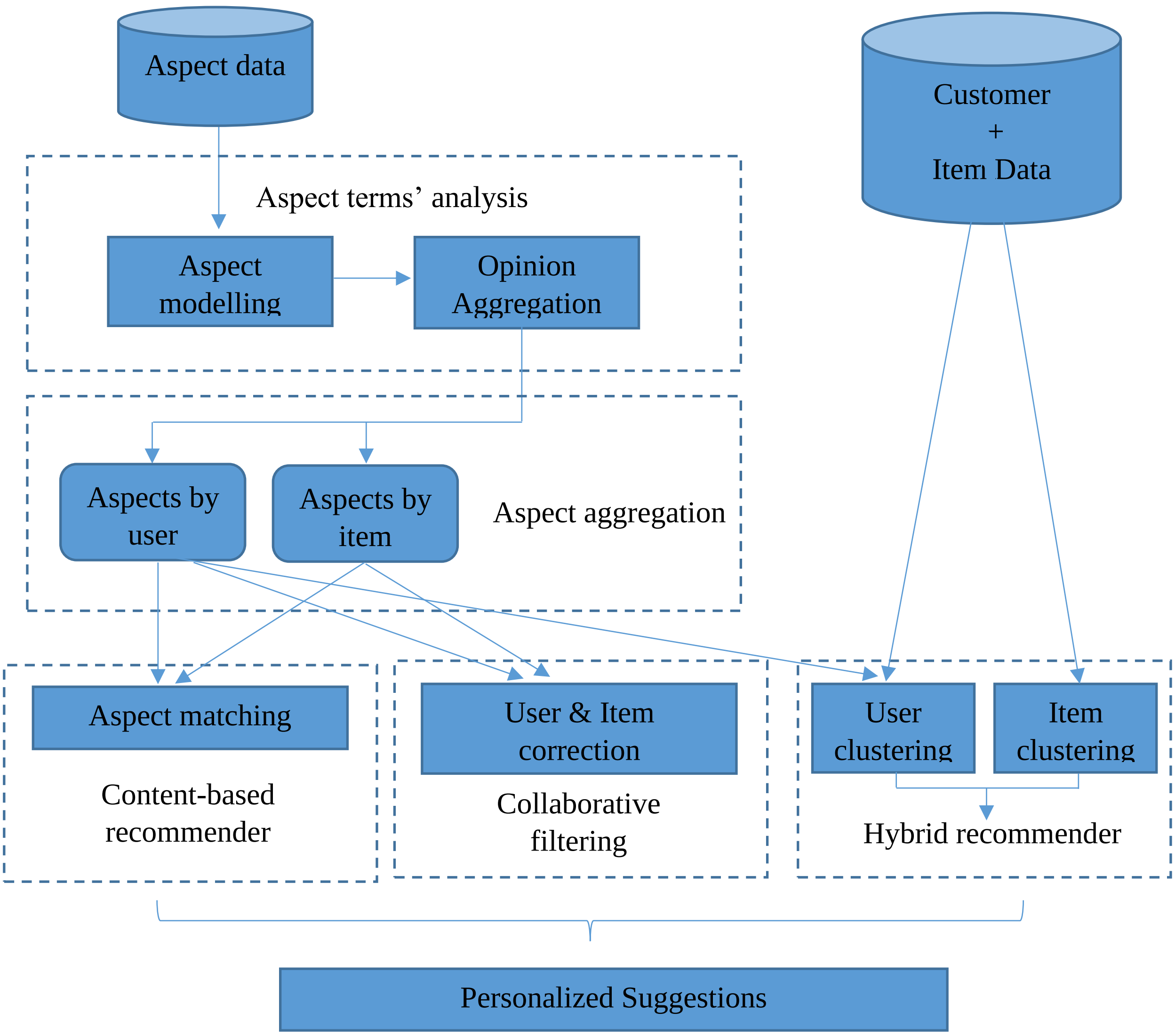


Figure 14: Overview of the proposed Personalized Recommendation System

In the proposed recommender system, there are two datasets utilized to form different clusters: aspect data, customer, and item dataset. The aspect data is obtained from the aspect-based opinion component, where the aspect extraction process results in an aspect list. The customer and item data are web scrapped data prior to the research tasks.

The proposed approach is to have a hybrid system that comprises content-based, collaborative filtering, user clustering and item clustering. After obtaining the aspect list, the aspects are get modelled with opinions and classified into two groups as aspects by users and aspects by items.

The knowledge extracted is utilized by different algorithms and finally produces a set of personalized suggestions. These suggestions are given to the user in a particular ranking order starting from strongly recommended. The suggestion results from the hybrid system are ranked first since it takes the aspect opinions into account. The suggestions from the other sub-modules are ranked based on the filtering option.

- **Content-based recommender**

In this sub-module, the suggestions are generated based on the features. The user is get recommended with items similar to the items he/she liked in the past. To perform this, the aspects by users and aspects by item data are used, and an aspect-matching process is carried out. If there is a matching record, that means the items similar to the items the user has rated or given reviews in the past are get considered.

To provide the suggestion, the items with only positive opinions are get filtered, and only those items are get recommended to the customer.

- **Collaborative Filtering**

In this method, the items that have positive opinions and are preferred by like-minded people are get suggested. The Matrix Factorization technique is used to provide suggestions in this sub-module. It forms a matrix of user-provided ratings and the corresponding items.

Like-minded people are with similar interests, preferences and maybe personal factors. Hence, the suggestions are provided on the basis that if there are positive opinions towards aspects of a product which is given by a similar mind user, then the item gets suggested.

- **Hybrid Recommender**

This approach uses the domain data and the aspects by users. The users in the system are get clustered based on the opinions they have expressed in the past. The aspects by user's knowledge from opinion mining are utilized here to group people with the same opinions towards aspects of products. The suggestions are provided based on their past opinion and opinions of other users in the same cluster.

3.8.5 Intelligent Customer Insight Generation

Figure 15 shows the overview of the intelligent customer insight generation component. The results from the previous two components are utilized here to analyse the different clusters of customers and their personalized recommendation products. This knowledge can be used to target groups to send marketing campaigns and show personalized advertising.

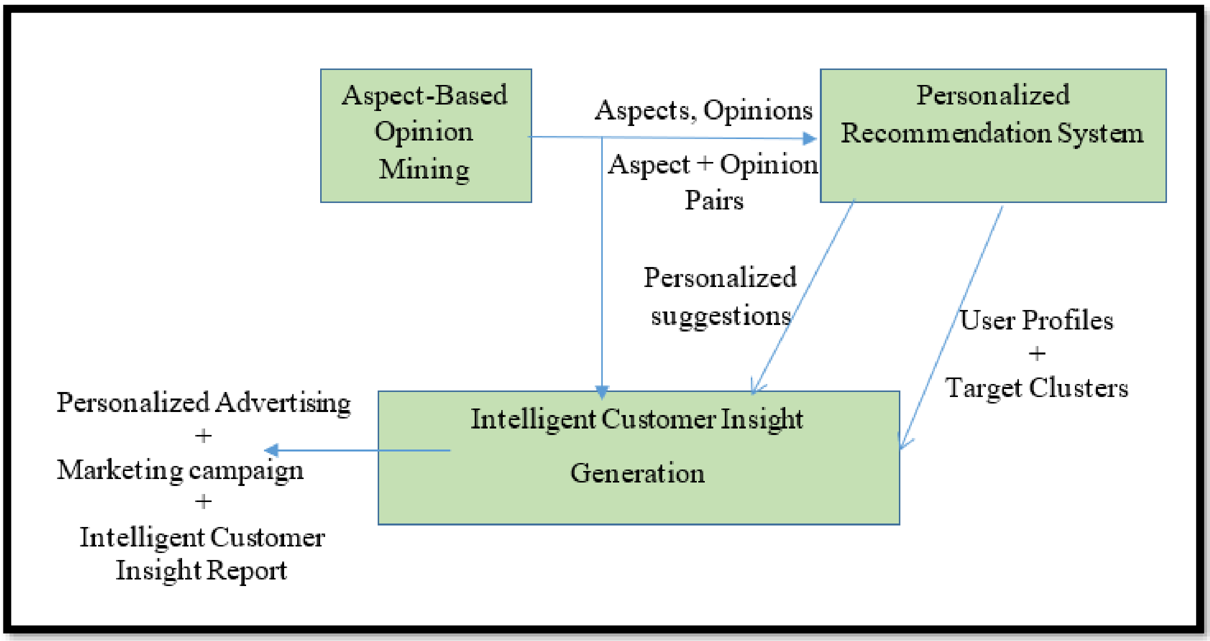


Figure 15: Overview of Intelligent Customer Insight Generation

- **Identification of Product's Strengths and Weaknesses**

The aspect-based opinion mining components outputs the list of aspects, opinions and aspect-opinion pairs, which can be used to analyse which products and on what aspects the customer expresses a positive opinion and negative opinion.

The business can get an insight that the products with a high positive opinion can be manufactured more and promoted, whereas products with negative opinions can be omitted from the production. This way of insight helps the retailer to increase sales and minimize the production cost.

In addition to the products, the insight about specific aspects can also be analyzed since the proposed work adopting aspect-based opinion mining.

- **Target groups of customers**

Since the recommendation module utilizes three different approaches to suggest items, the three different clusters of users can be obtained. By getting the results from the personalized recommendation component, the different clusters can be treated as target groups.

Clustering of own customers helps to understand the customer behaviour better and makes it easy to approach easily. The different targeted groups can be aimed to send marketing campaigns and personalized advertising.

3.8.6 Augmented Reality Virtual Dressing Room

In this section, the methodology of the virtual dressing room using Augmented Reality (AR) is discussed. In this approach, ARKit is used to build the AR model to try on clothes virtually. The ARKit performs combining motion sensing and scene analysis to visualize three-dimensional virtual content as a part of real-world content.

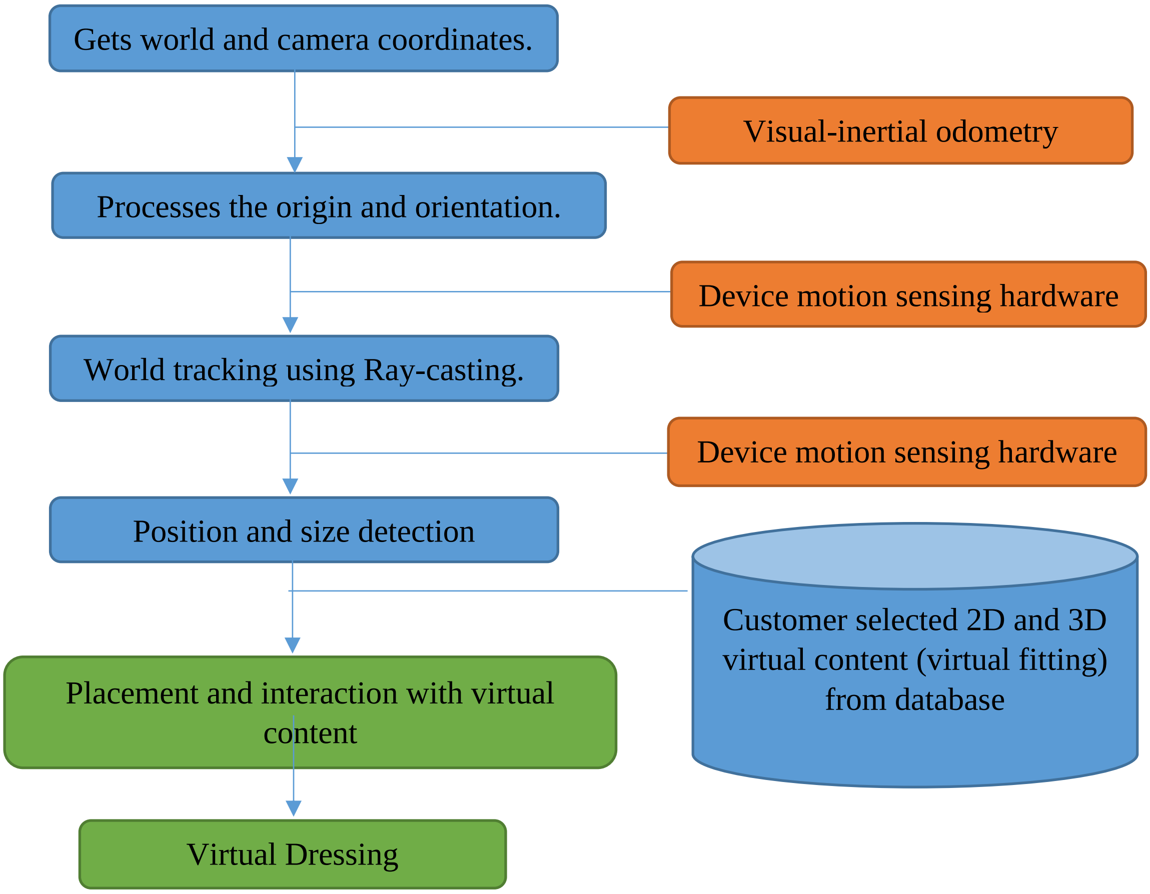


Figure 16: Flowchart Augmented Reality Virtual Dressing Room

In Figure 16, a flow chart is shown to visualize the methodology of the virtual fitting room research using ARKit from Apple.

The ARKit will be used to process and get the camera coordinates of the real world. Along with that, ARKit contains API (Application Programming Interface) to make changes to the origin and coordinate system with respect to the real world.

The ARKit uses visual-inertial odometry technology to correspond between the real world and the virtual space. This information will be used to track the real world. This is achieved in combination with the information from the device motion-sensing hardware and computer vision analysis of the scene visible using the device’s camera. This results in a high precision model of device position and motion. In this project, it is achieved using the ARKit as well.

Ray-casting methods are the most common techniques to find the distance from a point to another given point in the virtual world. In this research work, the ray-casting method will be used in ARKit to find the real-world surface corresponding to point a point in the camera image. This method detects flat surfaces in the camera image and reports their position and size to the website.

From the front-end website, a customer is able to select a cloth to try using this method. Therefore, the desired object related to the selected item must be retrieved from the database. These data will be 2D object maps, textures, etc. These results will be rendered on the website with camera-enabled.

The results from the ray-casting or the detected planes will be used to place or interact with virtual content in the application. In the end, the website allows the customer to quickly fit and check the desired cloth virtually, and the customer can purchase or send a review directly via the website.

The ARKit incorporates tracking facilities of the user's face in an application that displays an AR experience with the camera. The ARKit performs image processing to deliver image position and expression along with the world-tracking using both the front and back cameras.

3.9 Implementation

The sections below describe how each main module of the proposed model is implemented. As discussed in section 3.8, the system architecture consists of 4 modules: Aspect Extraction and Opinion Classification, Personalized Recommendation, Intelligent Insight, and Augmented Reality Virtual Dressing.

3.9.1 Workstation Setup

Hardware specification for the study is explained in this section. NLP libraries and Machine learning algorithms tasks require high performing hardware for mining and predictions.

Machine learning algorithms are trained on a single processor since parallel training is impossible in most cases. However, it takes a considerable amount of time to run using a single processor. Therefore, the machine should possess a decent amount of processing unit and graphical processing unit (GPU).

As augmented reality is also built as part of the system, it requires more processing power to render and create 2D/ 3D models. The tools used for AR development such as Unity3D, Vuforia, AR Foundation and AR Kit requires a graphical processing unit with high performance.

The proposed approach used a hardware setup with the specification as listed in Table 4.

Table 5: Hardware Specification of the Workstation Setup

Machine Type	*Workstation Hardware Specification*
CPU	Intel(R) Core(TM) i7-1065G7 CPU @ 1.30GHz 1.50 GHz
RAM	8 GB
GPU	NVIDIA GeForce MX250
Operating System	Windows 10

3.9.2 Software & Frameworks

The proposed model is trained and tested in Windows 10 environment and python 3.9 is used as the primary language to build the aspect-based opinion mining module. Due to the fact that python provides NLP library support and machine learning algorithms, it is selected for the implementation of the module.

In terms of software, the Anaconda platform has been installed to access jupyter notebooks to enable python modules. The following open-source python libraries and frameworks are used to build the aspect extraction and opinion classification modules.

The python libraries and frameworks used to train and test models on aspect extraction, opinion classification and personalized recommendation are listed in Table 5.

Table 6: Python Libraries and Usage

Python Library/ Framework	*Purpose of Use*
Natural Language Toolkit (NLTK)	Used as the main toolkit for text processing that includes tokenizing, lemmatizing, removing stop words, stemming and etc.
Scikit-learn Library	Used to have most of the unsupervised and supervised machine learning algorithms support.
Numerical Python (NumPy)	Used to have multidimensional array object data structure to perform efficient computation and faster access.
Matplotlib Library	Used for the data visualization of the experimental results and the analysis.

In addition, some other linguistic resources were used. These resources include synonyms for words and sentiment lexicons. WordNet is used to find out the similarity between words to cluster and extract aspect category and TextBlob is used to get the sentiment polarity measures to classify positive, negative and neutral words.

To build AR virtual dressing room application, Unity 2020.3.17 f1, Vuforia 9.5, ARFoundation 4.0 and ARKit is used.

3.9.3 Dataset for Training and Testing

The initial model is built using the reviews data from the five main cloth categories. Before starting the training phase, the collected dataset is divided into training at testing datasets. Hence the number of items in each category is different, each category is partitioned into 80% percentage for training and 20% for testing. The details about the separated two datasets are listed in Table 6 below.

Table 7: Separation of Dataset for Training and Testing

Category	*Total Reviews*	*Number of Reviews*	
		Training	*Testing*
Gowns	9563	7651	1912
Party	5693	4555	1138
Night Out	5632	4506	1126
Wedding	5963	4771	1192
Work	4886	3909	977
Active wear	2036	1629	407
Jumpsuits	9568	7655	1913
Blouses	9563	7651	1912
Total	52904	42327	10577

Figure 17 shows a snip of the collected dataset. It consists of the information about the brand, item name, customer name, title of the review and the review text written by the customers.

Brand	ItemName	Customer	Title	Reviews
Victor Alfaro Collective	Green Off Shoulder Sweater Dress	Silvia	More interesting than I expected	Warm enough for a late winter day without bein...
Victor Alfaro Collective	Green Off Shoulder Sweater Dress	Katrina	Definitely does not hang over the shoulder unl...	Fits true to size. Beautiful material and nice...
Victor Alfaro Collective	Green Off Shoulder Sweater Dress	Meagan	Cute but stretches with all day wear	Cute but stretches with all day wear
Victor Alfaro Collective	Green Off Shoulder Sweater Dress	Lindsey rai	Awesome, awesome winter dress	Fit is true to size and hangs in all of the ri...
Victor Alfaro Collective	Green Off Shoulder Sweater Dress	Alisa	Sweater dress	This was a cute change up on a typical sweater...
...	...	...	...	...
Free People	Black Fake Pretend Top	Jenny	People complimented this one a lot!	Wore it for work
Free People	Black Fake Pretend Top	Trieva	really cute and comfy for work, lots of compli...	a little high waisted for me but really cute w...
Free People	Black Fake Pretend Top	Jayme	Runs large	I rented this in a size medium but it is so lo...
Free People	Black Fake Pretend Top	Sapana	I didn't love this outfit -- it was kind of bu...	I wouldn't rent this again.
Free People	Black Fake Pretend Top	Alice	Great summer to fall transition piece	Loved the detail on dress and very comfortable...

Figure 17: Sample of the Dataset

3.9.4 Preparing Data

After splitting the dataset into training and testing, the dataset for training needs to be prepared for the aspect extraction and opinion mining problem. Since the research study is focused to classify opinions at the aspect level, the review texts should be separated into sentences.

Figure 18 shows how the reviews look like after breaking the whole review text into sentences. For each review, a new row is get added based on the number of sentences.

ï»¿Brand	ItemName	Customer	Title	Reviews	Review_Sentence
Victor Alfaro Collective	Green Off Shoulder Sweater Dress	Silvia	More interesting than I expected.	Warm enough for a late winter day without being bulky. Didn't fall off my shoulder fetchingly, but definitely work appropriate. The skirt actually has a mix of textures and the dolman sleeves were fun and different. I wore with a belt to encourage the blouson effect and tights. My dog liked it for sure!	Warm enough for a late winter day without being bulky.
Victor Alfaro Collective	Green Off Shoulder Sweater Dress	Silvia	More interesting than I expected.	Warm enough for a late winter day without being bulky. Didn't fall off my shoulder fetchingly, but definitely work appropriate. The skirt actually has a mix of textures and the dolman sleeves were fun and different. I wore with a belt to encourage the blouson effect and tights. My dog liked it for sure!	Didn't fall off my shoulder fetchingly, but definitely work appropriate.
Victor Alfaro Collective	Green Off Shoulder Sweater Dress	Silvia	More interesting than I expected.	Warm enough for a late winter day without being bulky. Didn't fall off my shoulder fetchingly, but definitely work appropriate. The skirt actually has a mix of textures and the dolman sleeves were fun and different. I wore with a belt to encourage the blouson effect and tights. My dog liked it for sure!	The skirt actually has a mix of textures and the dolman sleeves were fun and different.
Victor Alfaro Collective	Green Off Shoulder Sweater Dress	Silvia	More interesting than I expected.	Warm enough for a late winter day without being bulky. Didn't fall off my shoulder fetchingly, but definitely work appropriate. The skirt actually has a mix of textures and the dolman sleeves were fun and different. I wore with a belt to encourage the blouson effect and tights. My dog liked it for sure!	I wore with a belt to encourage the blouson effect and tights.
Victor Alfaro Collective	Green Off Shoulder Sweater Dress	Silvia	More interesting than I expected	Warm enough for a late winter day without being bulky. Didn't fall off my shoulder fetchingly, but definitely work appropriate. The skirt actually has a mix of textures and the dolman sleeves were fun and different. I wore with	My dog liked it for sure!

Figure 18: Dataset after Splitting Reviews into Sentences

The next step in preparation is counting total words in a review sentence as shown in Figure 19. This is important to remove sentences that have only one or two words from the training dataset. In the context of aspect extraction and opinion classification, the review texts with only a few words affect the learning process that leads to inaccurate outcomes.

ï»¿Brand	ItemName	Customer	Title	Reviews	Review_Sentence	Total Words
Victor Alfaro Collective	Green Off Shoulder Sweater Dress	Silvia	More interesting than I expected.	Warm enough for a late winter day without being bulky. Didn't fall off my shoulder fetchingly, but definitely work appropriate. The skirt actually has a mix of textures and the dolman sleeves were fun and different. I wore with a belt to encourage the blouson effect and tights. My dog liked it for sure!	Warm enough for a late winter day without being bulky.	10.0
Victor Alfaro Collective	Green Off Shoulder Sweater Dress	Silvia	More interesting than I expected.	Warm enough for a late winter day without being bulky. Didn't fall off my shoulder fetchingly, but definitely work appropriate. The skirt actually has a mix of textures and the dolman sleeves were fun and different. I wore with a belt to encourage the blouson effect and tights. My dog liked it for sure!	Didn't fall off my shoulder fetchingly, but definitely work appropriate.	10.0
Victor Alfaro Collective	Green Off Shoulder Sweater Dress	Silvia	More interesting than I expected.	Warm enough for a late winter day without being bulky. Didn't fall off my shoulder fetchingly, but definitely work appropriate. The skirt actually has a mix of textures and the dolman sleeves were fun and different. I wore with a belt to encourage the blouson effect and tights. My dog liked it for sure!	The skirt actually has a mix of textures and the dolman sleeves were fun and different.	16.0
Victor Alfaro Collective	Green Off Shoulder Sweater Dress	Silvia	More interesting than I expected.	Warm enough for a late winter day without being bulky. Didn't fall off my shoulder fetchingly, but definitely work appropriate. The skirt actually has a mix of textures and the dolman sleeves were fun and different. I wore with a belt to encourage the blouson effect and tights. My dog liked it for sure!	I wore with a belt to encourage the blouson effect and tights.	12.0
Victor Alfaro Collective	Green Off Shoulder Sweater Dress	Silvia	More interesting than I expected.	Warm enough for a late winter day without being bulky. Didn't fall off my shoulder fetchingly, but definitely work appropriate. The skirt actually has a mix of textures and the dolman sleeves were fun and different. I wore with a belt to encourage the blouson effect and tights. My dog liked it for sure!	My dog liked it for sure!	6.0

Figure 19: Word count for each Review Sentence

3.9.5 Pre-processing

As the importance of pre-processing discussed in previous sections, the data should be cleaned and converted to a form appropriate for a machine learning problem. At this stage, the Natural Language Toolkit (NLTK) is used to clean the natural language and tools like Spacy and TextBlob are used to remove stop words and correct the spelling of the words.

The algorithm developed in the research design is implemented as follows in Figure 20.

```
# remove special characters, numbers and punctuations
dataset_sub['Clean Review'] = dataset_sub['Review_Sentence'].str.replace("[^a-zA-Z#]", " ")

dataset_sub['Review_Sentence'] = dataset_sub['Review_Sentence'].str.lower()

reviews = dataset_sub['Review_Sentence'].values.tolist()
#dataset_temp['Review_Sentence'] = TextBlob(reviews)
for x in dataset_sub['Review_Sentence']:
    TextBlob(x).correct()

for x in dataset_sub['Review_Sentence']:
    x= word_tokenize(str(x))


tokenized_review = dataset_sub['Clean Review'].apply(lambda x: word_tokenize(x))
tokenized_review

#pip install -U spacy

#from nltk.corpus import stopwords

import spacy
from spacy.lang.en.stop_words import STOP_WORDS
stop_words = list(STOP_WORDS)
print(stop_words)

# Remove stop words
tokens_without_stop = [word for word in tokenized_review if word not in stop_words]
tokens_without_stop

dataset_sub.head()

# individual words considered as tokens
tokenized_rev = dataset_sub['Clean Review'].apply(lambda x: str(x).split())
tokenized_rev.head()

# stem the words
from nltk.stem.porter import PorterStemmer
stemmer = PorterStemmer()

tokenized_rev = tokenized_rev.apply(lambda sentence: [stemmer.stem(word) for word in sentence])
tokenized_rev.head()
```

Figure 20: Sample code of Pre-processing

After the complete pre-processing, the cleaned tokenized review is generated, and the pre-processed dataset is saved as a CSV file to be used for the training phase. The difference between the original review sentence, cleaned review and tokenized review is shown in Figure 21 below.

Brand	ItemName	Title	Review_Sentence	Clean Review	Cleaned_Tokenized_Review
Tory Burch	Colorblock Poplin Tunic	Great Pop of Color	like the standout colors and color blocking.	like the standout colors and color blocking	like the standout color and color block
Tory Burch	Colorblock Poplin Tunic	Great Pop of Color	this is a great spring shirt.	this is a great spring shirt	thi is a great spring shirt
Tory Burch	Colorblock Poplin Tunic	Great Pop of Color	a bit too thick for texas summers.	a bit too thick for texas summers	a bit too thick for texa summer
Tory Burch	Colorblock Poplin Tunic	Great Pop of Color	something i would wear at the beach when it's still a bit cool out.	something i would wear at the beach when it s still a bit cool out	someth i would wear at the beach when it s still a bit cool out
Tory Burch	Colorblock Poplin Tunic	Great Pop of Color	cons: none really.	cons none really	con none realli
Tory Burch	Colorblock Poplin Tunic	Great Pop of Color	i may have bought if it were not so bright.	i may have bought if it were not so bright	i may have bought if it were not so bright
Tory Burch	Colorblock Poplin Tunic	Great Pop of Color	it stands out quite a bit.	it stands out quite a bit	it stand out quit a bit
Tory Burch	Colorblock Poplin Tunic	Great Pop of Color	wouldn't be able to wear that many times.	wouldn t be able to wear that many times	wouldn t be abl to wear that mani time
Tory Burch	Colorblock Poplin Tunic	Fun and spirited top	this was a great shirt i that received so many compliments on due to the bold colors and style of the shirt.	this was a great shirt i that received so many compliments on due to the bold colors and style of the shirt	thi wa a great shirt i that receiv so mani compliment on due to the bold color and style of the shirt
Tory Burch	Colorblock Poplin Tunic	Fun and spirited top	i paired it with jean capris one day and short jean cutoffs another time with heels.	i paired it with jean capris one day and short jean cutoffs another time with heels	i pair it with jean capri one day and short jean cutoff anoth time with heel

Figure 21: Cleaned Reviews vs. Cleaned Tokenized Review

3.9.6 Implementation Aspect Extraction

The aspect-based sentiment analysis module is carried out in two stages: aspect extraction and sentiment classification. Since an unlabelled dataset is used to train the aspect extraction model, an unsupervised approach called topic modelling is used with Latent Dirichlet Allocation (LDA) is used to extract the aspects.

	Topic0	Topic1	Topic2	Topic3	Topic4	Topic5	Topic6	Topic7	Topic8	Topic9	dominant_topic
Doc0	0.030000	0.030000	0.030000	0.030000	0.370000	0.030000	0.030000	0.030000	0.030000	0.370000	4
Doc1	0.030000	0.030000	0.030000	0.030000	0.030000	0.030000	0.030000	0.520000	0.030000	0.280000	7
Doc2	0.020000	0.020000	0.020000	0.420000	0.020000	0.020000	0.020000	0.020000	0.220000	0.220000	3
Doc3	0.020000	0.020000	0.020000	0.020000	0.820000	0.020000	0.020000	0.020000	0.020000	0.020000	4
Doc4	0.550000	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	0
Doc5	0.030000	0.700000	0.030000	0.030000	0.030000	0.030000	0.030000	0.030000	0.030000	0.030000	1
Doc6	0.030000	0.030000	0.370000	0.030000	0.030000	0.030000	0.030000	0.370000	0.030000	0.030000	2
Doc7	0.030000	0.030000	0.030000	0.030000	0.030000	0.030000	0.030000	0.030000	0.030000	0.770000	9
Doc8	0.030000	0.270000	0.530000	0.030000	0.030000	0.030000	0.030000	0.030000	0.030000	0.030000	2
Doc9	0.030000	0.030000	0.030000	0.030000	0.030000	0.530000	0.030000	0.030000	0.030000	0.270000	5
Doc10	0.030000	0.030000	0.030000	0.030000	0.030000	0.030000	0.770000	0.030000	0.030000	0.030000	6
Doc11	0.020000	0.220000	0.220000	0.020000	0.020000	0.020000	0.020000	0.020000	0.420000	0.020000	8

Figure 22: Top Ten Topics with Similarity Scores

Since the machine cannot understand the raw texts, it needs to be converted to a vector form using word embedding techniques. CountVectorizer, TF-IDF Vectorizer word embedding methods are used to extract topic keywords.

Only the first ten topics that are mostly distributed among the reviews are taken into consideration and each doc that is the review phrases are allocated with the dominant topic it is talking about.

Figure 22 shows the similarity score of each doc and the relevant topic identified. The topic that has the higher similarity score is selected as the dominant topic for the doc (review phrase).

3.9.7 Implementation of Sentiment Classification

After extracting the aspects, sentiment for each review is classified using a hybrid approach combining both the unsupervised and supervised approaches.

Initially, the sentiment is classified using the unsupervised technique to make the dataset ready for the supervised approach.

Based on reference given in Figure 23 for the sentiment polarity, if the score is greater than 0 the sentiment is considered as positive, if less than 0 sentiments are considered as negative and if the score is equal to 0, then the sentiment is neutral.

```python
def getAnalysis(score):
    if score < 0:
        return 'Negative'
    elif score == 0:
        return 'Neutral'
    else:
        return 'Positive'
```

Figure 23: Reference Code for Sentiment Classification

Depending on that reference, TextBlob is used to get the sentiment subjectivity and the sentiment polarity scores for each review phrase. The sample records given in Figure 24, shows the assigned aspect and the sentiment class based on the sentiment polarity score.

Brand	ItemName	Title	Review_Sentence	Clean Review	Aspect	Sentiment_Subjectivity	Sentiment_Polarity	Sentiment
Victor Alfaro Collective	Green Off Shoulder Sweater Dress	More interesting than I expected.	warm enough for a late winter day without being bulky.	warm enough for a late winter day without being bulky	Event/Occasion	0.566667	0.10000	Positive
Victor Alfaro Collective	Green Off Shoulder Sweater Dress	More interesting than I expected.	didn't fall off my shoulder fetchingly, but definitely work appropriate.	didn t fall off my shoulder fetchingly but definitely work appropriate	Experience	0.500000	0.25000	Positive
Victor Alfaro Collective	Green Off Shoulder Sweater Dress	More interesting than I expected.	the skirt actually has a mix of textures and the dolman sleeves were fun and different.	the skirt actually has a mix of textures and the dolman sleeves were fun and different	Texture	0.300000	0.10000	Positive
Victor Alfaro Collective	Green Off Shoulder Sweater Dress	More interesting than I expected.	i wore with a belt to encourage the blouson effect and tights.	i wore with a belt to encourage the blouson effect and tights	Pairing	0.000000	0.00000	Neutral
Victor Alfaro Collective	Green Off Shoulder Sweater Dress	More interesting than I expected.	my dog liked it for sure!	my dog liked it for sure	Likeliness	0.844444	0.55000	Positive
...	...	...	...	...	...	...	...	...
Free People	Black Fake Pretend Top	Runs large	I'm usually a size 6.	i m usually a size	Size/Fit	0.250000	-0.25000	Negative
Free People	Black Fake Pretend Top	I didn't love this outfit – it was kind of bunchy and unflattering at the waist.	i wouldn't rent this again.	i wouldn t rent this again	Experience	0.000000	0.00000	Neutral
Free People	Black Fake Pretend Top	Great summer to fall transition piece	loved the detail on dress and very comfortable.	loved the detail on dress and very comfortable	Details/Color/Fabric	0.900000	0.61000	Positive
Free People	Black Fake Pretend Top	Great summer to fall transition piece	can wear with or without leggings/tights.	can wear with or without leggings tights	Pairing	0.000000	0.00000	Neutral
Free People	Black Fake Pretend Top	Great summer to fall transition piece	keeping this piece a little longer while returning other rtr pieces	keeping this piece a little longer while returning other rtr pieces	Material	0.437500	-0.15625	Negative

Figure 24: Assigned Aspect with its Sentiment Polarity

3.9.8 Implementation of Personalized Recommendation

As discussed in the proposed model, the results from the aspect-based opinion mining model can be used to enhance the personalized recommendation system. The items that showed positive sentiments are only selected to build content-based and collaborative filtering recommendations.

Content-based is where the products which are similar to the products liked by the customer in past are suggested and collaborative filtering is where suggestions are based on the products liked by similar minded people.

The proposed model suggests building a hybrid approach to provide personalized recommendations enhanced with sentiment analysis. Therefore, the item list from the previous models of collaborative and content-based filtering methods are combined using a weighted score and the top ten of the results list is get suggested to the user.

3.9.9 Implementation of Intelligent Customer Insight

Finally, considering both the sentiment analysis and personalized suggestion results intelligent customer and product insight can be produced. Exploratory Data Analysis (EDA) is carried out on the results to identify customer, product and brand insight.

The matplotlib library supported by python is used to visualize the positive and negative words that are frequently used by the customers in the reviews. In addition, EDA is used to identify popular, unpopular products, important aspects of the items and insight on brands.

In the intelligent customer insight module, the analysis results from EDA are saved as Google excel files and connected to the Google Data Visualization platform in order to generate have advertising and marketing campaigns.

3.9.10 Implementation of AR Virtual Dressing Room

The proposed study implements an Augmented Reality (AR) virtual dressing room along with the sentiment analysis and personalized recommendation system. Unity3D platform is used to develop the AR dressing application using ARFoundation and ARKit tools.

Unity3D platform with Vuforia engine is used to enable augmented reality features. A human object is detected automatically since ARFoundation is used. The targets are the 2D images of the cloths which get added to the unity scene over the Vuforia engine.

An AR camera is added to the application to make the target embeds over the human virtual scene when the camera is opened on the mobile device. Initially, ARKit is added from the XR plugin management, and the AR scene is built by allowing one AR camera game object.

ARRaycastManager and ARPlaneManager are used to access the ground plane feature of Vuforia with ARFoundation.

3.10 Overview of the Proposed System

The research work delivers a web application and mobile application that can be accessed from mobile phones. Figure 25 shows the overview of the proposed system. The customer needs to register themselves using the mobile application. While registering, the user’s personal data are getting collected. Once they successfully register with the system, users can input their requirements as text. The user preference is identified by investigating the input text by means of Natural Language Processing (NLP) techniques.

The system lists down the items matching the requirement depending on their preferences, personal factors, and aspect-based opinions.

Figure 25: Overview of the Proposed Real-Time System

The user can select an item and see all the details, available colours, sizes, and prices. If the customer wishes to fit on clothes or accessories which they are going to buy, the system virtually enables the customers to outfit. Augmented Reality (AR) techniques are used to provide virtual fitting room and take the correct body measurements of the customer. When a customer confirms the order, the details get transferred from the mobile application to the web application.

The merchants need to register their stores with the system using the web application. Once they successfully registered, the stores can add their items (clothes and accessories). The required fields and specifications for images will be provided through the system, which enables the utilisation of Augmented Reality (AR).

As part of the implementation, the actual system proposed by the study is also built. As discussed above the final system includes a web application for the merchants to perform sentiment analysis for any given reviews and get the customer, product and brand insight. The web application is connected to Google360 to enable targeting and marketing campaigns.

A sample interface that shows product insight from the actual web application is depicted in Figure 26. All the interfaces of the insight generation are attached in Appendix A for reference.

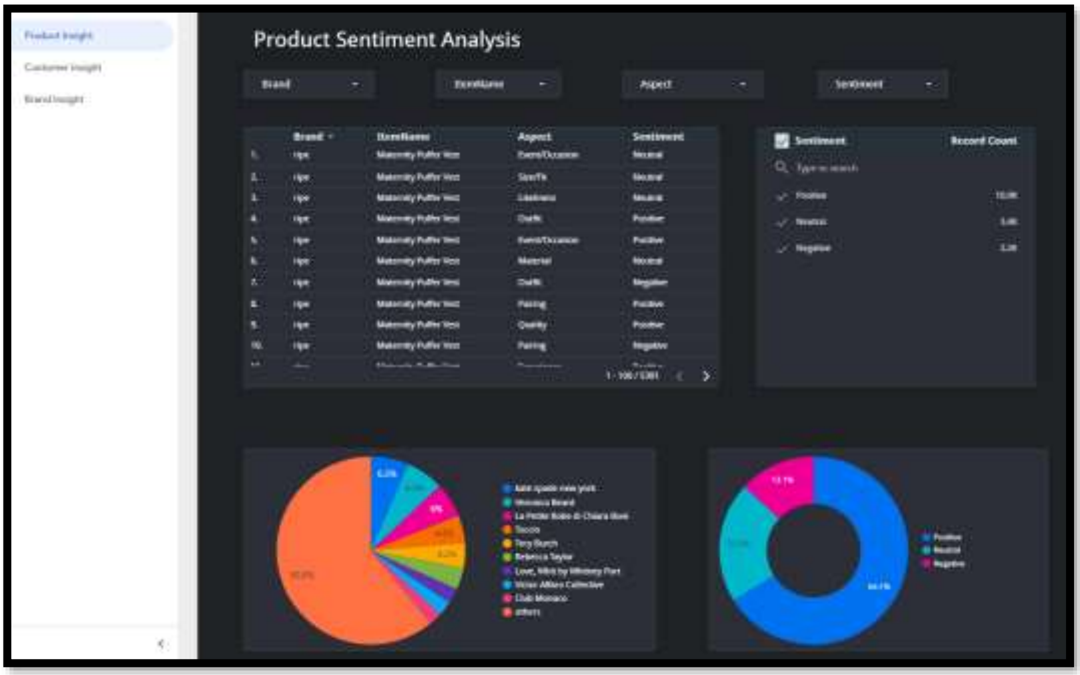


Figure 26: Web Application Interface displaying Product Insight

In addition to the web application, the users (customers) of the system can use the built mobile application to receive personalized suggestions and try augmented reality virtual dressing room application. Figure 27 shows the interfaces of the mobile application built.

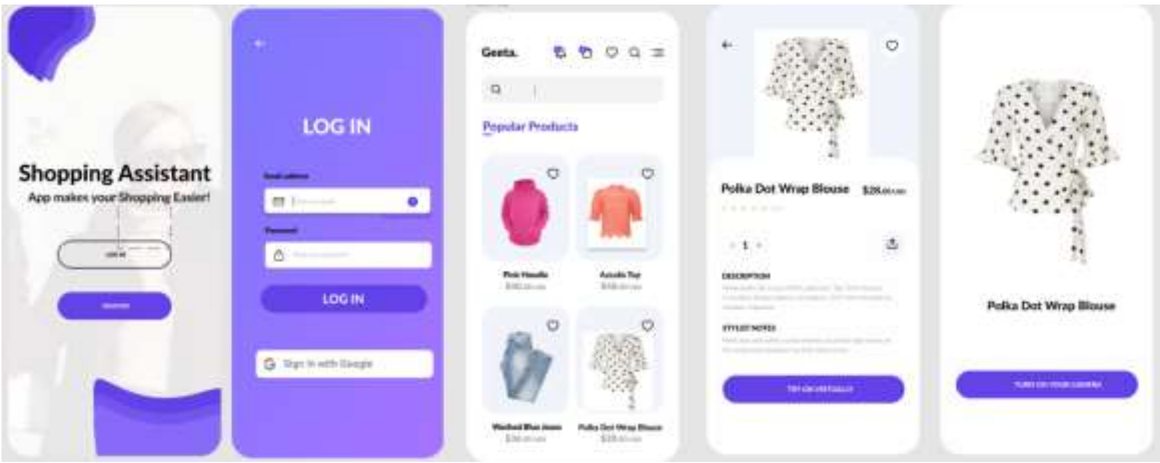


Figure 27: Developed Mobile Application Interfaces

3.11 Summary

In this chapter, a novel approach to solve the identified problem is proposed. The proposed works solve the research problem by covering four research areas: Aspect-based opinion mining, personalized recommendation, intelligent customer insight generation and AR virtual dressing room. The architecture of the system and the technologies and algorithms adopted to develop the proposed model is discussed in this chapter in more detail.

CHAPTER 4

RESULTS AND EVALUATION

4.1 Introduction

In this chapter, the proof of concept and the results obtained from the proposed model have been discussed initially and then the validity of the proposed approach is evaluated. In addition, research hypothesis questions, and the evaluation techniques used to test the trained models are discussed. The performance of each trained model is quantitatively analysed based on the evaluation metrics identified. The accuracy of the implemented system is tested by setting up experiments with real users.

4.2 Results of Implementation

There are some interesting facts derived from the results of the implementation. According to the word frequency in the review phrases, the words like 'dress', 'fit', 'size', and 'comfortable' are the most frequent words expressed by the customers. Figure 28 shows the word cloud generated using Matplotlib representing the word frequencies.

Figure 28: Word Cloud of Text Reviews

From the results obtained, it is clear that customers are more concerned with the size and fit aspect. The results are further fine-grained to understand the positive and negative reviews separately. There are words that denote different aspects and categories of cloths are identified in the word cloud generated for both positive and negative reviews.

While comparing both the word clouds obtained, it is clear that customers are more concerned with the size and fit aspect. It strengthens one of the objectives of the research study to incorporate augmented reality virtual dressing rooms.

As discussed in the proposed design, the aspect extraction module generated the top ten topics which are most talked about in the reviews by the customers. Those ten topics conclude, size/fit, experience, quality, likeliness, texture, event/occasion, pairing, colour/fabric, pairing and outfit.

The total number of items and reviews per topic are listed below in Table 7.

Table 8: Summary Table of Number of Reviews and Items per Aspects

Aspect	*Number of Items*	*Number of reviews*
Details/Color/Fabric	102	1556
Event/Occasion	109	1968
Experience	105	1687
Likeliness	106	1696
Material	105	1397
Outfit	105	1542
Pairing	106	1330
Quality	98	1010
Size/Fit	110	2079
Texture	267	1230

Based on the aspect-sentiment pairs generated from the aspect-based opinion mining model, the personalized suggestions can be enhanced. Figure 29 shows products suggested based on the popularity where the products with high positive sentiments are suggested. The popularity recommendation can also be done for a particular customer depending on their previous reviews.

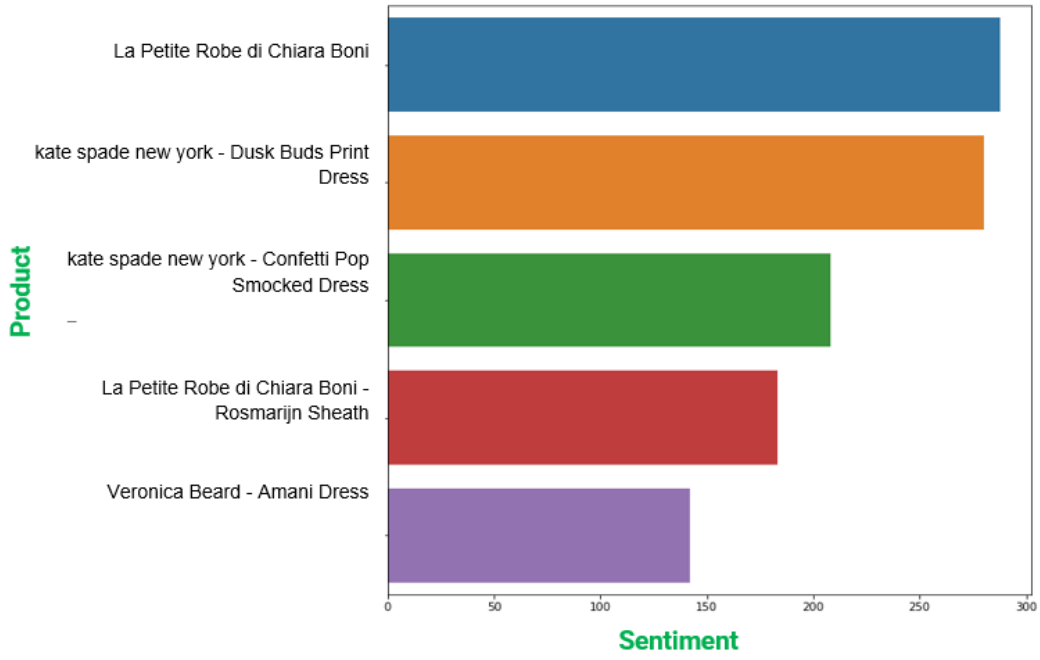


Figure 29: Top 10 Products based on Popularity

Another important result is product insight and brand insight. Since the proposed study aims to utilize sentiment analysis to produce intelligent insight, the product or the brand can be studied in terms of extracted aspect topics. Figure 30 and Figure 31 shows the top ten topics for a particular product and brand respectively.

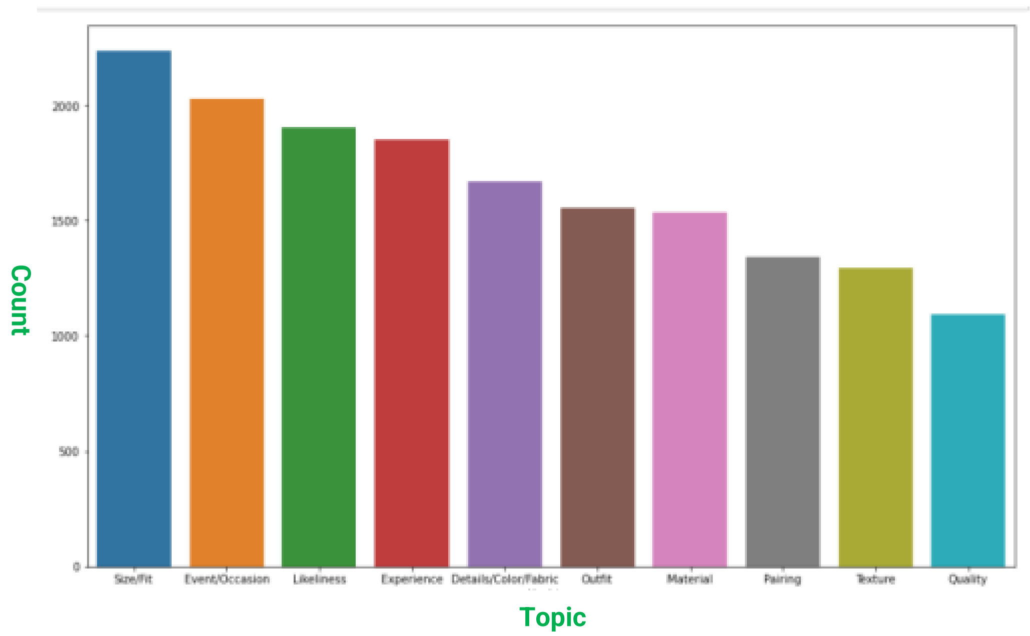


Figure 30: Top 10 Positive Topics for the product ‘Green Off Shoulder Sweater Dress’

By having the analysis of these results, the products or the brands with high positive opinions for a particular aspect, for example, size and fit can be identified.

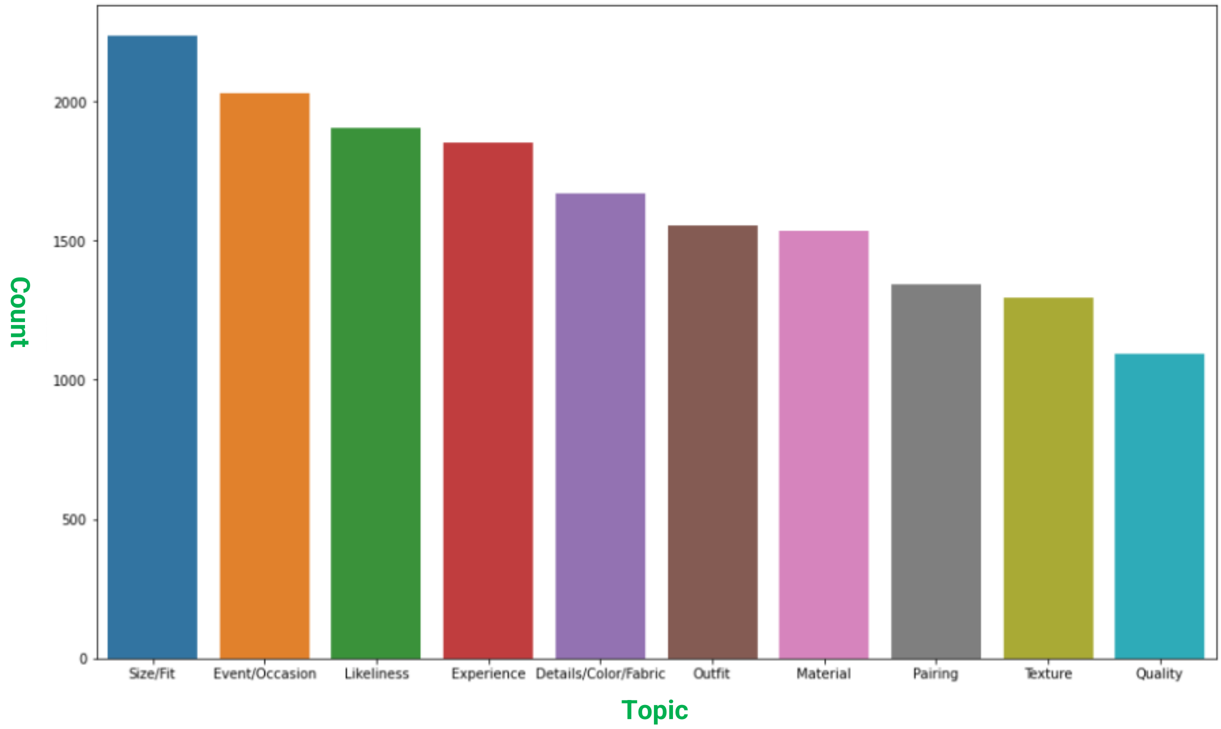


Figure 31: Top 10 Positive Topics for the brand Victor Alfaro Collective

4.3 Dataset for Evaluation

The dataset used to train is divided into training and test datasets on the ratio of 80:20. The trained models are evaluated using this test dataset. In addition, the experiment was also performed on a real dataset to test how well the proposed model works in practice. The experiments are carried out on a private dataset that provides user reviews, product details and user details in order to evaluate the proposed model.

The data are extracted from a UK based online clothing store because there is no suitable dataset available publicly that consist of the required fields of data. The customer reviews for each product, customer details and product details are extracted using a web scrapping tool ‘Octoparse’.

The users who have published more than 20 item reviews are chosen as seed users. The reviews written by the seed user are extracted to experiment.

4.4 Ethics and Consent Process

The satisfaction of the developed system of personalized recommendations and AR virtual dressing room are evaluated by conducting a survey. The data collected through surveys from the users are protected with highly confidential and security measures and the consent forms for the participants are given before their participation. The consent form is given to participants before the survey is attached in Appendix B.

4.5 Experiment Setup

Different experiments are planned to test each hypothesis question listed below.

1. What are the best aspect extraction and selection approaches for Aspect-Based Opinion Mining?
2. What is the mechanism to classify sentiment towards aspects in opinion mining to achieve efficient results?
3. What are the metrics to measure the accuracy and effectiveness of Aspect-Based Opinion Mining?
4. How sentiment analysis can be incorporated with a personalized recommendation engine to improve the quality in terms of accuracy compared to other existing approaches.
5. How can an Augmented Reality model increase the overall performance of traditional online cloth shopping by providing virtual dressing?

The experiments to evaluate each hypothesis are described briefly in the following sections.

4.6 Evaluation Metrics

The performance of the models is evaluated using measures such as accuracy, precision, recall. The measures are calculated based on the following equations.

$$accuracy = \frac{TP + TN}{(TP + FP + TN + FN)} \quad (1)$$

Where, TP – True Positive

TN – True Negative

FP – False Positive

FN – False Negative

$$precision = \frac{Extracted\ Aspects\ \cap True\ Aspects}{Extracted\ Aspects} \tag{2}$$

$$recall = \frac{Extracted\ Aspects\ \cap\ True\ Aspects}{True\ Aspects} \tag{3}$$

$$F\ measure = \frac{2\ \times recall\ \times precision}{recall + precision} \tag{4}$$

The following sections will discuss the evaluation methods and their results in more detail.

The evaluation process is comprised of testing all the following models developed.

- Aspect Extraction Model
- Opinion Extraction and Sentiment Classification Model
- Hybrid Personalized Recommendation
- Augmented Reality Virtual Dressing Room Application

4.7 Evaluation of Aspect Extraction Model

The collected dataset is divided into training and test datasets on the ratio of 80:20. The best hyper parameters for the proposed model are identified by running cross-validation on the training dataset.

The performance of the aspect extraction and selection approaches are evaluated by performing experiments on various combinations of word embedding techniques with a topic modelling approach using Latent Dirichlet Allocation (LDA).

The proposed model is developed with the Bag of Words (BOW) and TF-IDF word embedding techniques. The experiments are carried out with other techniques such as Word2Vec, GloVe, ELMo and FastText.

4.7.1 Evaluation Results of Aspect Extraction Model

The evaluation tests on the divided test data yielded the following results when performed with different word embedding techniques.

Table 9: Evaluation Results of Aspect Extraction Model

Word Embedding Technique	*Accuracy*	*Precision*
Bag of Words (BOW)	80%	71%
TF-IDF	92%	78%
Word2Vec	91%	75%
GloVe	89%	72%
Elmo	82%	71%
FastText	90%	70%

4.8 Evaluation of Opinion Extraction and Sentiment Classification Model

The performance of the sentiment classification approaches is evaluated by performing experiments on various combinations of word embedding techniques with different supervised learning methods.

The proposed model is developed by combining word embedding techniques CountVectorizer and TF-IDFVectorizer with Logistic Regression and State Vector Machine (SVM). The experiments are carried out by combining these word embedding techniques with other supervised learning approaches as follows.

- Naïve Bayes
- Random Forest
- Decision Tree
- K-nearest Neighbour

4.8.1 Results of Opinion Extraction and Sentiment Classification Model

The performance of the different methods is evaluated using accuracy, precision, recall and F score measures.

The evaluation test on the divided test dataset was performed with accuracy as follows with different supervised models. Figure 32 shows the accuracy of the logistic regression model with CountVectorizer (92%) and TF-IDF Vectorizer (90%) respectively.

```
# training
model = LogisticRegression()
model.fit(x_train, y_train)

LogisticRegression()

# testing
pred = model.predict(x_test)

accuracy_score(y_test,pred)

0.9217364720269031
```

```
# training
model = LogisticRegression()
model.fit(x_train, y_train)

LogisticRegression()

# testing
pred = model.predict(x_test)

accuracy_score(y_test,pred)

0.9079792112503822
```

Figure 32: Performance of Logistic Regression Model

Figure 33 shows the accuracy of the Support Vector Machine (SVM) regression model with CountVectorizer (92%) and TF-IDF Vectorizer (91%) respectively.

```
from sklearn.feature_extraction.text import TfidfVectorizer
bow_vectorizer = TfidfVectorizer(max_df=0.90, min_df=2, max_features=1000, stop_words='english')
bow = bow_vectorizer.fit_transform(df['Review_Sentence'])

model = svm.SVC(kernel="linear", probability=True)
x_train, x_test, y_train, y_test = train_test_split(bow, df['label'], test_size=0.33, random_state=42)
model.fit(x_train, y_train)

SVC(kernel='linear', probability=True)

pred = model.predict(x_test)
accuracy_score(y_test,pred)

0.9161648911533117
```

```
model = svm.SVC(kernel="linear", probability=True)
x_train, x_test, y_train, y_test = train_test_split(bow, df['label'], test_size=0.33, random_state=42)
model.fit(x_train, y_train)

SVC(kernel='linear', probability=True)

pred = model.predict(x_test)
accuracy_score(y_test,pred)

0.9214914312181566
```

Figure 33: Performance of SVM model

The trained model is tested with a new dataset extracted from another UK based online store. The users who have published more than 20 item reviews are chosen as seed users. The reviews written by the seed user are extracted to experiment.

The accuracy of the model was observed as in Table 9 given below.

Table 10: Evaluation Results of Sentiment Classification Model

Word Embedding Technique /Supervised Learning Models	*Logistic Regression*	*Support Vector Machine*	*Random Forest*
CountVectorizer	90%	91%	87%
TF-IDF Vectorizer	89%	92%	89%
Word2Vec	85%	89%	83%

4.9 Evaluation of Personalized Recommendation Model

The experiment is set up with 30 participants to use the developed personalized recommendation system. A survey is collected to check whether the users are satisfied with the suggested items.

The accuracy is calculated based on the following equation.

$$Accuracy = \frac{No. of\ participant\ agreed}{No. of\ participants\ disagreed} \times 100 \qquad (5)$$

In the survey, customers are being asked about their personal details, body measurements, and their satisfaction with the generated personalized suggestions. The screenshot of the questionnaire is attached in Appendix C for further reference

According to the survey results obtained, more than half of the people, that is nearly 56% are satisfied with the given suggestions. It is assumed this rate will go higher when the sample size is increased

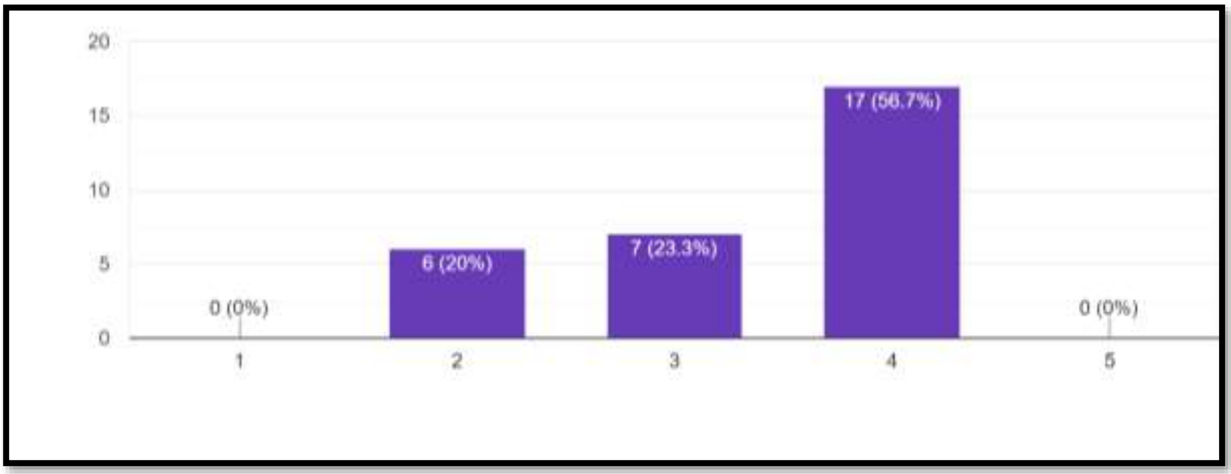


Figure 34: Survey Results on Personalized Suggestion Satisfaction

4.10 Evaluation of Augmented Reality Virtual Dressing Room Application

The experiment is set up with 30 participants from different gender groups and different body sizes to use the Augmented Reality Virtual Dressing Room Application. The accuracy of the application in body measurements and outfit embedding is measured with the actual body measurements provided by the user and the readings of the application.

In the survey people of different sizes and ages are selected to try the Augmented Reality feature. Among all the participants, the people between the age of 25 to 29 and the size of 10 are the majority.

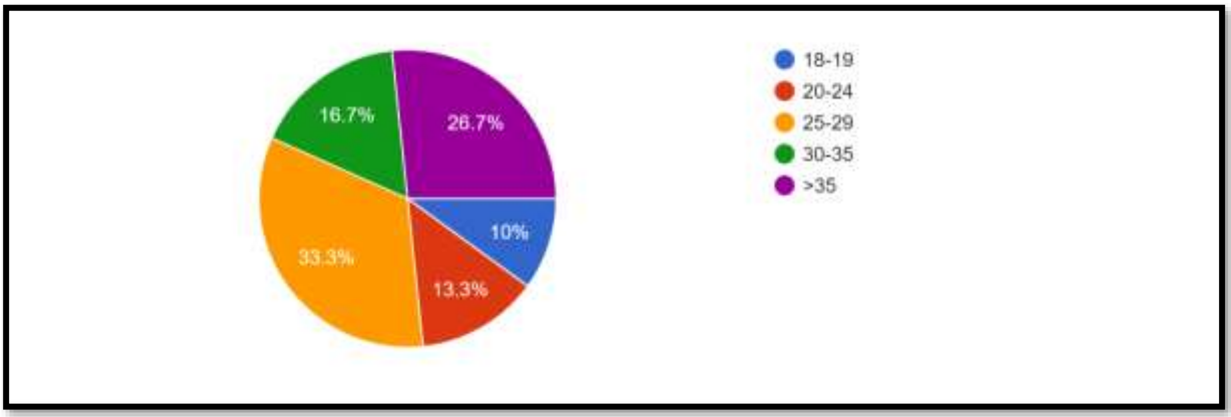


Figure 35: Age Group of Survey Participants

When the actual measurements are compared with the application readings, it is concluded that the developed system achieves 64% of accuracy for the people of size 12 and only 42% for the people of size 14 and 16 in predicting body measurements of the user. It is clear that the body type and size affects the effectiveness of the AR virtual dressing application.

According to the feedback given by the users, it can be concluded that the level of satisfaction with the AR dressing application is neutral. As denoted in Figure 36 most of the participants selected a rating of 3 on a scale of 1 to 5. This shows that AR virtual dressing room application needs more concern towards user-friendliness and accuracy.

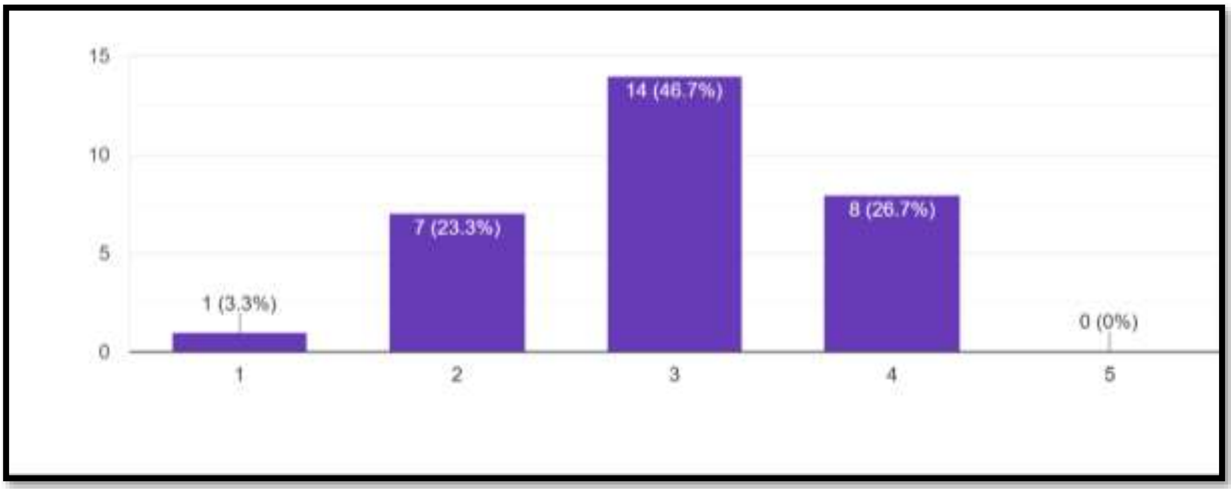


Figure 36: Survey Results on Augmented Reality Dressing Satisfaction

The complete survey results can be found in the Appendix C section.

4.11 Summary

The chapter discussed various evaluation approaches carried out to test the models trained and the applications built. The experiments on the models were carried out based on two datasets: the test dataset divided from the original dataset used for training and the new dataset collected from another UK based online woman clothing store.

The performance of each model is analysed based on the evaluation metrics such as precision, accuracy, recall and F1 score. The evaluation results proved that the trained models and the developed application satisfy the research objectives with the appropriate accuracy level.

CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1 Conclusion

In today's digital world, the web stores a numerous volume of opinionated information from people all around the world. This makes it very difficult to manually analyse the user opinions towards products or services. Even though there were some markable early works on sentiment analysis, opinion mining at aspects level motivates many researchers in recent times heavily.

In the context of sentiment analysis, the majority of the proposed works are based on opinion mining at document and sentence levels. Aspect based opinion mining provides more meaning for reviews by considering each aspect individually. The concept of aspect level sentiment analysis enables new thoughts and approaches that can be used in any potential domain.

This research study proposed a novel approach for aspect extraction and sentiment classification along with how a personalized recommender system can be enhanced with sentiment analysis. In this thesis, all the steps in the proposed approach are explained with design and implementation.

The primary objective of this research is to extract aspects and form aspect-sentiment pairs with improved accuracy and performance. The development of an aspect-based opinion mining novel approach is one of the significant contributions of the research study.

In addition, the study also focused on enhancing personalized suggestions systems with sentiment analysis. The results from the aspect-based opinion mining and personalized suggestions are utilized to make value for businesses. The research showed how these insights can be analysed to perform targeted advertising and marketing campaigns.

A hybrid approach comprising both unsupervised and supervised techniques was proposed as a novel approach for the research problem identified. For performance evaluation, different word embedding techniques are combined with the sentiment classification and tested on multiple datasets.

In all of the experiments, it is found that the recommended aspect-level method is always a few steps ahead. With an average accuracy of 92%, it definitely displays very promising outcomes. This experiment yields excellent results, demonstrating that the proposed method is suitable for both aspect extraction and sentiment classification.

5.2 Future Work

The current system developed is only supported for the English language to perform aspect level opinion mining. To make the system support multilingual, lexical resources like POS taggers, dependency parsers are required for other languages. The development of lexical databases for other languages are considered a future work

Since user written texts are used in opinion mining tasks, there may be syntactical or grammatical errors or users may provide sentences with sarcasm and internet slang. These kinds of errors and texts cause a serious issue in accuracy and performance. This can be limited by implementing a text filter to avoid these sample texts.

Even though the proposed study implements a real system as a proof-of-concept prototype, the study can further expand by considering real-time data in different cross domains.

APPENDICES

Appendix A: Web Application Interfaces

Figure A1: Screenshot of Web Application providing Insights

Figure A2: Screenshot of Brand Insight Interface

Appendix B: Ethics & Consent Form

PARTICIPANT CONSENT FORM

Name of the study: Aspect-Based Opinion Mining on Fashion & Clothing

Purpose of the study: Find fashion and clothing that fits the user requirement and opinion

Researcher: Keerthiga Rajenthiram

Supervisor: Dr. M.G.N.A.S. Fernando

1. I confirm that I have read and understand the information sheet dated 20.12.2020 concerning participation in experimental studies conducted in the Aspect-Based Opinion Mining on Fashion & Clothing have had the opportunity to ask questions, and have had satisfactory answers to any questions. Yes No

2. I understand that my participation is voluntary and that I am free to withdraw at any time, without giving any reason, and without any adverse consequences. Yes No

3. I understand that the information I provide in questionnaires may be looked at by responsible individuals running the experiments. I give permission for these individuals to have access to the information provided for the research project (thesis), and to store anonymised data for further analysis and academic publishing. Yes No

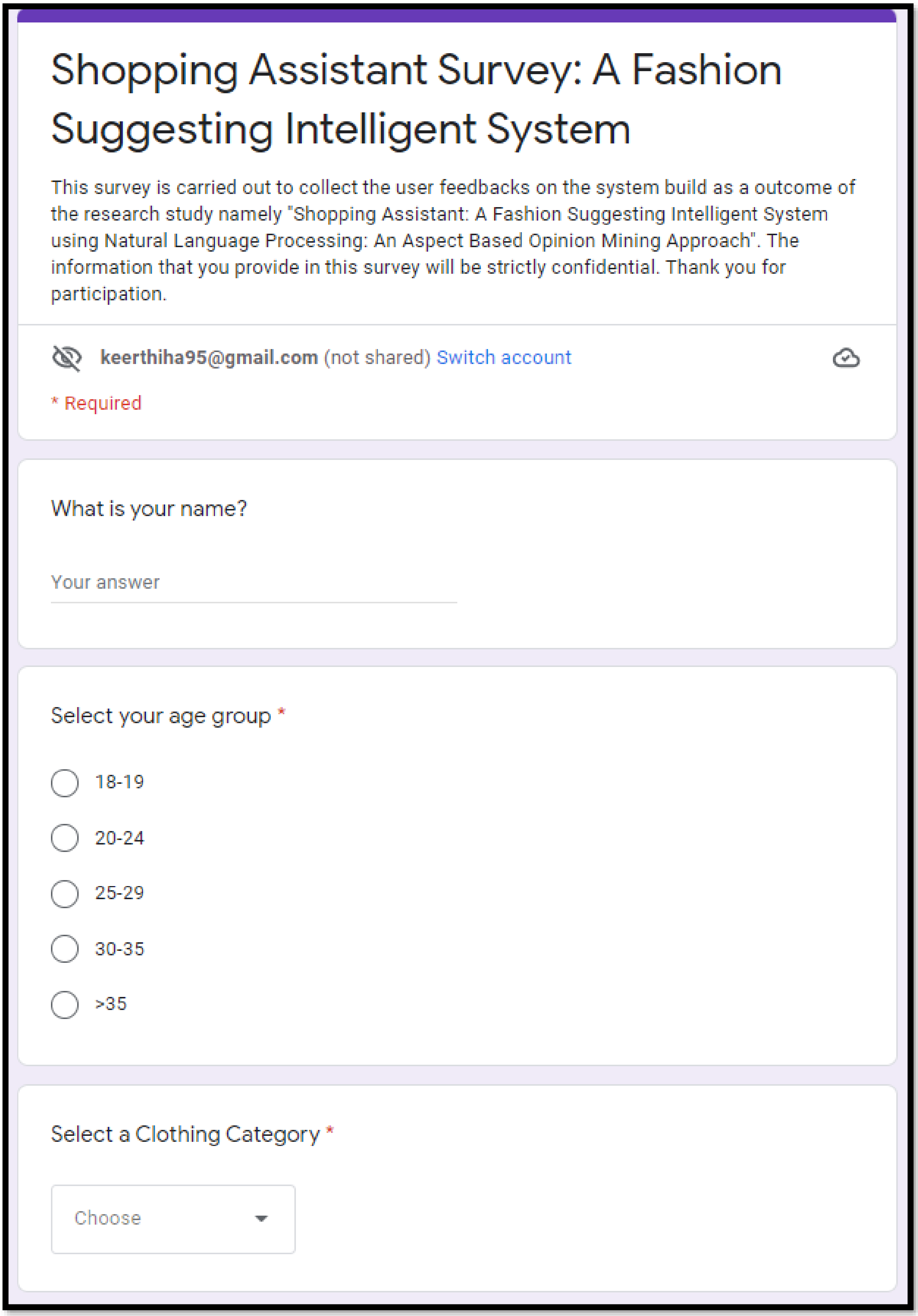
4. I understand that this project has been reviewed by, and received ethics clearance through, the Imagineering Institute Research Ethics Committee, and understand how to raise a concern and make a complaint. Yes No

5. I agree to participate in this study.

________________	______________	________
Name of Participant	Signature	Date
________________	______________	________
Researcher	Signature	Date

Figure B1: Participants Consent Form

Appendix C: Survey Questionnaire & Results



Shopping Assistant Survey: A Fashion Suggesting Intelligent System

This survey is carried out to collect the user feedbacks on the system build as a outcome of the research study namely "Shopping Assistant: A Fashion Suggesting Intelligent System using Natural Language Processing: An Aspect Based Opinion Mining Approach". The information that you provide in this survey will be strictly confidential. Thank you for participation.

keerthiha95@gmail.com (not shared) Switch account

* Required

What is your name?

Your answer

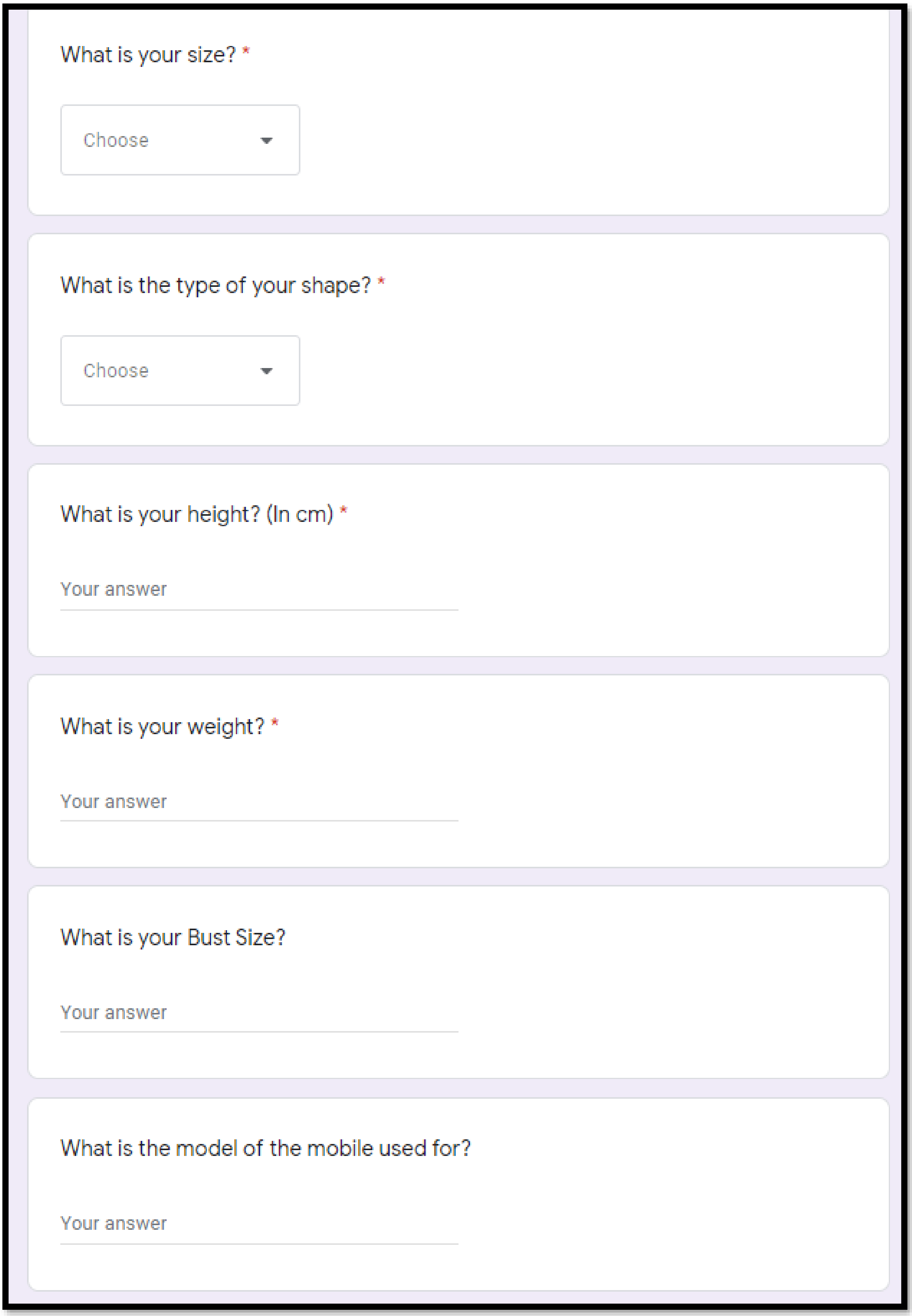
Select your age group *

- 18-19
- 20-24
- 25-29
- 30-35
- >35

Select a Clothing Category *

Choose

Figure C1: Screenshot of Questionnaire Survey



What is your size? *

Choose

What is the type of your shape? *

Choose

What is your height? (In cm) *

Your answer

What is your weight? *

Your answer

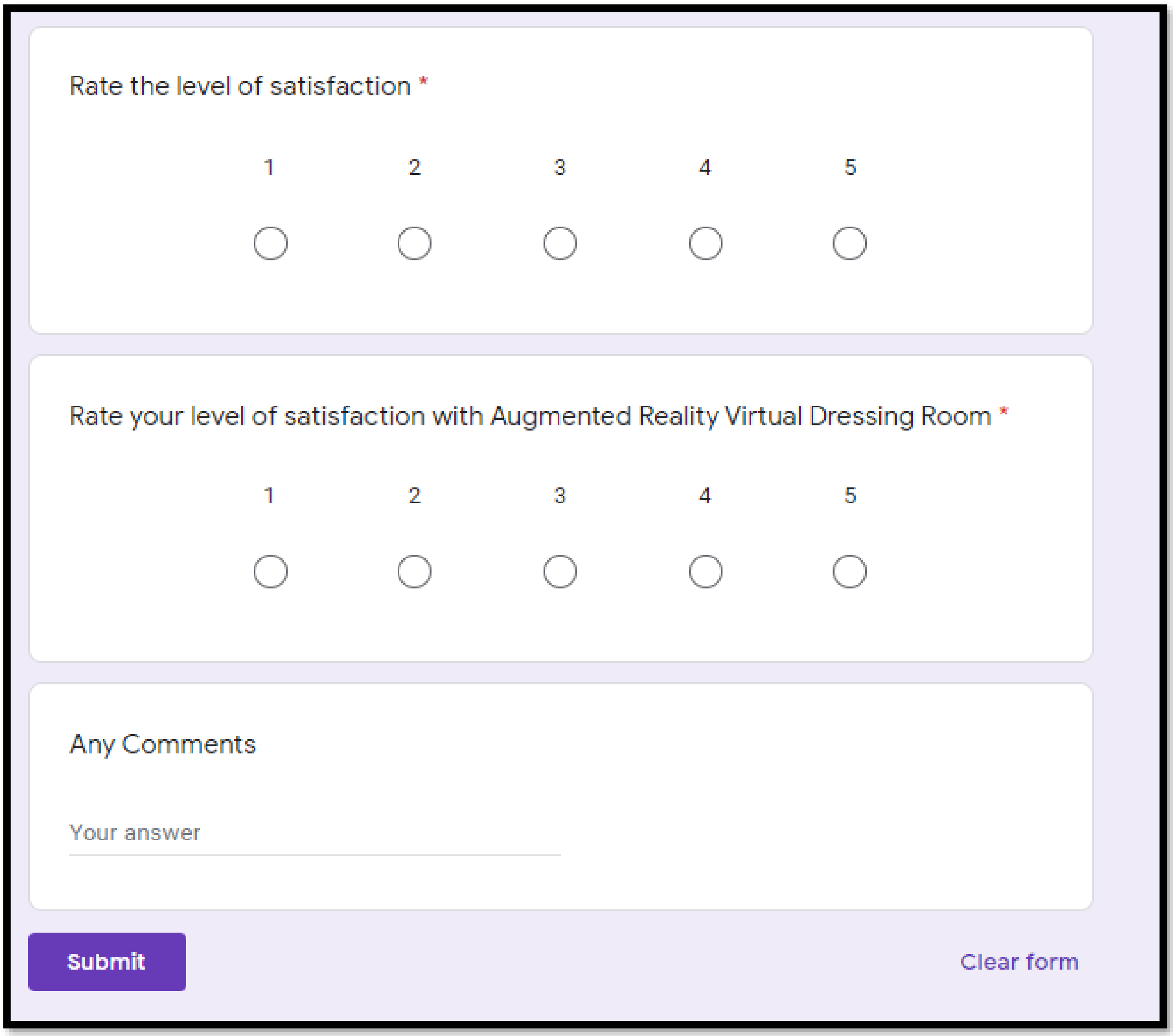
What is your Bust Size?

Your answer

What is the model of the mobile used for?

Your answer

Figure C2: Screenshot of Questionnaire Survey



Rate the level of satisfaction *

1 2 3 4 5

Rate your level of satisfaction with Augmented Reality Virtual Dressing Room *

1 2 3 4 5

Any Comments

Your answer

Submit

Clear form

Figure C3: Screenshot of Questionnaire Survey

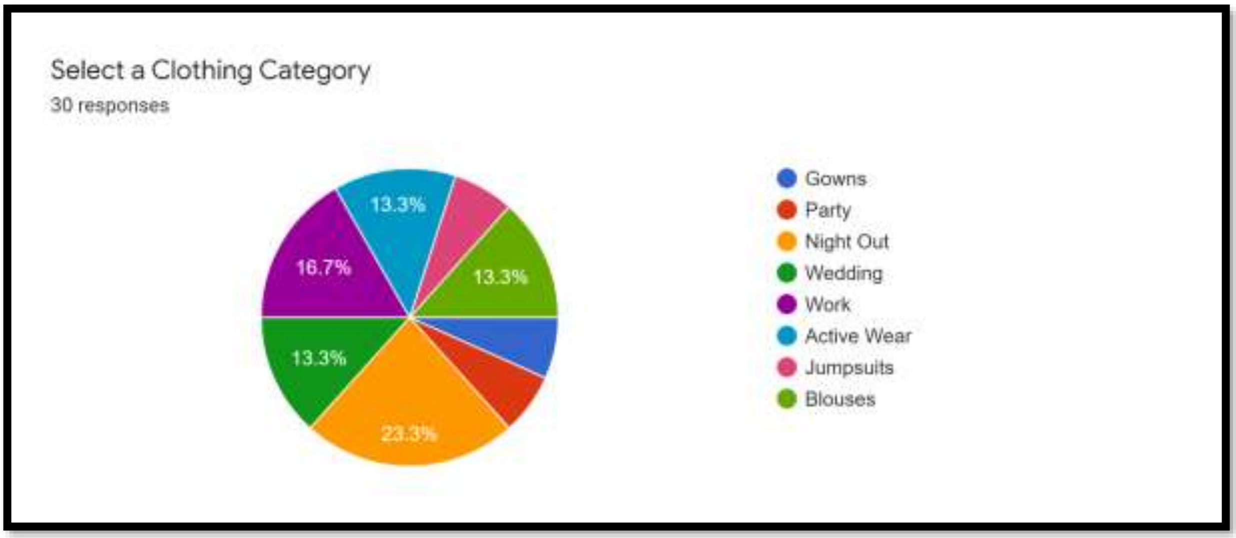
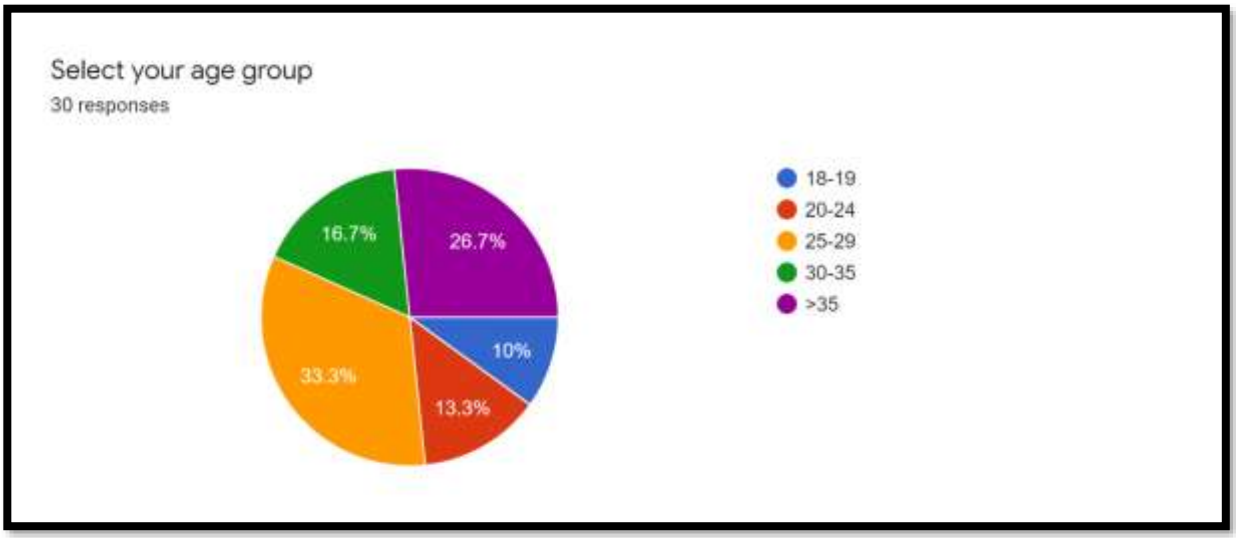
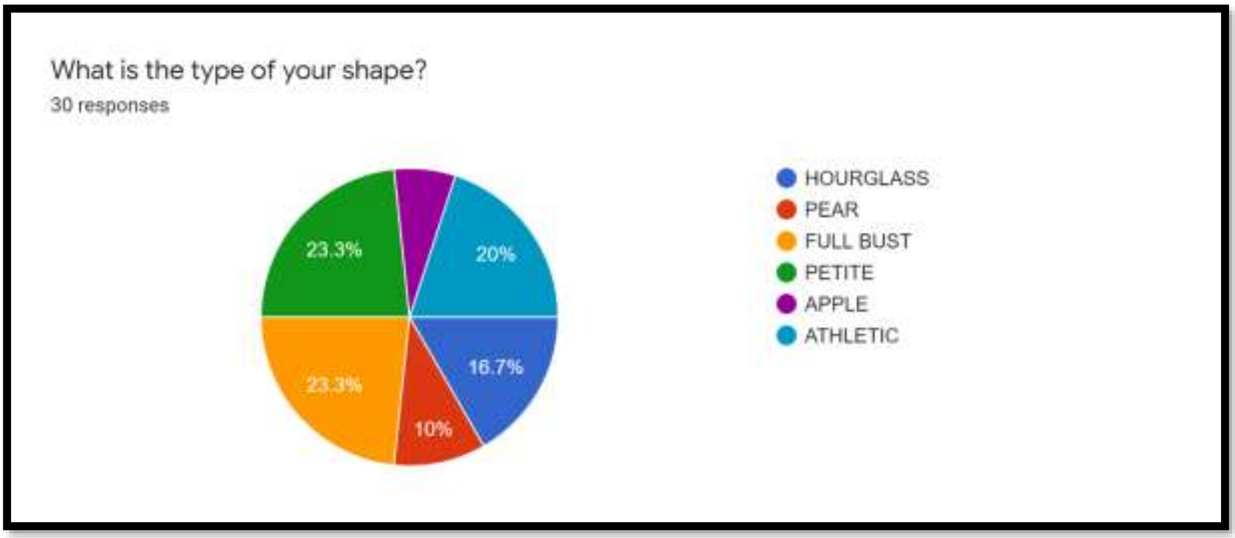


Figure C4: Charts on Survery Results





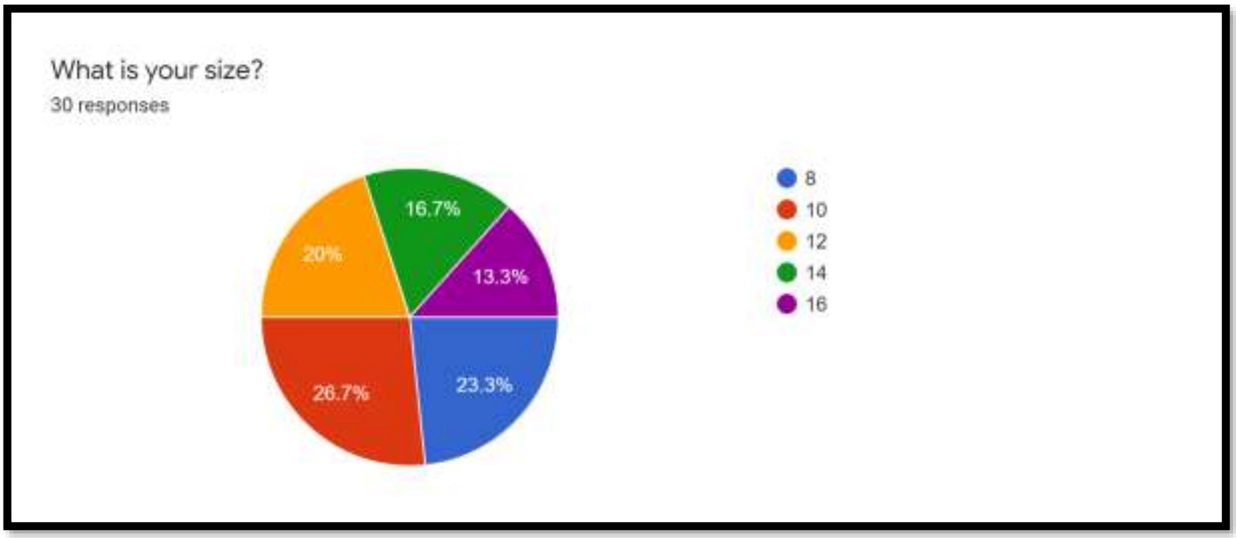
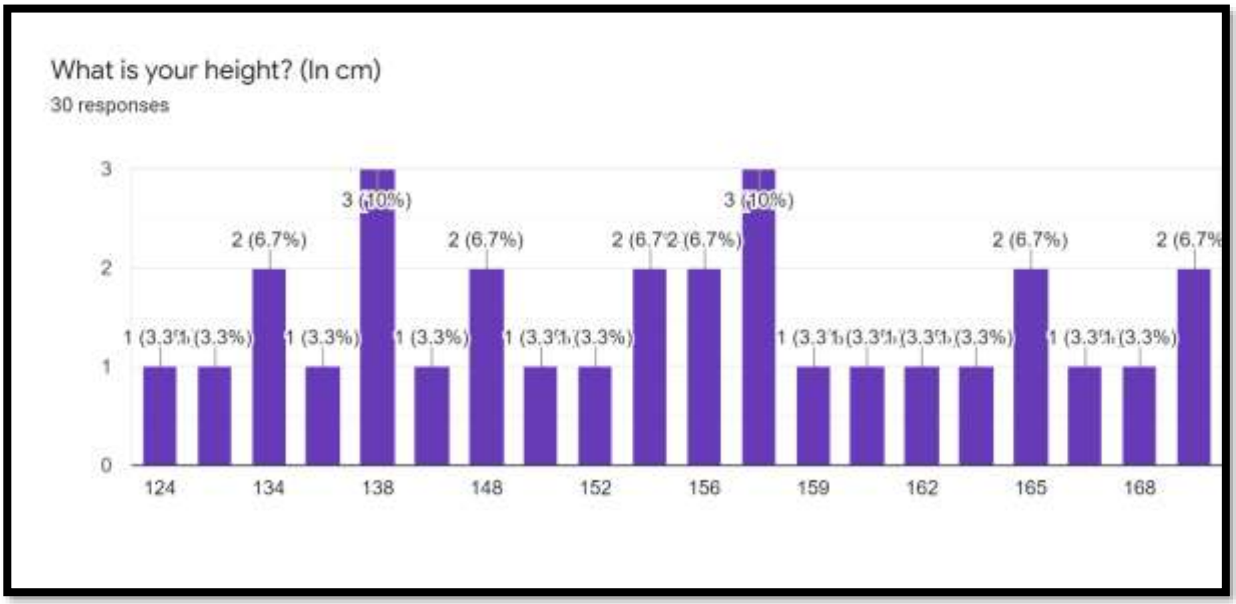
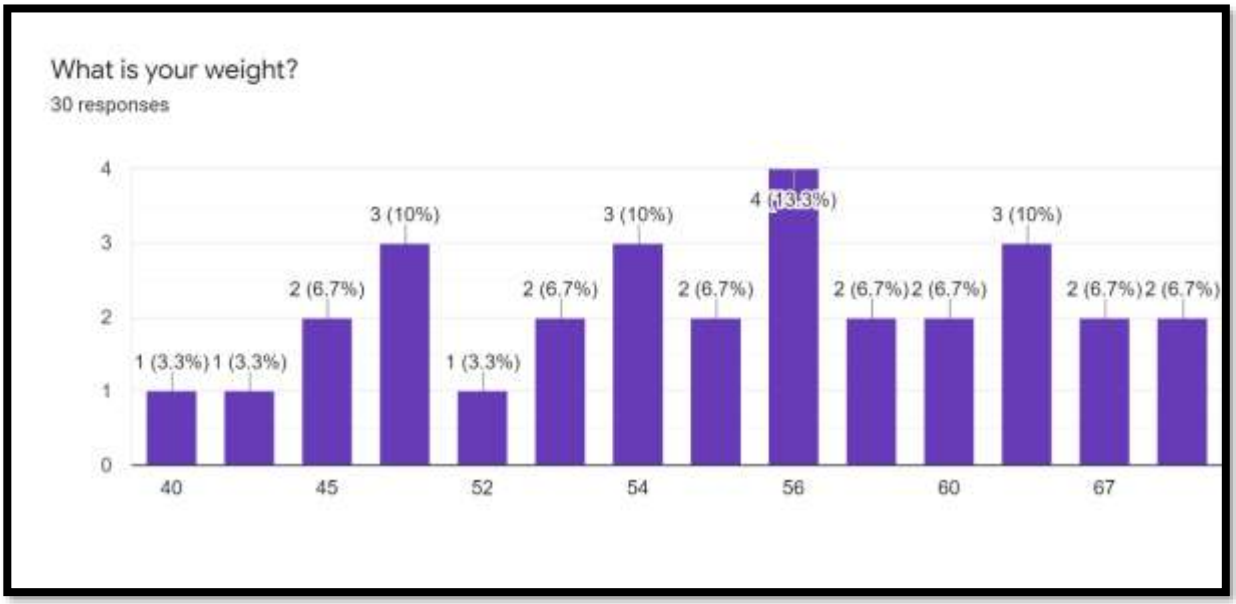


Figure C5: Charts on Survery Results





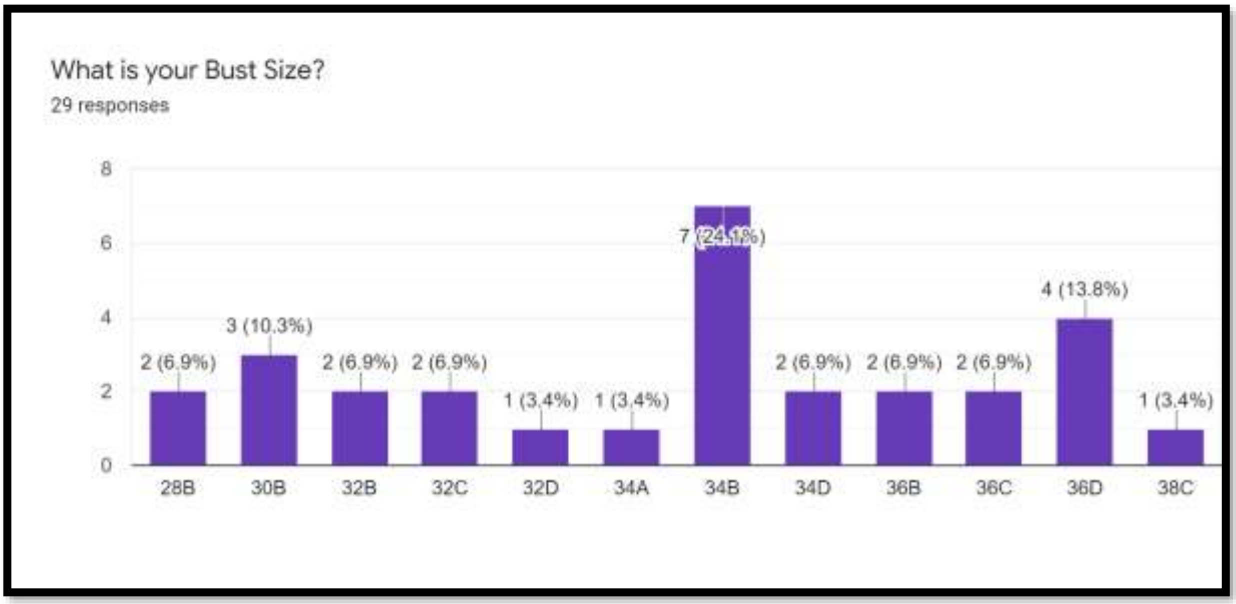


Figure C6: Charts on Survery Results

REFERENCES

Abbasi Moghaddam, S., 2013. Aspect-based opinion mining in online reviews (Thesis). Applied Sciences: School of Computing Science.

Abro, S., Shaikh, S., Abro, R., Fatimah, S., Malik, H.A.M., 2020. Aspect Based Sentimental Analysis of Hotel Reviews: A Comparative Study. Sukkur IBA Journal of Computing and Mathematical Sciences 4, 2520–0755.

Afzaal, M., Usman, M., Fong, A., 2019. Predictive aspect-based sentiment classification of online tourist reviews. Journal of Information Science 45, 341–363. https://doi.org/10.1177/0165551518789872

Al-Matarneh, S.M.A., 2018. CORPUS-BASED CONSTRUCTION OF SENTIMENT LEXICON TO IDENTIFY EXTREME OPINIONS BY SUPERVISED AND UNSUPERVISED MACHINE LEARNING METHODS 140.

Al-Safadi, L.A.E., 2010. A Dual-Mode Intelligent Shopping Assistant 2, 12.

Arboleda, F.J.M., Velásquez, G.A.A., Jiménez, G.L.P., 2017. A Proposal for Brand Analysis with Opinion Mining, in: Perakovic, D. (Ed.), E-Business - State of the Art of ICT Based Challenges and Solutions. InTech. https://doi.org/10.5772/66567

Asghar, M.Z., Khan, A., Ahmad, S., Qasim, M., Khan, I.A., 2017. Lexicon-enhanced sentiment analysis framework using rule-based classification scheme. PLOS ONE 12, e0171649. https://doi.org/10.1371/journal.pone.0171649

Bauman, K., Liu, B., Tuzhilin, A., 2017. Aspect Based Recommendations: Recommending Items with the Most Valuable Aspects Based on User Reviews, in: Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. Presented at the KDD ’17: The 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, ACM, Halifax NS Canada, pp. 717–725. https://doi.org/10.1145/3097983.3098170

Blei, D.M., Ng, A.Y., Jordan, M.I., 2003. Latent dirichlet allocation. J. Mach. Learn. Res. 3, 993–1022.

Boiy, E., Hens, P., Deschacht, K., Moens, M.-F., 2007. Automatic sentiment analysis of on-line text, in: Proceedings of the 11th International Conference on Electronic Publishing. pp. 349–360.

Boonbrahm, S., Kaewrat, C., Sewata, L., Katelertprasert, P., Boonbrahm, P., 2015. 3D Real Time Virtual Fitting Room for Women, in: Marcus, A. (Ed.), Design, User Experience, and Usability: Users and Interactions, Lecture Notes in Computer Science. Springer International Publishing, Cham, pp. 162–171. https://doi.org/10.1007/978-3-319-20898-5_16

Caputo, A., Basile, P., de Gemmis, M., Lops, P., Semeraro, G., Rossiello, G., 2017. SABRE: A Sentiment Aspect-Based Retrieval Engine, in: Lai, C., Giuliani, A., Semeraro, G. (Eds.), Information Filtering and Retrieval: DART 2014: Revised and Invited Papers, Studies in Computational Intelligence. Springer International Publishing, Cham, pp. 63–78. https://doi.org/10.1007/978-3-319-46135-9_4

Dave, K., Lawrence, S., Pennock, D.M., 2003. Mining the peanut gallery: opinion extraction and semantic classification of product reviews, in: Proceedings of the 12th International Conference on World Wide Web, WWW ’03. Association for Computing Machinery, New York, NY, USA, pp. 519–528. https://doi.org/10.1145/775152.775226

Ekman, P., Friesen, W.V., O’Sullivan, M., Chan, A., Diacoyanni-Tarlatzis, I., Heider, K., Krause, R., LeCompte, W.A., Pitcairn, T., Ricci-Bitti, P.E., Scherer, K., Tomita, M., Tzavaras, A., 1987. Universals and cultural differences in the judgments of facial expressions of emotion. Journal of Personality and Social Psychology 53, 712–717. https://doi.org/10.1037/0022-3514.53.4.712

Erra, U., Scanniello, G., Colonnese, V., 2018. Exploring the effectiveness of an augmented reality dressing room. Multimed Tools Appl 77, 25077–25107. https://doi.org/10.1007/s11042-018-5758-2

Gallagher, C., Furey, E., Curran, K., 2019. The Application of Sentiment Analysis and Text Analytics to Customer Experience Reviews to Understand What Customers Are Really Saying: International Journal of Data Warehousing and Mining 15, 21–47. https://doi.org/10.4018/IJDWM.2019100102

Göker, M.H., Thompson, C.A., 2000. Personalized Conversational Case-Based Recommendation, in: Blanzieri, E., Portinale, L. (Eds.), Advances in Case-Based Reasoning, Lecture Notes in Computer Science. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 99–111. https://doi.org/10.1007/3-540-44527-7_10

Gomez-Uribe, C.A., Hunt, N., 2016. The Netflix Recommender System: Algorithms, Business Value, and Innovation. ACM Trans. Manage. Inf. Syst. 6, 13:1-13:19. https://doi.org/10.1145/2843948

Gupta, I., Joshi, N., 2020. Enhanced Twitter Sentiment Analysis Using Hybrid Approach and by Accounting Local Contextual Semantic. Journal of Intelligent Systems 29, 1611–1625. https://doi.org/10.1515/jisys-2019-0106

Hatzivassiloglou, V., McKeown, K.R., 1997. Predicting the semantic orientation of adjectives, in: Proceedings of the 35th Annual Meeting of the Association for Computational Linguistics and Eighth Conference of the European Chapter of the Association for Computational Linguistics, ACL ’98/EACL ’98. Association for Computational Linguistics, USA, pp. 174–181. https://doi.org/10.3115/976909.979640

Hernández-Rubio, M., Cantador, I., Bellogín, A., 2019. A comparative analysis of recommender systems based on item aspect opinions extracted from user reviews. User Modeling and User-Adapted Interaction 29, 381–441. https://doi.org/10.1007/s11257-018-9214-9

Hofmann, T., Pavlopoulos, I., Damianou, A., Polysemy, O., 2001. o Construction of Latent Semantic space.

Holte, M.B., Gao, Y., Petersson Brooks, E., 2015. The Virtual Dressing Room: A Usability and User Experience Study, in: Shumaker, R., Lackey, S. (Eds.), Virtual, Augmented and Mixed Reality, Lecture Notes in Computer Science. Springer International Publishing, Cham, pp. 429–437. https://doi.org/10.1007/978-3-319-21067-4_44

Hu, M., Liu, B., 2004. Mining Opinion Features in Customer Reviews 6.

Isabelle, G., Maharani, W., Asror, I., 2018. Analysis on Opinion Mining Using Combining Lexicon-Based Method and Multinomial Naive Bayes 2, 6.

Kamps, J., Marx, M., Mokken, R.J., Rijke, M.D., 2004. Using WordNet to measure semantic orientation of adjectives, in: In Proceedings of LREC-04, 4th International Conference on Language Resources and Evaluation. pp. 1115–1118.

Karimi, A., Rossi, L., Prati, A., 2021. Adversarial Training for Aspect-Based Sentiment Analysis with BERT, in: 2020 25th International Conference on Pattern Recognition (ICPR). Presented at the 2020 25th International Conference on Pattern Recognition (ICPR), pp. 8797–8803. https://doi.org/10.1109/ICPR48806.2021.9412167

Kastrati, Z., Imran, A.S., Kurti, A., 2020. Weakly Supervised Framework for Aspect-Based Sentiment Analysis on Students' Reviews of MOOCs. IEEE Access 8, 106799–106810. https://doi.org/10.1109/ACCESS.2020.3000739

Keith, B., Fuentes, E., Meneses, C., 2017. A Hybrid Approach for Sentiment Analysis Applied to Paper Reviews. Nova Scotia 10.

Khan, K., Baharudin, B., Khan, A., Ullah, A., 2014. Mining opinion components from unstructured reviews: A review. Journal of King Saud University - Computer and Information Sciences 26, 258–275. https://doi.org/10.1016/j.jksuci.2014.03.009

Kumar, S., De, K., Roy, P.P., 2020. Movie Recommendation System Using Sentiment Analysis From Microblogging Data. IEEE Transactions on Computational Social Systems 7, 915–923. https://doi.org/10.1109/TCSS.2020.2993585

Lafferty, J.D., McCallum, A., Pereira, F.C.N., 2001. Conditional Random Fields: Probabilistic Models for Segmenting and Labeling Sequence Data, in: Proceedings of the Eighteenth International Conference on Machine Learning, ICML '01. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, pp. 282–289.

Lee, H., Xu, Y., 2020. Classification of virtual fitting room technologies in the fashion industry: from the perspective of consumer experience. International Journal of Fashion Design, Technology and Education 13, 1–10. https://doi.org/10.1080/17543266.2019.1657505

Leung, C.W., Chan, S.C., Chung, F., 2017. Integrating Collaborative Filtering and Sentiment Analysis: A Rating Inference Approach 5.

Liu, B., 2012. Sentiment Analysis and Opinion Mining. Synthesis Lectures on Human Language Technologies 5, 1–167. https://doi.org/10.2200/S00416ED1V01Y201204HLT016

Liu, B., 2010. Sentiment Analysis and Subjectivity. in Handbook of Natural Language Processing, Second Edition, (editors: N. Indurkhya and F. J. Damerau) 38.

Liu, B. (Ed.), 2007. Opinion Mining, in: Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data, Data-Centric Systems and Applications. Springer, Berlin, Heidelberg, pp. 411–447. https://doi.org/10.1007/978-3-540-37882-2_11

Lu, B., 2010. Identifying Opinion Holders and Targets with Dependency Parser in Chinese News Texts, in: Proceedings of the NAACL HLT 2010 Student Research Workshop. Association for Computational Linguistics, Los Angeles, CA, pp. 46–51.

Lu, Y., Zhai, C., Sundaresan, N., 2009. Rated aspect summarization of short comments, in: Proceedings of the 18th International Conference on World Wide Web - WWW '09. Presented at the the 18th international conference, ACM Press, Madrid, Spain, p. 131. https://doi.org/10.1145/1526709.1526728

Maedche, A., 2002. Ontology Learning for the Semantic Web, The Springer International Series in Engineering and Computer Science. Springer US. https://doi.org/10.1007/978-1-4615-0925-7

Miller, G.A., 1995. AI commonsense problems WordNet: A Lexical Database for.

Nawaz, A., Awan, A.A., Ali, T., Rana, M.R.R., 2020. Product's behaviour recommendations using free text: an aspect based sentiment analysis approach. Cluster Comput 23, 1267–1279. https://doi.org/10.1007/s10586-019-02995-1

Pang, B., Lee, L., 2008. Opinion mining and sentiment analysis 94.

Pang, B., Lee, L., 2005. Seeing stars: exploiting class relationships for sentiment categorization with respect to rating scales, in: Proceedings of the 43rd Annual Meeting on Association for Computational Linguistics - ACL '05. Presented at the the 43rd Annual Meeting, Association for Computational Linguistics, Ann Arbor, Michigan, pp. 115–124. https://doi.org/10.3115/1219840.1219855

Pang, B., Lee, L., Vaithyanathan, S., 2002. Thumbs up? sentiment classification using machine learning techniques, in: Proceedings of the ACL-02 Conference on Empirical Methods in Natural Language Processing - Volume 10, EMNLP '02. Association for Computational Linguistics, USA, pp. 79–86. https://doi.org/10.3115/1118693.1118704

Proios, D., Eirinaki, M., Varlamis, I., 2015. TipMe: Personalized advertising and aspect-based opinion mining for users and businesses, in: Proceedings of the 2015 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2015. Presented at the ASONAM '15: Advances in Social Networks Analysis and Mining 2015, ACM, Paris France, pp. 1489–1494. https://doi.org/10.1145/2808797.2809324

Qiu, G., Liu, B., Bu, J., Chen, C., 2011. Opinion Word Expansion and Target Extraction through Double Propagation. Computational Linguistics 37, 9–27. https://doi.org/10.1162/coli_a_00034

Rabiner, L.R., 1989. A tutorial on hidden Markov models and selected applications in speech recognition. Proceedings of the IEEE 77, 257–286. https://doi.org/10.1109/5.18626

Scaffidi, C., Bierhoff, K., Chang, E., Felker, M., Ng, H., Jin, C., 2007. Red Opal: product-feature scoring from reviews, in: Proceedings of the 8th ACM Conference on Electronic Commerce, EC '07. Association for Computing Machinery, New York, NY, USA, pp. 182–191. https://doi.org/10.1145/1250910.1250938

Schler, J., 2005. The importance of neutral examples for learning sentiment, in: In Workshop on the Analysis of Informal and Formal Information Exchange during Negotiations (FINEXIN.

Sebastiani, A.F., Esuli, A., Sebastiani, F., 2006. Determining Term Subjectivity and Term Orientation for Opinion Mining Andrea Esuli, in: In Proceedings of the 11th Conference of the European Chapter of the Association for Computational Linguistics (EACL'06.

Seki, Y., Evans, D.K., Ku, L.-W., Sun, L., Chen, H.-H., Kando, N., 2008. Overview of Multilingual Opinion Analysis Task at NTCIR-7 19.

Shafqat, W., Byun, Y.-C., 2020. A Recommendation Mechanism for Under-Emphasized Tourist Spots Using Topic Modeling and Sentiment Analysis. Sustainability 12, 320. https://doi.org/10.3390/su12010320

Shardanand, U., Maes, P., 1995. Social information filtering: algorithms for automating “word of mouth”, in: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, CHI '95. ACM Press/Addison-Wesley Publishing Co., USA, pp. 210–217. https://doi.org/10.1145/223904.223931

Snyder, B., Barzilay, R., 2007. Multiple Aspect Ranking using the Good Grief Algorithm 8.

Turney, P.D., 2002. Thumbs up or thumbs down? semantic orientation applied to unsupervised classification of reviews, in: Proceedings of the 40th Annual Meeting on Association for Computational Linguistics, ACL '02. Association for Computational Linguistics, USA, pp. 417–424. https://doi.org/10.3115/1073083.1073153

Tuzhilin, A., 2012. Customer relationship management and Web mining: the next frontier. Data Min Knowl Disc 24, 584–612. https://doi.org/10.1007/s10618-012-0256-z

Wang, Y., Liu, Y., Yu, X., 2012. Collaborative Filtering with Aspect-Based Opinion Mining: A Tensor Factorization Approach, in: 2012 IEEE 12th International Conference on Data Mining. Presented at the 2012 IEEE 12th International Conference on Data Mining, pp. 1152–1157. https://doi.org/10.1109/ICDM.2012.76

Wiebe, J., Wilson, T., Cardie, C., 2005. Annotating Expressions of Opinions and Emotions in Language. Language Res Eval 39, 165–210. https://doi.org/10.1007/s10579-005-7880-9

Wilson, T.A., 2008. Fine-grained Subjectivity and Sentiment Analysis 214.

Xue, W., 2017. Aspect Based Sentiment Analysis On Review Data. FIU Electronic Theses and Dissertations. https://doi.org/10.25148/etd.FIDC004076

Yaoyuneyong, G., Foster, J.K., Flynn, L.R., 2014. Factors impacting the efficacy of augmented reality virtual dressing room technology as a tool for online visual merchandising. Journal of Global Fashion Marketing 5, 283–296. https://doi.org/10.1080/20932685.2014.926129