ONLINE SHOPPING SITES RESEARCH AND ANALYSIS
(FOCUSING ON ONLINE SHOPPING BEHAVIOUR)

Declaration

I hereby declare that this research project titled "Online Shopping Sites Research and Analysis" is my work and has not been previously submitted for any degree or other qualification at any institution. The research presented herein is conducted with due diligence, adhering to academic integrity and ethical standards. All sources of information and contributions from other researchers have been duly acknowledged. I confirm that the work is original and has been carried out under the guidance of my advisor.

Acknowledgment

It provides me immense pleasure to present my dissertation entitled ***"Online Shopping Sites Research and Analysis (Focusing on Online Shopping Behavior)"***. I wish to extend my most sincere gratitude to those who have helped me to lead this research work toward a reality. Firstly, I thank those who have helped me to gather data throughout the research. I would like to present my heartiest thanks to my professors who have helped me to understand this topic and have also helped me to conclude this study. I would also like to thank my fellow mates and friends who provided me with enough assistance to reach a definite goal. I acknowledge the support of batch mates, supervisors as well as professors for this study and I declare myself to be solely responsible for the shortcomings of this research.

Abstract

Chapter 1: Introduction, the impact of selected features and new technologies, like AI and AR, in virtual shopping sites and the responses of consumers. This research aims to estimate the impacts of design, functionality, and technological innovations on user experiences, satisfaction, and engagement. This will involve the knowledge of these elements to better facilitate online shopping websites to enable businesses and consumers in this rapidly changing retail environment. The findings help in the advancement of customer-oriented e-shopping environments and future developments for e-commerce.

Chapter 2: Literature Review, the theoretical underpinning, trends, and technologies that have shaped online shopping behavior. The drivers of impulse buying in social commerce, consumer behavior across e-channels, and perceived risks affecting satisfaction and purchase intention will be looked upon. A discussion of a proposed model that integrates the Technology Acceptance Model with the Online Purchase Decision-Making Process in assessing consumer behavior is done. Literature gaps concern a lack of studies on long-term behavior changes, psychological processes involved, and emerging technologies used in e-commerce.

Chapter 3: Methodology, signifies the research uses the Exploratory Data Analysis (EDA) approach and feature engineering to examine online buying consumer behavior. K-means clustering is used to categorize the clients while Linear Regression, Logistic Regression, Random Forest, and XGBoost can be used to make predictions. The study tends to utilize quantitative data collection and analysis to evaluate online shopping experiences with the ethical use of data for improved and added value.

Chapter 4: Results and Discussion, focusing on the results of the analysis of online buying behavior. It shows key outcomes of exploratory data analysis, feature selections and creating predictive models such as K-means clustering to distinguish customer segments. The correlation heatmap identified that ‘Hour’ had a negligible effect on ‘Quantity’ and ‘TotalPurchase’ was directly proportional to ‘Quantity’. The future buying trend models including Linear Regression, Logistic Regression, Random Forest and XGBoost analysis offered useful information. The chapter is closed with the e-commerce consequences and recommendations for further studies.

Chapter 5: Evaluation and Conclusion, provides a brief of accomplishments correlates the result found with the goal and aims set ahead and proposes suggestions for improvement of online shopping interfaces. Recommendations for future research are noted, focusing on Longitudinal

research, psychological factors and, Qualitative research. Also, the role and influence of social commerce and user-generated content are established as vital research themes. The chapter emphasizes constant research on developments in online shopping as it is a constantly evolving phenomenon.

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Chapter 1: Introduction

1.1 Introduction

E-commerce has defined a new epoch in the domain of retailing thereby making online shopping sites the core constituents of present-day consumption patterns. As new technologies emerge, it is critical to analyze the tendencies of consumers' interactions with digital tools and the efficiency of certain characteristics. This research focuses on the websites that involve online shopping and the impact of usability, feasibility, and key technologies concerning users' interactions and buying behavior. The study seeks to present recommendations on the proper functioning of online shopping platforms. It is about making the overall retail environment for e-commerce better for the ultimate consumer and other stakeholders in the process.

1.2 Research Background

E-shopping has become an integral aspect of modern retailing globally which is enhanced by the use of technology as well as consumers' changing preferences. The increased use of mobile devices and the internet to make purchases has put the consumer in possession of a vast choice of products as well as services hence changing the retail environment. These advancements have birthed several forms of e-commerce with various methodologies to observe and maintain consumers. This paper discusses several aspects such as user perspective, technicalities, and promotional aspects in this realm of research (Saoula *et al.* 2023). Past research has identified several important aspects, including site design, searching capabilities, and customization as important drivers for consumer behaviour. Well-designed site maps and search options improve site usability and increase consumer satisfaction in buying products. Personalization, on the other hand, customizes shopping to personal preferences which might lead to more interactions and the resulting conversion. Thus, it becomes critical to examine such factors as IT developments in the e-commerce environment. In particular, AI and AR, and shifts in customer preferences influence the efficacy and productivity of e-commerce platforms. This exploration helps to understand how these factors affect users' engagement and site effectiveness.

1.3 Research Rationale

This kind of research rationale is derived from the emergence of new online buying and selling and the need for enterprises to keep up with the changing market forces. With the increased use of digital platforms for consumers' shopping, awareness of the features that motivate users and affect their decisions is even more important. After discussing present e-commerce research efforts in detail, a profound deficit in understanding the impact of specific site characteristics. Also, newer technologies on both user experience and site performance remain apparent (Fadillah and Kusumawati, 2021). This is particularly important to fill the gap of delivering insights that may help online shopping sites improve their layout and performance.

This gap is examining the effects of features and technology on consumers' experiences with online shopping sites. Such elements are crucial to discovering significant findings that can contribute to improving user experience and customer satisfaction and ultimately lead to business development. Furthermore, with increased focus on individualism and increased incorporations of new technologies, provides additional comprehension of the various tendencies affecting the consumers and the website results. Finally, it is expected that the results of the study will be useful in enhancing the effectiveness of online shopping sites.

1.4 Research Aim and Objectives

Aim

The project aim is to investigate the effects of various features and new technologies on web-based shopping sites and the effects on the behaviour of shoppers.

Objectives

- To assess the effects of design and functionality factors on customers' experience and their choice of a particular product.
- To determine the extent to which emerging technologies have helped in making online shopping better.
- To establish the factors that influence consumer interaction and satisfaction with online shopping websites.
- To determine which of the two groups of features for e-commerce is more effective in driving the users' engagement and conversion rates.
- To offer a practical course of action that can be implemented on online shopping sites about the research.

1.5 Research Questions

1. How do tools and services provided by online shopping sites like search tools and customer reviews affect consumers and their buying behavior?
2. How do technologies, like ***"Artificial Intelligence"*** or ***"Augmented Reality"***, influence the usability and efficiency of online shopping platforms?

3. Which age groups and cultural demographics visit online shopping sites and what are their particular behaviours, strengths, and weaknesses?
4. What extent does the general appearance and structure of a website facilitate overall consumer satisfaction and loyalty on e-commerce platforms?
5. What extent do target advertising messages and recommendation systems influence active consumer engagement and purchasing behaviour on such sites?

1.6 Research Significance

This research is important as it discusses the facets of or relating to online shopping sites that affect both the business persons and the users. These research findings are useful in highlighting strategies that may help in enhancing shopping websites. The implications offer insights to improve the overall online strategy, user experience, and customer satisfaction. Such changes can result in additional sales production and cultivated and enhanced competitive position in the continually progressing environment for e-business. Consumers benefit from the research by gaining insight into how the online shopping environment can be modified to suit their expectations. The opportunities of the future and advanced technologies, including artificial intelligence and augmented reality, show how innovation can enhance the purchase journey in online shops (Ismagilova *et al.* 2020). This study points to the potential of directing the design and operations of digital retail sites to accommodate the needs of today’s consumers and support business success. Furthermore, it contributes to the understanding of the online shopping concept and contributes to future developments in this area.

1.7 Research Structure

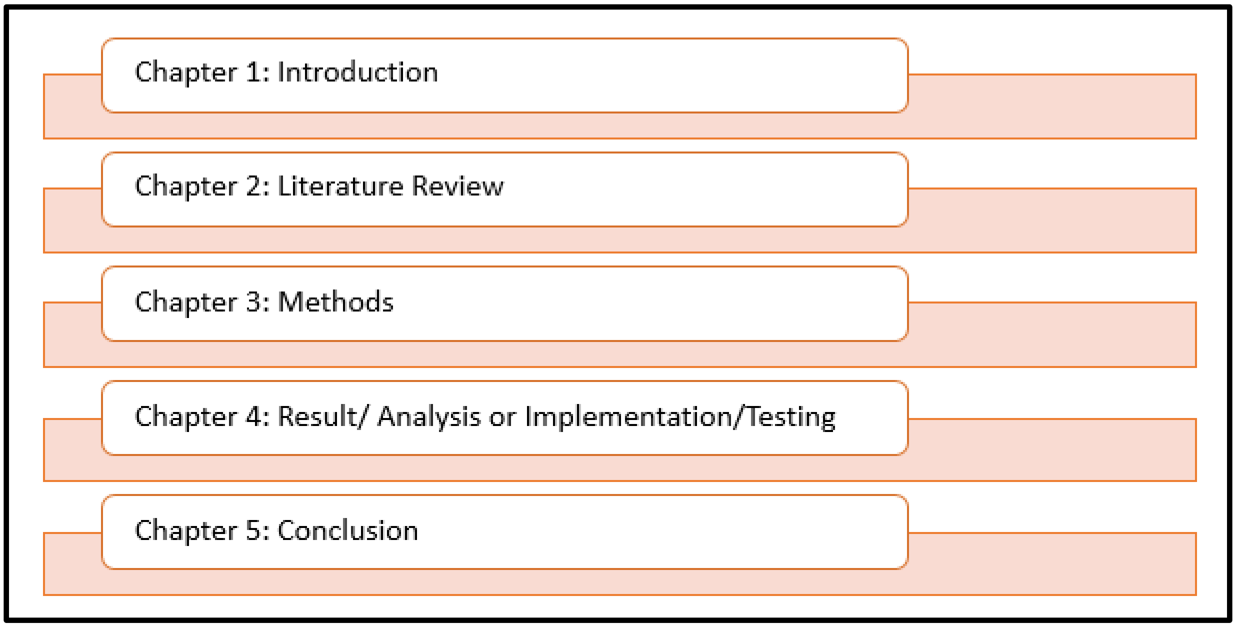

Figure 1.7.1: Structure of the Research

1.8 Summary

This chapter begins the research on online shopping sites and describes the significance of their effects on consumer behavior with the help of newer technologies. These include the research background, rationale, aim, objectives, and significance which form the basis for a detailed evaluation of digital retail platforms. Again, the chapter outlines the research questions as well as the flow of the research; therefore, creates the direction of the study. Thus, by considering these aspects, the research seeks to contribute to improving consumers' online shopping experience and increasing the efficiency of e-retail initiatives.

Chapter 2: Literature Review

2.1 Introduction

The study is used to establish an understanding of related research and various theories surrounding online shopping sites. It is expected to provide an understanding of the e-commerce environment and trends in the relevant field and key technologies that underpin the digital retail construct. This chapter discusses initial theoretical frameworks for consumer behaviour, discusses the effects of new technologies on the online buying process, and reviews such trends in website usability. The literature review section provides a theoretical framework based on an analysis of prior research examining the effects of online shopping platforms on consumer communication and behaviour.

2.2 Use of Literature

2.2.1 Antecedent of Online Impulse Buying Behavior in Social Commerce

“Impulse Customer Buying Behavior” has become very prominent in the digital commerce landscape, particularly in social commerce. ***“Social Commerce”*** is a subset of e-commerce that integrates social networking as well as user-generated content with online shopping. It creates a highly interactive environment that stimulates impulse purchases (Abdelsalam *et al.* 2020). The unique nature of S-commerce platforms is characterized by social interactions, peer influence, and seamless integration of shopping features. It has amplified the prevalence of impulse buying behaviors among consumers.

Key Drivers of Online Impulse Buying in S-Commerce

The drivers of ***“Online Impulse Buying Behavior”*** in S-commerce need to be clearly understood by both researchers and practitioners. The different literature identified key drivers of impulse buying, which can be broadly categorized into three groups: psychological, social, and technological factors. It is also highly dependent on the psychological factors of the customer: their emotions, moods, and perceptions. Easy access to products and instant satisfaction from purchases also contribute to unplanned buying. The attractiveness of the products, scarcity in supply, and personal recommendation also trigger such impulsive behavior.

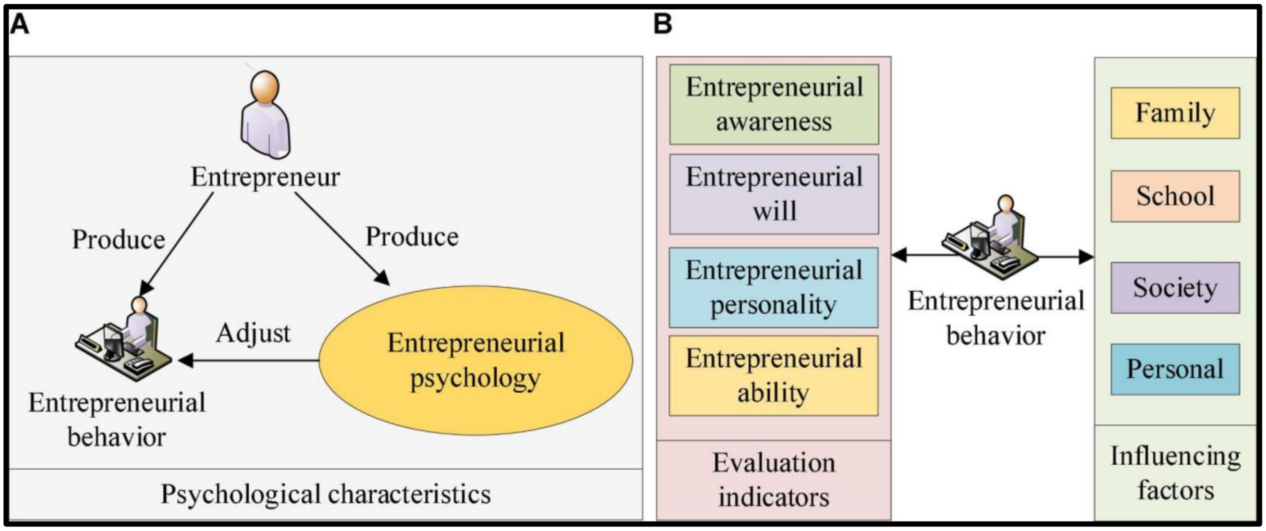

Figure 2.2.1.1: Online Impulse Buying Behavior

(Source: frontiersin, 2024)

The social factors of S-commerce, such as peer recommendations, reviews, and endorsements, are great influencers of buying behavior. The need for social conformity or, rather, social proof, whereby people do what others do, tends to motivate many buyers into making impulse purchases. Also, the nature of these social interactions is the promotion of urgency and excitement, and this compels unplanned buying. It is facilitated by the technological design of the S-commerce sites including the user interface design, ease of navigation, integrated payment systems, one-click purchasing, and AI-driven product recommendations (Moon *et al.* 2021). It has personalized shopping experiences among others that combine to increase unplanned consumer purchasing.

Development of a Causal-Chain Framework

These methods have been effective in capturing consumer attitudes, behaviors, and the impact of various stimuli on impulse purchases. The broad application of the S-O-R model in these studies underlines how external stimuli, such as marketing cues or social interactions, impact internal consumer states. This study has casually generated the chain framework on ***"Online Impulse Buying in S-Commerce"***, with a clear classification of inputs to the IBB: marketing stimuli and social influence; moderators: consumer traits and situational factors; mediators: emotional responses and cognitive processing; and outputs: purchase decisions. This gives a structured insight into the interaction among the various factors that drive impulse buying within the digital social environment.

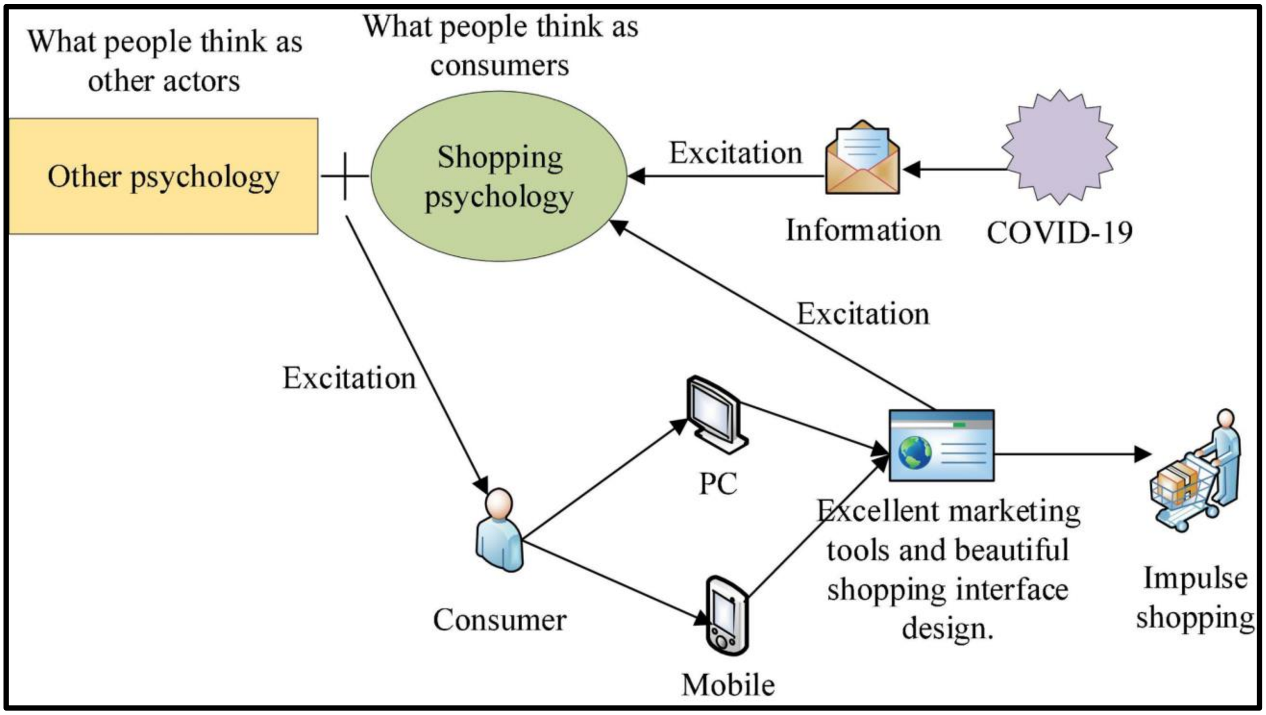

Figure 2.2.1.2: Online Impulse Buying Behavior and Marketing Optimization Guided

(Source: frontiersin, 2024)

The authors of the reviewed studies themselves have emphasized the need for more studies to be conducted on under-researched areas. Including the long-term effect of online impulse purchases on consumer satisfaction and loyalty. The role emergent technologies like augmented reality play in shaping impulse buying behavior, and also S-commerce cross-cultural perspectives (Peña-García *et al.* 2020). In addition, future research needs to be directed at the construction of advanced models incorporating real-time data analytics that can provide better predictions and influence consumer behaviour in the dynamic S-commerce environment.

2.2.2 Online Retailing Across E-Channels and E-Channel Touchpoints: Literature Review of Consumer Behavior in Multichannel E-Commerce Context

According to the multichannel and multi-touchpoint influences affecting the consumers, in today's dynamic e-commerce environment, multiple electronic channels or channels. The more buyers interact with online retailers through different kinds of devices and platforms, the more apparent the need to treat online retailing differently (Wagner *et al.* 2020). This section examines some of the empirical studies on how consumers engage with online retailing across channels and touchpoints for a deeper understanding of the multichannel e-commerce environment.

Gaining Insight into E-Channels and Touchpoints

E-channels are the various electronic platforms on which consumers engage in online shopping. The e-channel touchpoints are the different formats or interfaces of these channels, such as for shopping mobile apps, the web, and social media sites. All the e-channels and touchpoints elicit distinct impressions and values for consumers and therefore influence their shopping patterns and choices. During the studies, wide-ranging scenario profiles and patterns of how various consumer e-channels and points of contact were utilized in shopping were obtained by one online survey. An experimental study is more capable of providing valuable insights into what specific factors drive the choices and behaviors of consumers across the channels.

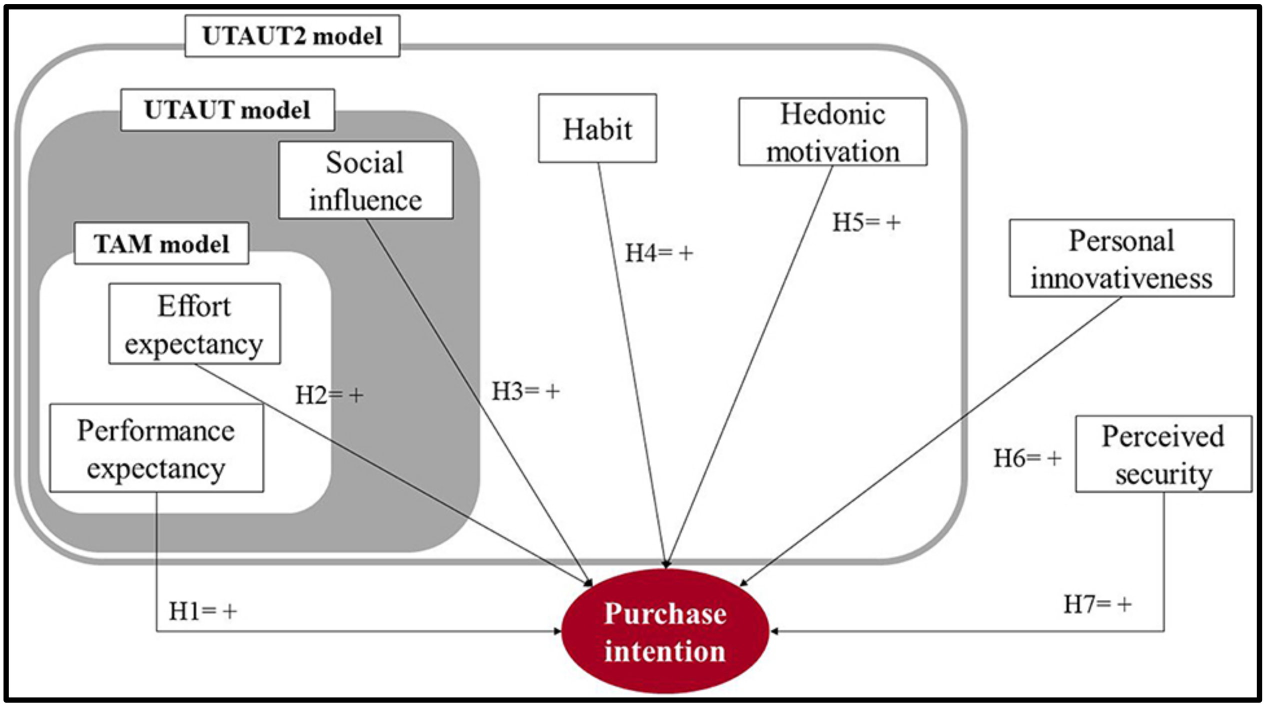

Figure 2.2.2.1: Omnichannel Customer Behavior

(Source: frontiersin, 2024)

"Online Retailing" is segmented into four clear categories of e-commerce, each with its associated ***"E-Channel Touchpoints"***. These categories also indicate the multifarious ways in which consumers engage with online retailers and the need to tailor retail strategies to these varied touchpoints (Giao *et al.* 2020). The results can one approach work in online retailing for all, but the experiences and preferences of consumers also sharply vary across different e-channels and touchpoints.

Impact of Technology-Related Quality and Context-Related Situational Benefits

Technology-related quality is defined as the technical performance and user experience brought forth by the e-channel, such as website speed, mobile app functionality, and ease of navigation. The better the technology, the smaller the bridge to satisfaction, and increased use of the e-channel.

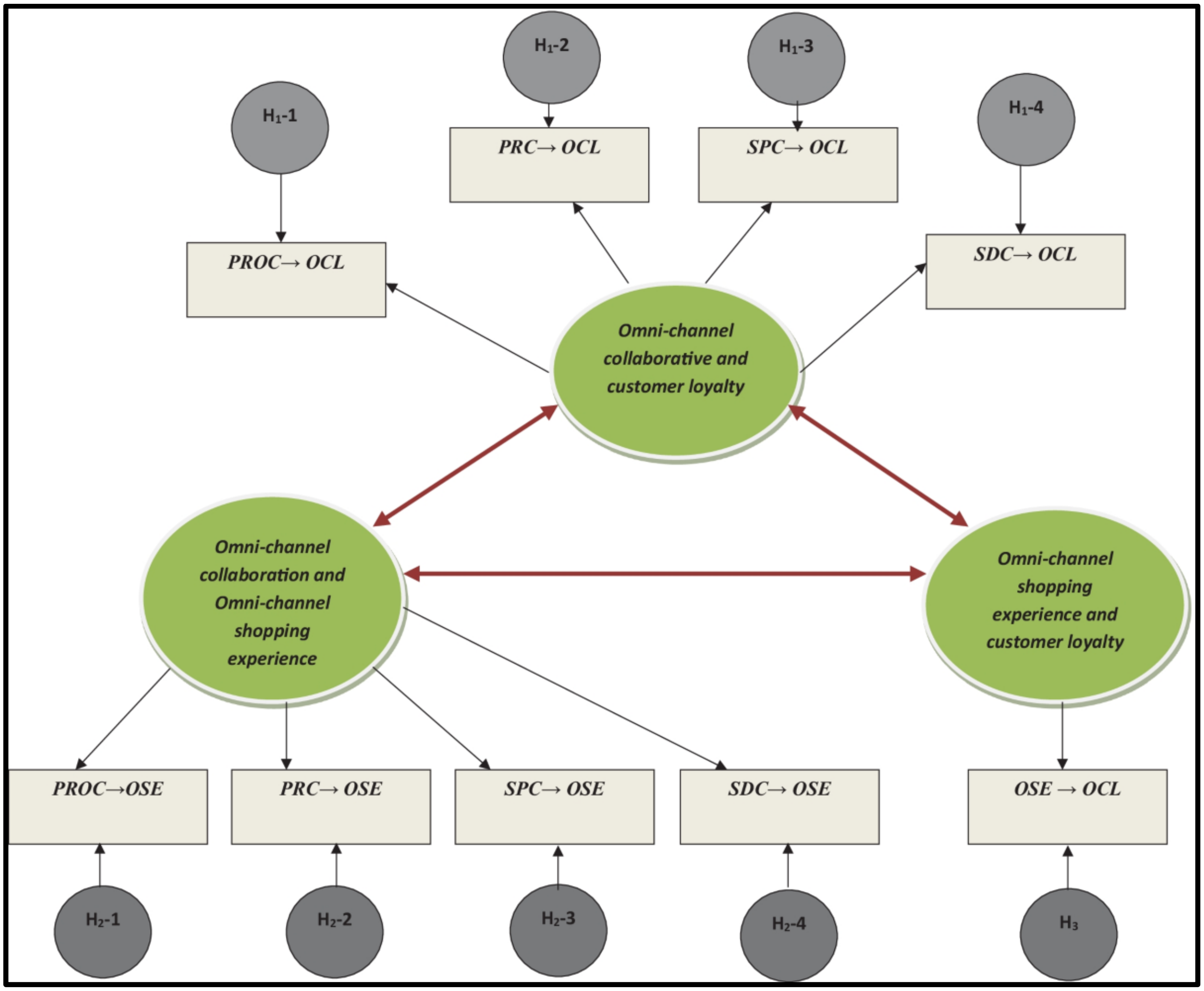

Figure 2.2.2.2: Impact of Customer Loyalty

(Source: SpringerLink, 2024)

The context-related situational benefits allude to those particular advantages that an e-channel offers based on the situation or context of a consumer. Mobile shopping apps are most convenient for on-the-move consumers while browsing via desktop websites could be more comprehensive (Koch *et al.* 2020). These situational benefits drive both choice and behavior and, hence, it is relevant for retailers to understand these contextual needs.

Implications for Retailers

The study indicated that retailers can diversify consumers' shopping experiences by offering a variety of e-channel touchpoints, which fall into different needs and preferences. Offering alternative formats for digital shopping can make the online customer journey more personalized and engaging. This multi-channel option is implied to increase customer satisfaction and, possibly, increase customers' likelihood to make purchases and repeat business.

2.2.3 Consequences of Product Risk: Perceived Satisfaction and Buying Propensity for Online Purchases

Along with the rapid growth of online shopping, significant changes have been noticed in consumer behavior. It has also invited a variety of perceived risks that can influence the purchasing decision (Tran, 2020). The section discusses in sequence the interlinking association between different categories of perceived ***"risk-products risk, financial risk, security risk, privacy risk, consumer satisfaction, as well as purchase intention online"***.

Perceived Risks of Online Shopping

Perceived risk in the context of a buying decision implies uncertainty in a loss in the form of an adverse outcome. For an online customer, the perceived risks are multi-dimensional, including:

- ***Product Risk*****:** This is whereby the consumer receives a particular product with a perceived quality, functionality, and appearance.
- ***Financial Risk*****:** The risk of an employee or the supplier charging more than agreed in the payment process or charging incidences that are not clearly stated to be the risk in the payment process.
- ***Security Risk*****:** There is one broad problem concerning the security of transactions primarily fraud and identity theft.
- ***Privacy Risk*****:** This entails concern about how personal information might be used negatively against the customers or shared or disclosed without consent (Liu *et al.* 2020). These two risks can make a consumer decline to purchase something online, reduce overall satisfaction, and thus decrease this purchasing.

The measures that have been employed in this study have been as a result validated from other literature. CFA has been employed by authors for assessing the measurement model while SEM has been employed for assessing the conceptual models with a view of testing hypothesized relations.

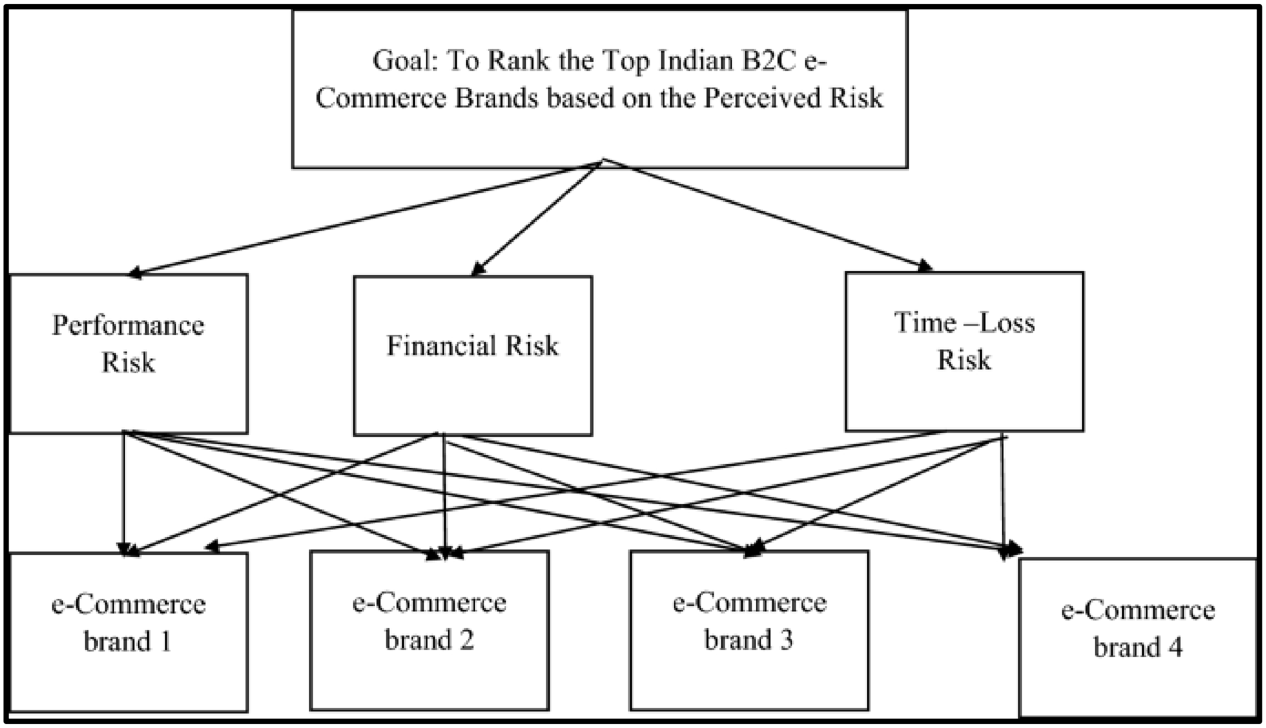

Figure 2.2.3.1: Perceived Risks in Online Shopping

(Source: SpringerLink, 2024)

The research results showed the four perceived risks, namely the product, financial, security, and privacy risks, had a positive and significant impact on the consumers’ perceived satisfaction with online shopping. The study has flagged the most important antecedents of purchase intention to be product risk and privacy risk. The study showed that:

- ***Product Risk*:** High product risk adversely affected perceived satisfaction as well as purchase intentions. A customer is not certain about a product's quality or performance.
- ***Financial Risk*:** Whereas perceived financial risk affects perceived satisfaction, its impact is less overwhelming on purchase intentions (Lăzăroiu *et al.* 2020). Nevertheless, it does show the concern of financial loss about overall satisfaction with online shopping experiences.

However, perceived satisfaction has been significantly reduced by security and privacy risks. Moreover, privacy risk had a direct negative effect on purchase intentions. These findings emphasize the need to ensure security measures and clear privacy practices to engender consumer confidence.

Implications for Online Retailers

This study identifies perceived risk as an important factor that comes into question in online shopping behavior. Every retailer has to know that customers regard an online shopping platform with cognitive attitudes influenced by the perceived risks of a transaction. To decrease the occurrence of such risks, an online retailer has to:

- ***Increase the quality of product information*:** Full, complete, and accurate information about the product, along with customer reviews and ratings about it, decreases product risk.
- ***Stringent Security*:** Investment in advanced encryption technologies and secure payment gateways helps to mitigate concerns about security and financial risks.
- ***Privacy Protection*:** A clear explanation of privacy policies, coupled with assurances regarding the protection of customer data, helps reduce anxiety stemming from privacy while increasing purchase intentions.

2.2.4 An Online Purchase Decision-Making Process and Retentive Consumer Behavior Assessment Model

The rapid proliferation of e-business platforms within the digital age has shaped the revolutionary changes in the consumer's shopping behavior. Therefore, upon the growing trend of online purchases, any business must identify the determinants that affect consumer satisfaction, purchase intentions, and repurchase behavior to retain consumers of their products or services (Petcharat and Leelasantitham, 2021). This section discusses a study that proposes a retentive consumer behavior assessment model, integrating the ***"Technology Acceptance Model"*** with the ***"Online Purchase Decision-Making Process"*** to examine such dynamics.

Theoretical Framework: Integration of TAM and Online Purchase Decision-Making Process

The proposed model extends the basic ideas of TAM, a widely used model. In an online shopping context, these translate into the quality and trustworthiness perceptions by consumers from an online platform, thus influencing their shopping behavior.

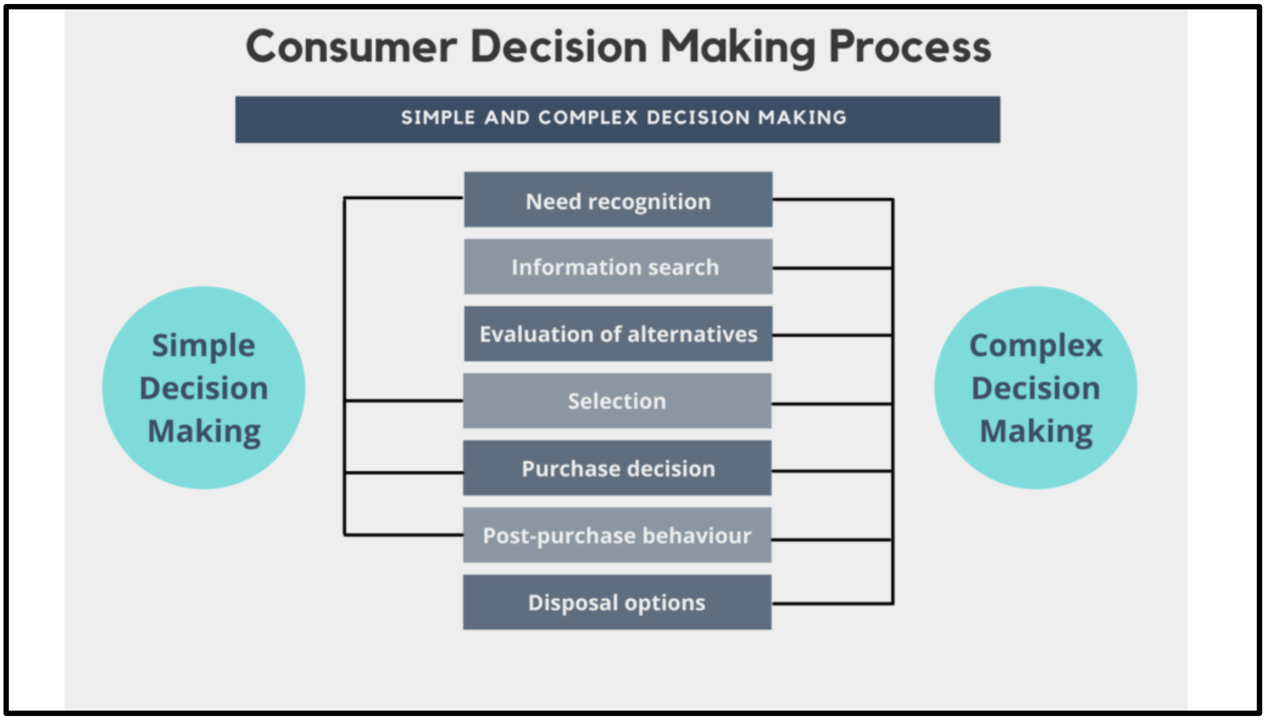

Figure 2.2.4.1: Consumer Decision Making Procedure

(Source: opentextbc, 2024)

This also includes the ***"Online Purchase Decision-Making Process"*** which specifies the stages that a consumer passes through in the process of deciding to purchase a product over the internet. These often encompass "problem recognition, decision making, evaluation of alternatives, information search, post-purchase behavior, as well as purchase decisions". The study seeks to get a perfect understanding of consumers' decision-making process in an online shopping context.

Key Factors: Trust and Quality

It identifies two critical input factors that help in understanding consumer behavior during an online shopping process, namely Trust and Quality.

- ***Trust*:** To earn the ultimate goal of purchase, there is a need to win trust in an online shopping platform (Gu *et al.* 2021). This dimension refers to confidence in transaction security, dependability of a platform, and protection of one's personal information. Continuous buying behavior is activated once customers trust a platform.
- ***Quality*:** the perceived quality of the online shopping platform in terms of website or app usability, accuracy in product descriptions, and efficiency in customer service. Such a high-quality platform, which would meet or surpass buyer expectations, would ultimately result in more repeat purchases.

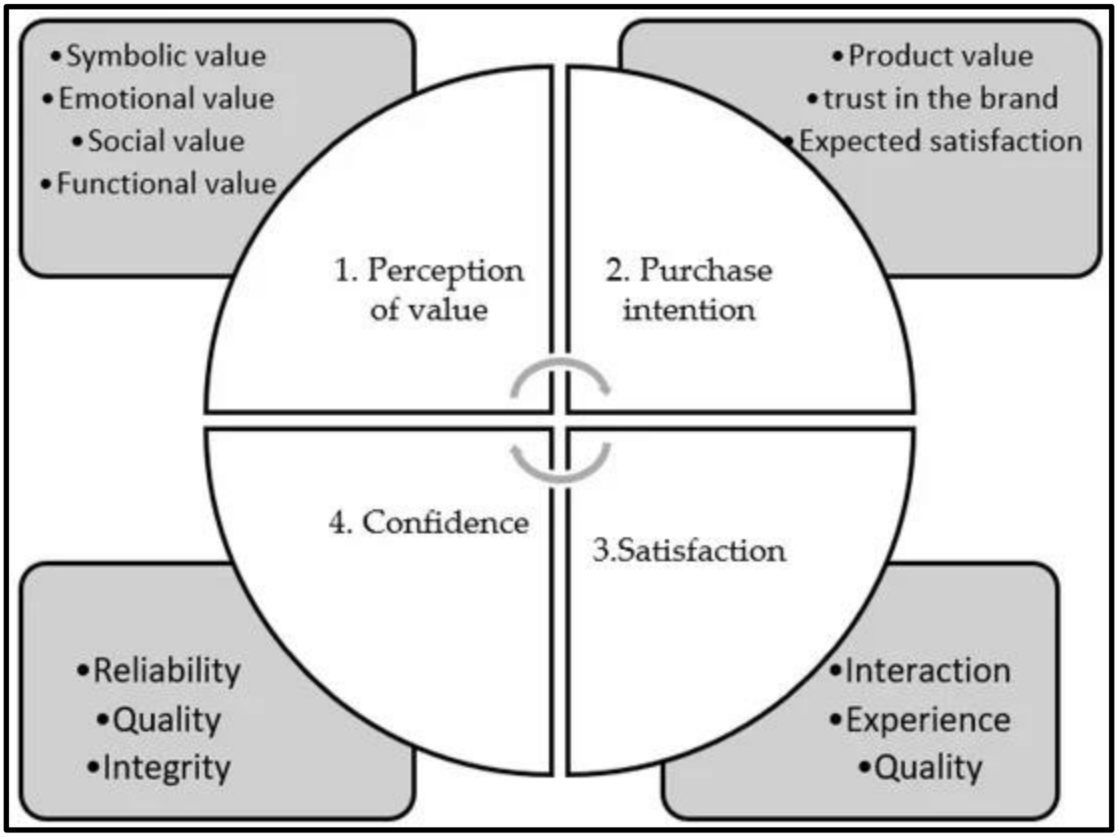

Figure 2.2.4.2: Consumer Behavior of Online Stores

(Source: mdpi, 2024)

Data captured through questionnaires involved all factors in the conceptual model: trust, quality, and stages of the ***"Decision-Making Process"***. The SEM is conducted to analyze the data and verify the causality between these factors. These results hint that this model explains the effects associated with e-business platforms: how trust and quality influence first-time purchase decisions or repeat purchases and recommendations (Alaimo *et al.* 2020). The consumers perceive a high level of trust as well as quality of an e business platform, it tends to complete a purchase and also re-purchase. This result cuts across various types of businesses such as, but not limited to, e-commerce, m-commerce, and e-commerce.

Implications for Online Retailers

These findings have very important implications for online retailers. If companies understand the drivers of satisfaction and loyalty among consumers, it is in a better position to strategize the design and development of online platforms. It can retain more consumers for satisfied consumers to make more purchases and recommend the platform to others.

2.2.5 Long-term Changes in Consumers' shopping behavior post-pandemic: An Exploratory Study

COVID-19 has brought new changes in the behaviors of consumers and how they engage through shopping facilities. Even though much effort has been devoted to studying the short-term impacts of the pandemic, far less attention has been devoted to the long-term changes. The data adopted in the research is of a qualitative nature which involved 159 study participants with the use of grounded theory analysis. This gains insights into how pandemic experiences have altered consumer behavior (Gu *et al.* 2021). One of the main implications of the research is that people who have had positive experiences during the pandemic have developed a positive change in sustainable consumption and online shopping. From the study, these nurtured a more positive sustainable, and environmental self-architecture that shaped their long-term purchasing behavior.

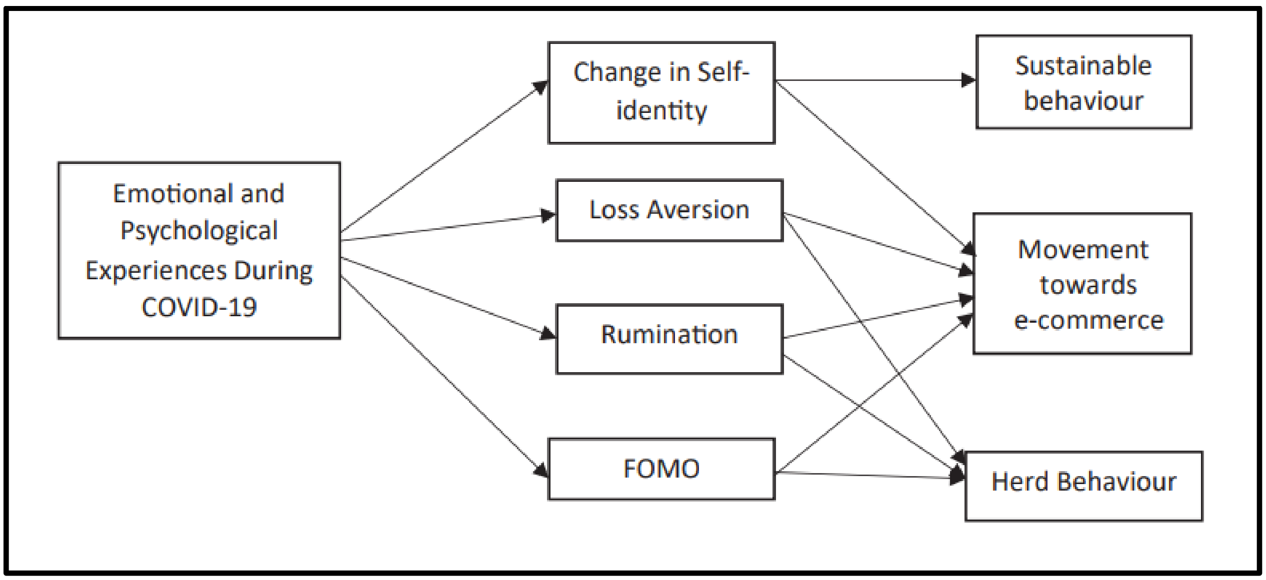

Figure 2.2.5.1: Changes in Shopping Behavior

(Source: emerald, 2024)

The pandemic limitations influenced these consumers to become more environmentally conscious and turn to online shopping as less environmentally negative than conventional shopping. These respondents had a higher FOMO score, loss aversion score, and rumination score than the other respondents. Shopping experiences during the pandemic also created a negative attitude which led to feelings of anxiety and uncertainty when shopping. Many of these consumers had fears, which are eliminated by behaving like a herd by following the purchasing trends set in the market. This group also commonly transitioned to buying products online due to concerns that are likely to be encountered when visiting physical stores (Zhao *et al.* 2020). The study identifies several important affective and psychological processes that are implicated in these long-term shifts in consumers' behavior. Transforming positively predisposed consumers into sustainable selves shows how positive values and sentiments can be harnessed for sustainable consumption.

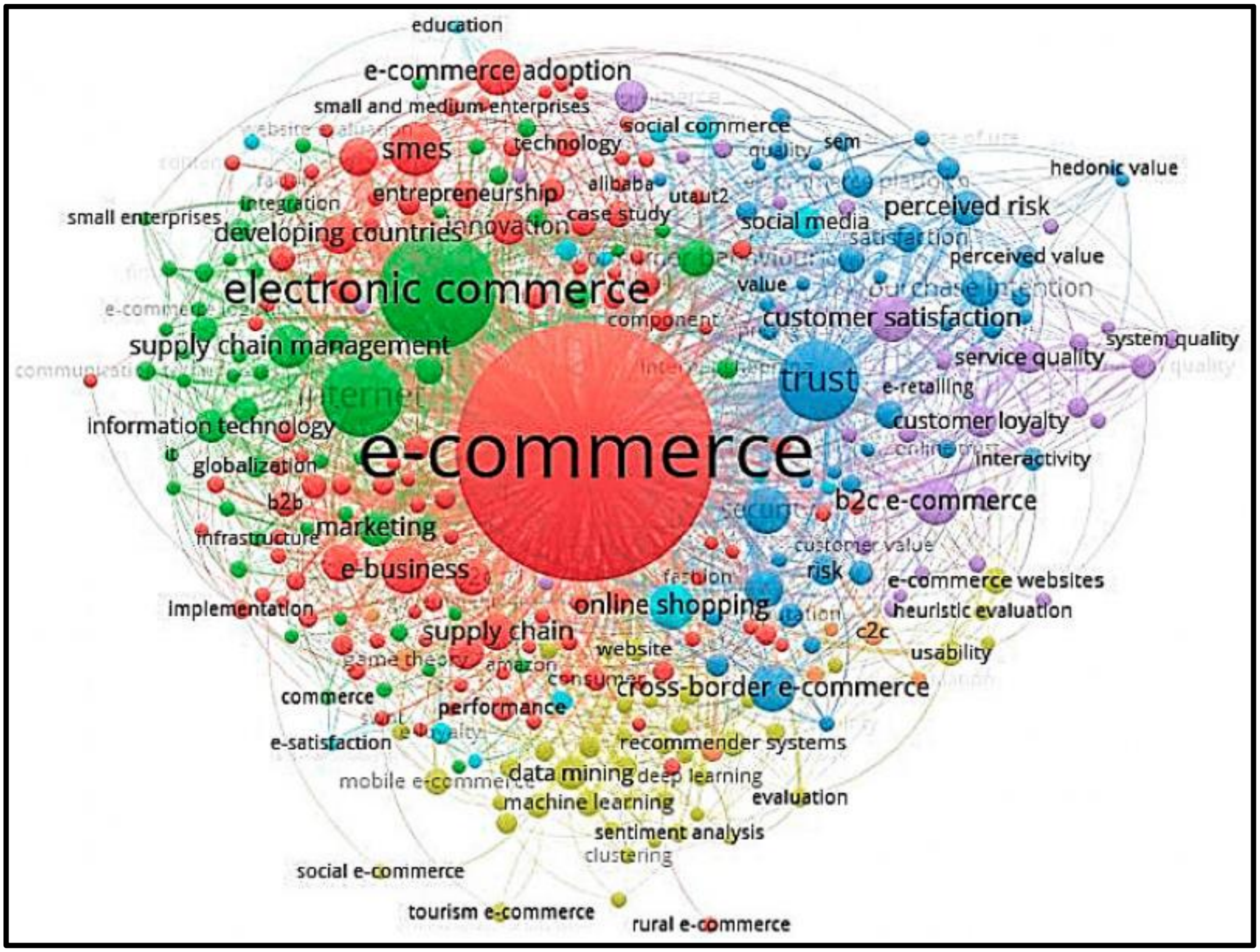

Figure 2.2.5.2: Impact on Online Shopping Behavior

(Source: mdpi, 2024)

On the other hand, the experiences of other consumers paint a picture of how psychological factors like FOMO and loss aversion cause shifts in buying behavior. It also entails the use of the internet for the purchase of goods as well as services like the purchase of groceries and other household items. The study also helps develop consumer behavior theory by proposing new antecedents that include self-identity, loss aversion, FOMO, and rumination that affect the change in long-term shopping behavior (Shen *et al.* 2021). These constructs provide a fresh angle on how the current COVID-19 crisis has affected consumers' emotional/psychological state which in turn affects their retail decision-making. A major limitation of the study may be due to the exploratory research design that was used by the authors of the study and the small sample size. Future researchers build on these findings to strengthen the proposed conceptual model and consider the other factors that might contribute to long-term behavioral changes among consumers.

The research contributes to a deeper understanding of how shoppers have adjusted to the post-pandemic retail environment. The discoveries offer a foundation for future ponders to construct upon and give practical suggestions for retailers looking to address advancing consumer needs and inclinations in a quickly changing market.

2.2.6 The Sales Volume and Satisfaction in Forecasting Organic Products through Text Mining from Web Customer Reviews

The study takes into consideration the need to analyze consumer feedback on predicting sales and other significant factors about purchases based on text mining of ***“Web Customer Reviews”*** for organic product sales volume as well as levels of satisfaction. This is conducted using data gathered from the leading online shopping website, Taobao, for the analyses of customer reviews on organic products (Lyu and Choi, 2020). The study generalizes on customers' perceptions by categorizing online customer reviews using techniques such as sentiment analysis as well as LDA. The study is to predict the volume of organic product sales online. It made use of the analysis method from the neural network to forecast sales based on variables such as product price, delivery options, sales volume, customer reviews, and a product fan.

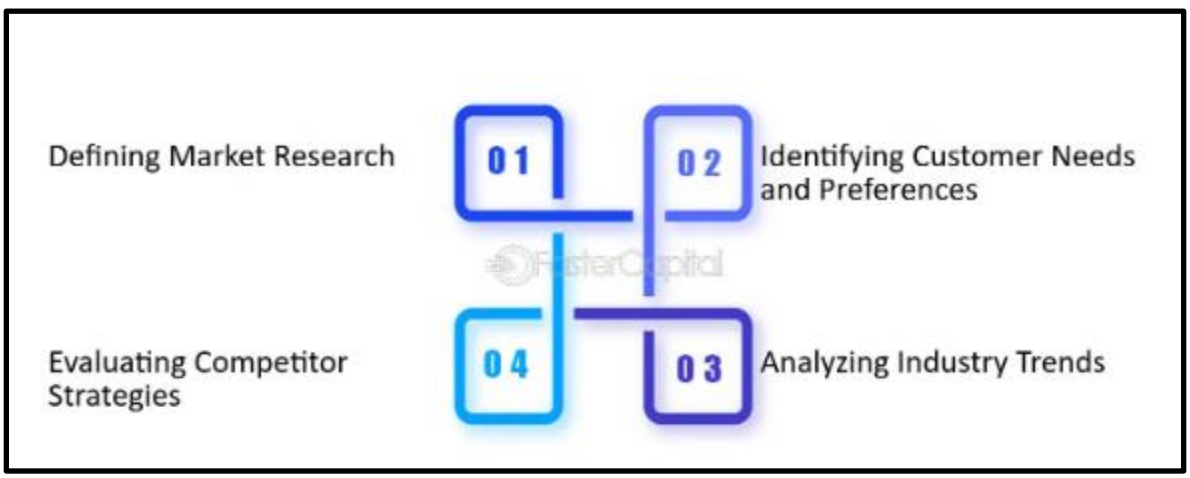

Figure 2.2.6.1: Market Research and Sales Forecasting

(Source: Fastercapital, 2024)

The study further applied regression analysis to assess the purchase intentions of the customers, thus providing further insight into what drives consumer behavior in buying organic products.

Some of the critical factors that might indicate the purpose that leads to sales, like the packaging design, food quality, freshness, nutritional information, delivery risk, as well as source risk. Other critical factors established for volume are price discounts, the number of reviews by customers, and the number of fans of the product (Veleva and Tsvetanova, 2020). As such, the variables pointed out here are of much importance in making the customer buy organic products and some of the major considerations in improving the strategy.

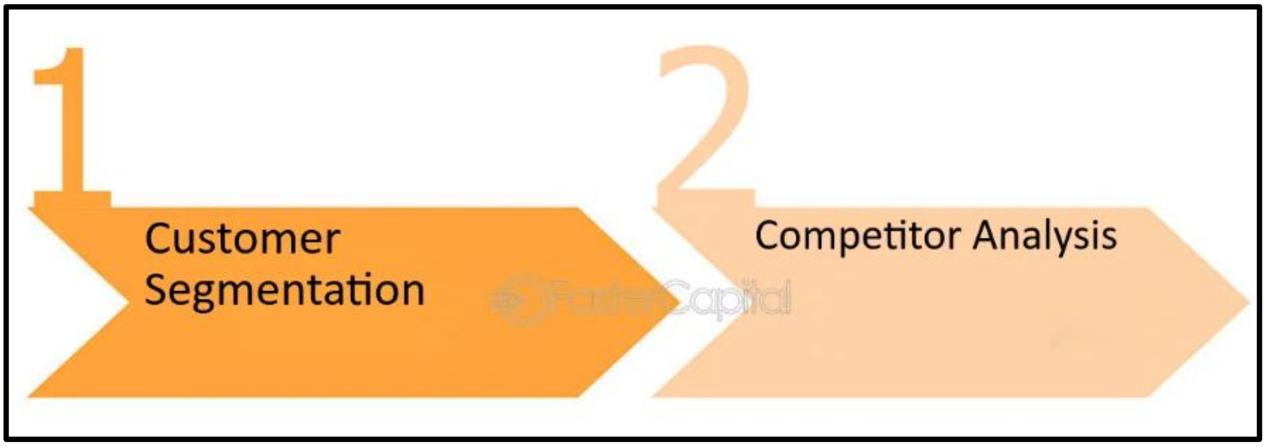

Figure 2.2.6.2: Role of Market Research in Sales Forecasting

(Source: Fastercapital, 2024)

In this regard, the recommendation for improving online services as well as logistics to enhance the customer experience inculcates high ***"Consumer Satisfaction"*** as well as thus increases sales of organic products. Beyond these implications for sustainable development, there exists the broader implication for organic product marketing through effective online marketing, contributing to environmentally friendly consumer habits (Mariani and Wamba, 2020). The study predicts sales trends and identifies factors of influence affecting consumer satisfaction and purchase decisions by applying text mining techniques on customer reviews.

2.2.7 Consumer Marketing Strategy and E-Commerce in the Last Ten Years

E-commerce has significantly transformed how businesses, particularly consumer-oriented firms, market their products. E-commerce simply is the process of selling and buying products through the internet, which is coupled with monetary transactions and electronic transfer of data. In almost every aspect, technology advances, with e-commerce setting up shop right at the middle of new waves of marketing through easy access of information products and easier consumer decision-making (Rosário and Raimundo, 2021). Therefore, data-driven marketing strategies are in growing demand due to the understanding that businesses get from consumer behavior and tailor their approach according to customer needs. E-commerce and emphasis on digital marketing will spell a drastic shift for traditional marketing models as online platforms and social media marketing become essentially critical to consumer outreach. Social networks have become important in building the relationship between brands and consumers.

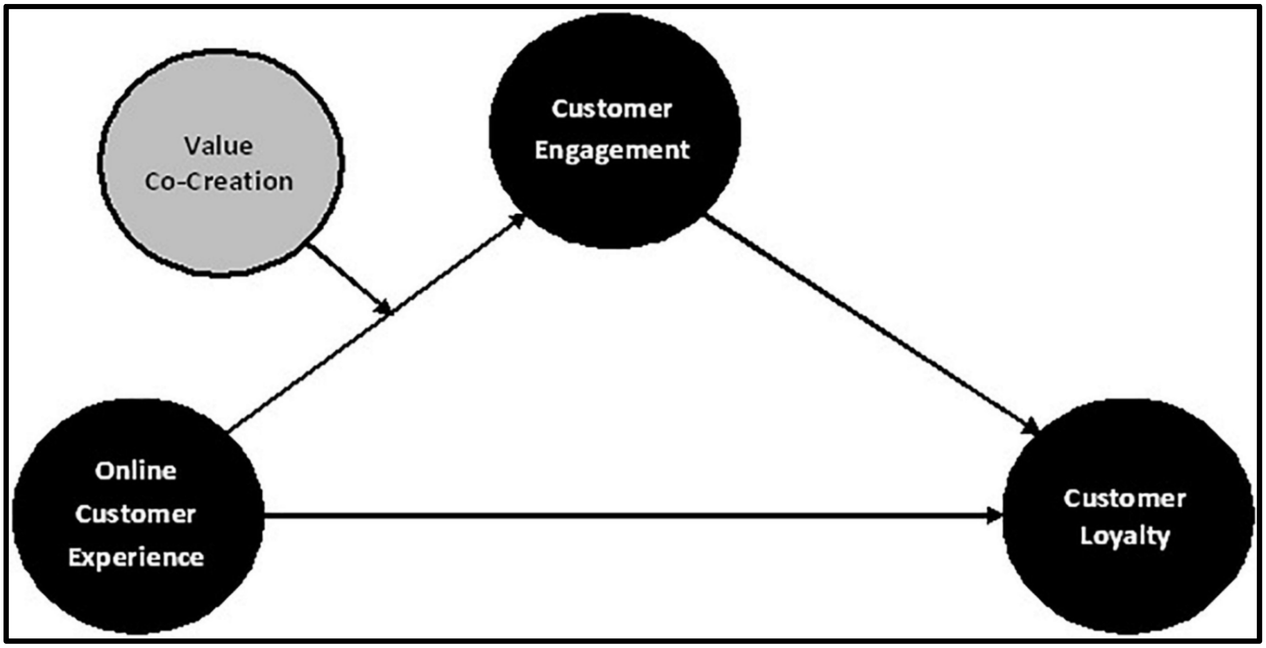

Figure 2.2.7.1: Online Customer Experience

(Source: frontiersin, 2024)

This is an area that has witnessed several developments based on what just happened. The study is still missing an investigation into every stream of e-commerce marketing and how it interconnects. To address the gaps and identify the emerging trends adopted in e-commerce marketing over the last decade, there needs to be a thorough literature review. The main objective is to synthesize findings from the existing literature and categorize emerging sub themes of consumer marketing strategies for e-commerce (Vander Schee *et al.* 2020). The current global market is highly competitive, and companies are now directed to use e-commerce sites and social networks to have a better understanding of consumer needs and behaviors. With online data and consumer interactions now, businesses come up with much more efficient marketing strategies with personalization, trust building, and customer engagement. Also, this being the case, companies have become necessities in any firm as a tool for a wider reach while cost efficiency is preserved.

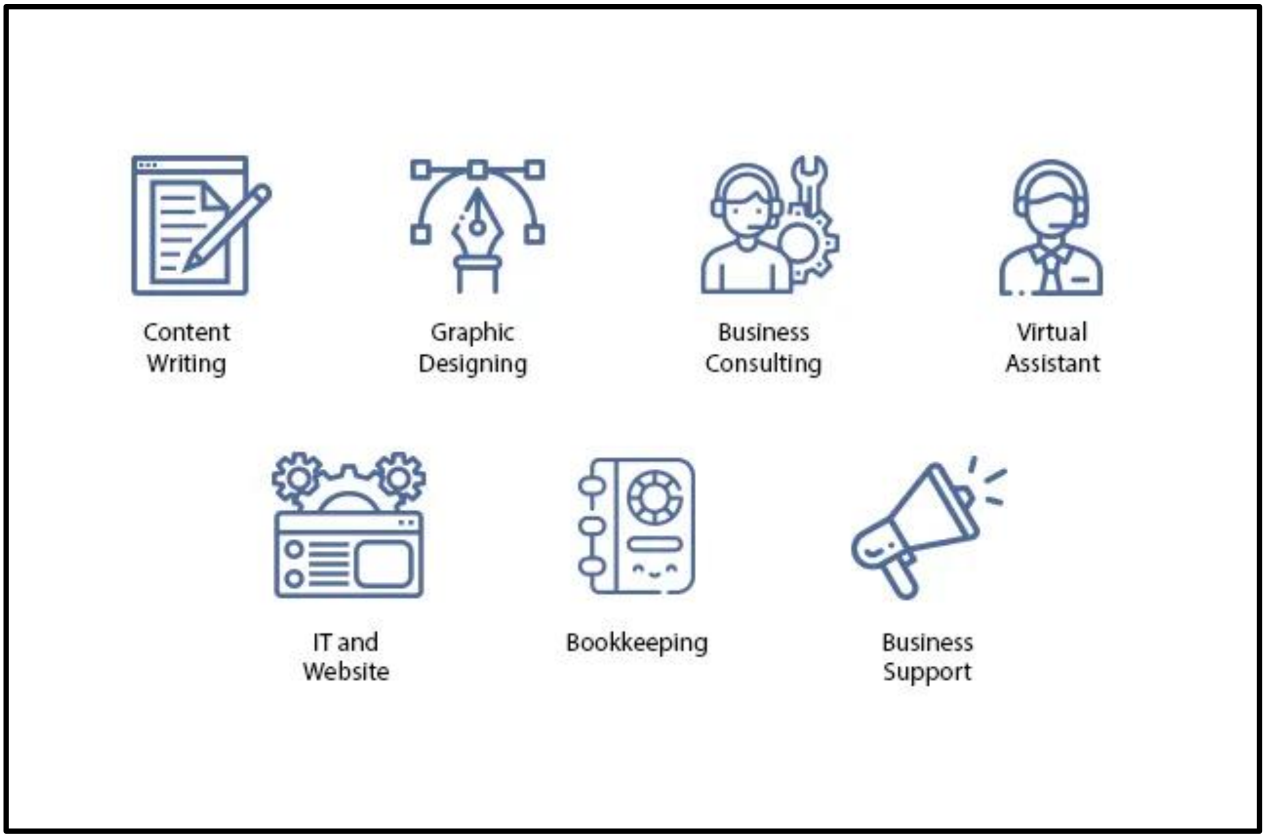

Figure 2.2.7.2: Ecommerce Marketing Strategies

(Source: Ossisto, 2024)

One other critical theme that emerged in the literature review is innovative information-sharing forms and different ways of engaging consumers using e-commerce. Businesses then have a potential opportunity to carve out competitive advantages in value propositions that can use these tools correctly. This also remains one area of further research into interactions between various e-commerce marketing strategies and the possibility of knowledge development. E-commerce has indeed revolutionized the consumer marketing of any firm by increasing its online use and implementations of social networks to reach audiences (Muda and Hamzah, 2021). The findings have characterized e-commerce marketing over the past ten years, emphasizing the need for data-driven strategies, social media marketing, and further research into the changing interplay between these elements.

2.3 Literature Gap

A majority of the existing research works have considered short-term dynamics, including an abrupt switch to online purchases. Nevertheless, there is little systematic research on how such short-term alterations have converted into long-durable behavioral changes. There is also a lack of comprehensive analysis of the long-term psychological processes that may underlie changes in consumption patterns. Existing research includes short-term research on how the pandemic affected impulsive buying and online consumption, but few have explored those effects' long-term impact (Xu and Li, 2020). The use of psychological factors like FOMO, loss aversion, and the emergence of a sustainable self-identity needs more research to determine essential effects on shopping behavior. The psychological processes underlying these behaviors are not yet fully understood, which means that there is a significant gap in knowledge about consumer psychology. Also, it is significant to research how these chronic shifts in behavior connect to novel technologies.

Some new technologies like artificial intelligence and augmented reality if introduced in e-shopping platforms may either enhance or even change the observed long-term trends. There is a lack of research in the current literature on how technological innovations can impact or transform consumer behavior in the world. Analyzing this interaction is crucial to understanding how customers' experiences can be improved and behavior change managed through the use of technology (Sarker, 202). The literature also has one more shortcoming, namely the relative absence of consideration of various consumer segments. Most of the current studies combine results concerning various generations not paying attention to the fact that people of different generations. Also, cultures or economic status may perceive and respond to shifts in shopping behavior in a different way. This may involve a more careful analysis of these discrepancies, which may help to obtain a better understanding of the peculiarities of different segments of consumers.

2.4 Summary

The following chapter gives an analytic overview of the literature concerning the conditions and motivations of shopping online and the characteristics of online shopping sites. The chapter examines the existing theories, trends, and technological innovations that define the digital retail market context. The review also looks at multichannel retailing and the consumer engagement with all the e-commerce Platforms. Further, information indicates how user experience influences consumers' choices and, therefore, the need for better usability and appearance to guarantee customer loyalty. AI and other technologies like AR are considered as essential when it comes to enhancing the online shopping platforms as well as customer engagement.

Chapter 3: Methodology

3.1 Introduction

The method section of this case study attempts to quantify some characteristics to determine the shopping behavior of consumers on the Internet. It begins with the utilization of a professional procedure known as Exploratory Data Analysis (EDA) to obtain information concerning the patterns/trends of the particular data set in question. Feature engineering helps improve the quality of data at the same time it helps in identifying the kind of data best suitable for processing. The predicted trends are given by techniques such as "Linear Regression, Logistic Regression, Random Forest, and XG Boost". Thus, it is appropriate and reasonable to give a detailed quantitative analysis here to provide a good starting point to address inference and planning of the change to the online shopping business.

3.2 Research Philosophy

The research philosophy applied in the case study that has been presented on online shopping. This approach is commonly employed to highlight the relationships and trends that come out of measurable and numerical characteristics. This concerns the evaluation of data, whereby numbers are utilized to evaluate hypotheses about perceived behaviors and outcomes (Kuswanto *et al.* 2020). The strength of applying Positivism in this context lies in the fact that Positivism uses empirical analysis and data. Thus, Positivism helps with the analysis of online shopping behavior in detail and also offers a prescription based on the evidence.

3.3 Research Design

The design that has been applied to the case study of online shopping sites is descriptive. This approach intends to come up with a narrative form of explanation of current events based on some characteristics and behavior patterns that have probably been theorized to exist in the datasets provided. Therefore, in this study, descriptive Design has been adopted to examine how various features and technologies influence the shoppers' behavior, with the help of exploratory data analysis (EDA) and customer segmentation techniques (Singh and Basu, 2023). This method makes it possible to determine characteristics of engagements and conversion rates and can act as a strong foundation for providing feasible solutions based on observation outcomes.

3.4 Research Approach

The type of research used in the case study on online shopping sites is the deductive type. This approach entails placing hypotheses as methods to the theoretical models that have been proposed for theory. Employing the deductive approach in this study, a research hypothesis is postulated in the form of a null hypothesis where it is assumed that some parts of design and technology influence the shopper's behavior, and empirical evidence is gathered to support the hypothesis (Lin *et al.* 2023). Therefore, it offers the right recommendations and recommendations that are simple to implement and improve the design and usability of the online shopping sites.

3.5 Research Strategy

The method employed when conducting case studies on online shopping sites is the exploratory research method combined with the confirmatory research method. It includes Exploratory Data Analysis (EDA) to define the correlation and distribution of the used datasets and requires such libraries as Pandas, Matplotlib, and Seaborn (Bhatti *et al.* 2020). Therefore, common predictive modeling techniques of hypothesis testing and buyer prediction include Linear Regression, Logistic Regression, Random Forest, and XGBoost.

3.6 Tools and Techniques Used

The process of exploring data, engineering features, clustering, and predictive modelling has been carried out using Python in this research. Mainly, the tools used included the Pandas library for data manipulation and cleaning (Chen *et al.* 2021). Predictive modeling involves applying different ML algorithms, including ***"Linear Regression"*** as well as ***"Logistic Regression Models"***, a ***"Random Forest model"***, as well as ***"XGBoost Models"***. The implementation of the model has been done using Scikit-learn; however, the best-performing models for classification have been provided by XGBoost in terms of efficiency and scalability. These improvements increased the accuracy of ML models. ***"Accuracy"***, ***"Precision"***, ***"Recall"***, as well as ***"F1-score"*** have been used during model testing to determine how good the model is at performing. "***Python***" is an open and powerful platform through which all the techniques could be streamlined to enable an in-depth analysis of the behavior of online shopping.

3.7 Data Collection

The data that has been utilized for this study is taken from the UCI Machine Learning Repository's ***"Online Retail"***. The dataset is the transactional data of a UK-based retailing firm mainly selling certain specific gift items through an online platform. The total rows of the dataset exceed 500,000, which reflects purchases between December 2010 and December 2011. The dataset contains the following fields namely; ***"Invoice No, Article No, Description, Quantity, Invoice Date, Unit Price, Customer No, and Country"***. The data is preprocessed to fill in missing values and remove duplicate variables to ensure that the data is sufficiently qualified for analysis (Febriyantoro, 2020). This data has been used to make use of different machine learning algorithms to build predictive models for forecasting customer actions and sales trends.

3.8 Data Analysis

Data analysis for this study has been subdivided into three important steps. These include EDA, customer segmentation, and predictive modeling. The process involved within EDA included summarizing the data, detection of outliers, and visualization of key characteristics which are the purchasing trend by customers, geographic sales, and average order value (Khan *et al.* 2022). Some of the examples of the algorithms entailing in the processing include ***"Random Forest"***, ***"Linear Regression"***, ***"XGBoost"***, and ***"Logistic Regression"***. The probability or likelihood of repeat purchases or repeat buying is expected behavior by the customers.

3.6 Ethical Consideration

As per the ethical considerations of the specific study under consideration, the study ensures legal requirements are met by anonymizing customers' data in a way that the customers themselves cannot be easily recognizable (Cheung and To, 2021). The analysis and recommendations are meant to enhance the opportunities of users, without taking advantage of their data. Thus, adherence to these ethical standards ensures that the research is ethical in its approach and that any conclusions made and recommendations given are ethical and credible.

3.7 Summary

The paper focuses on online shopping consumer behavior through a systematic approach that incorporates quantitative research data. Exploratory Data Analysis (EDA) is used to find out the shapes and patterns of datasets and then features the datasets to enhance their quality. In the study, K-means clustering is used to categorize customer behavior, while Linear Regression, Logistic Regression, Random Forest, and XGBoost models are employed for hypothesis testing and future trend prediction. The comprehensive analysis provides the foundation for deriving data-oriented strategies to maximize the users' interaction and conversion.

Chapter 4: Result and Discussion

4.1 Introduction

This chapter discusses the analysis of the data collected and the subsequent conclusions that can be drawn in the context of online shopping trends. The findings are based on EDA, feature creation, customer clustering via K-means clustering, and predictive modelling using linear regression, logistic regression, random forest, and XGBoost models. Every approach has been used to explain how individuals engage with OSPs, segment OSP customers, and forecast their actions. Again, this chapter considers the findings of the data analysis and relates them to the research objectives. The findings are derived from the literature reviewed above concerning consumer behavior, the effects of new technologies on online shopping, and multichannel retailing. Also, the chapter provides insights into the performance of the adopted machine learning algorithms in making forecasts of consumer behavior. Finally, the customer clustering process is explained in detail with an emphasis on some of the important characteristics of the customers.

4.2 Result Analysis

Data Cleaning

```
import pandas as pd
import matplotlib.pyplot as plt
```

```
df = pd.read_excel('Online Retail.xlsx')
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 541909 entries, 0 to 541908
Data columns (total 8 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   InvoiceNo    541909 non-null  object
 1   StockCode    541909 non-null  object
 2   Description  540455 non-null  object
 3   Quantity     541909 non-null  int64
 4   InvoiceDate  541909 non-null  datetime64[ns]
 5   UnitPrice    541909 non-null  float64
 6   CustomerID   406829 non-null  float64
 7   Country      541909 non-null  object
dtypes: datetime64[ns](1), float64(2), int64(1), object(4)
memory usage: 33.1+ MB
```

Figure 4.2.1: Importing Libraries and Uploading Dataset

The above figure illustrates the flow for washing an online retail data set where data pre-processing and analysis are carried out in the Pandas program. It begins by importing necessary libraries and then reading the ‘Online Retail. xlsx’ file into a determined Data Frame called ‘df’ using the Pandas read_excel function. The df. inf() method is then used to obtain additional information regarding the structure of the datasets (Morid and Del Fiol, 2021). This is to get familiar with what the table entails which includes the data types of columns and the presence of null values in the dataset.

```
# Drop rows where CustomerID or Description is missing
df_cleaned = df.dropna(subset=['CustomerID', 'Description'])

# Remove any duplicate rows
df_cleaned = df_cleaned.drop_duplicates()

# Verify that the cleaning was successful
print("\nCleaned Dataset Info:")
df_cleaned.info()
```

```
Cleaned Dataset Info:
<class 'pandas.core.frame.DataFrame'>
Index: 401604 entries, 0 to 541908
Data columns (total 8 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   InvoiceNo    401604 non-null  object
 1   StockCode    401604 non-null  object
 2   Description  401604 non-null  object
 3   Quantity     401604 non-null  int64
 4   InvoiceDate  401604 non-null  datetime64[ns]
 5   UnitPrice    401604 non-null  float64
 6   CustomerID   401604 non-null  float64
 7   Country      401604 non-null  object
dtypes: datetime64[ns](1), float64(2), int64(1), object(4)
memory usage: 27.6+ MB
```

Figure 4.2.2: Cleaning the Dataset

The above figure shows the extent of data cleaning of the online retail dataset in its subsequent stages. Firstly, all rows, which contain missing data in the “CustomerID” or “Description” column of df are deleted using the df. dropna() method. After that, using df, equal rows are described and eliminated further on. drop_duplicates(). Such a systematic approach increases the reliability of the data achieved and, therefore, offers a suitable background for further analysis and modelling. This step is particularly important to ensure that the results that are obtained when it comes to the other steps in the analysis are both accurate and valid.

EDA

```python
# Descriptive statistics for numerical columns
print("Descriptive Statistics:\n", df_cleaned.describe())
```

```
Descriptive Statistics:
             Quantity                    InvoiceDate      UnitPrice  \
count  401604.000000                         401604  401604.000000
mean       12.183273  2011-07-10 12:08:23.848567552       3.474064
min    -80995.000000            2010-12-01 08:26:00       0.000000
25%         2.000000            2011-04-06 15:02:00       1.250000
50%         5.000000            2011-07-29 15:40:00       1.950000
75%        12.000000            2011-10-20 11:58:30       3.750000
max     80995.000000            2011-12-09 12:50:00   38970.000000
std       250.283037                            NaN      69.764035

          CustomerID
count  401604.000000
mean    15281.160818
min     12346.000000
25%     13939.000000
50%     15145.000000
75%     16784.000000
max     18287.000000
std      1714.006089
```

Figure 4.2.3: Descriptive Statistics

The above figure depicts descriptive values of the cleaned online retail data using the df. describe() method. For the numerical columns, it gives basic descriptive analytics such as count, mean, standard deviation, minimum, first quartile, median, third quartile, and maximum. It also includes the count of categorical variables like ‘InvoiceDate’, and ‘CustomerID’ which counts the frequency and uniqueness attached to specific categories (Cheng *et al*. 2021). This is useful in examining the general distribution of the dataset and any value outliers that may be observed to possibly need further examination or enhancement when creating the model.

```
# Find the top 10 most sold products by quantity
top_products = df_cleaned.groupby('Description')['Quantity'].sum().sort_values(ascending=False).head(10)
print("\nTop 10 Most Sold Products:\n", top_products)
```

```
Top 10 Most Sold Products:
 Description
WORLD WAR 2 GLIDERS ASSTD DESIGNS     53119
JUMBO BAG RED RETROSPOT               44963
ASSORTED COLOUR BIRD ORNAMENT         35215
WHITE HANGING HEART T-LIGHT HOLDER    34128
PACK OF 72 RETROSPOT CAKE CASES       33386
POPCORN HOLDER                        30492
RABBIT NIGHT LIGHT                    27045
MINI PAINT SET VINTAGE                25880
PACK OF 12 LONDON TISSUES             25305
PACK OF 60 PINK PAISLEY CAKE CASES    24129
Name: Quantity, dtype: int64
```

Figure 4.2.4: Finding the top 10 most Sold Products

The above figure describes Data cleaning to find the 10 most frequently sold products from the cleaned online retail dataset. The grouped analysis addresses the level of ‘Description’ using the groupby() function showing the total ‘Quantity’ of each product which is then sorted using the sort_values() function. Finally, the head(10) function is used to display the ten most popular products. The results of this analysis can provide helpful information about the customers’ buying behaviours and can help with stock management, showing the top products in the given data set.

```
plt.figure(figsize=(10,6))
monthly_sales.plot(kind='line')
plt.title('Monthly Sales Trend')
plt.ylabel('Total Quantity Sold')
plt.xlabel('Month')
plt.show()
```

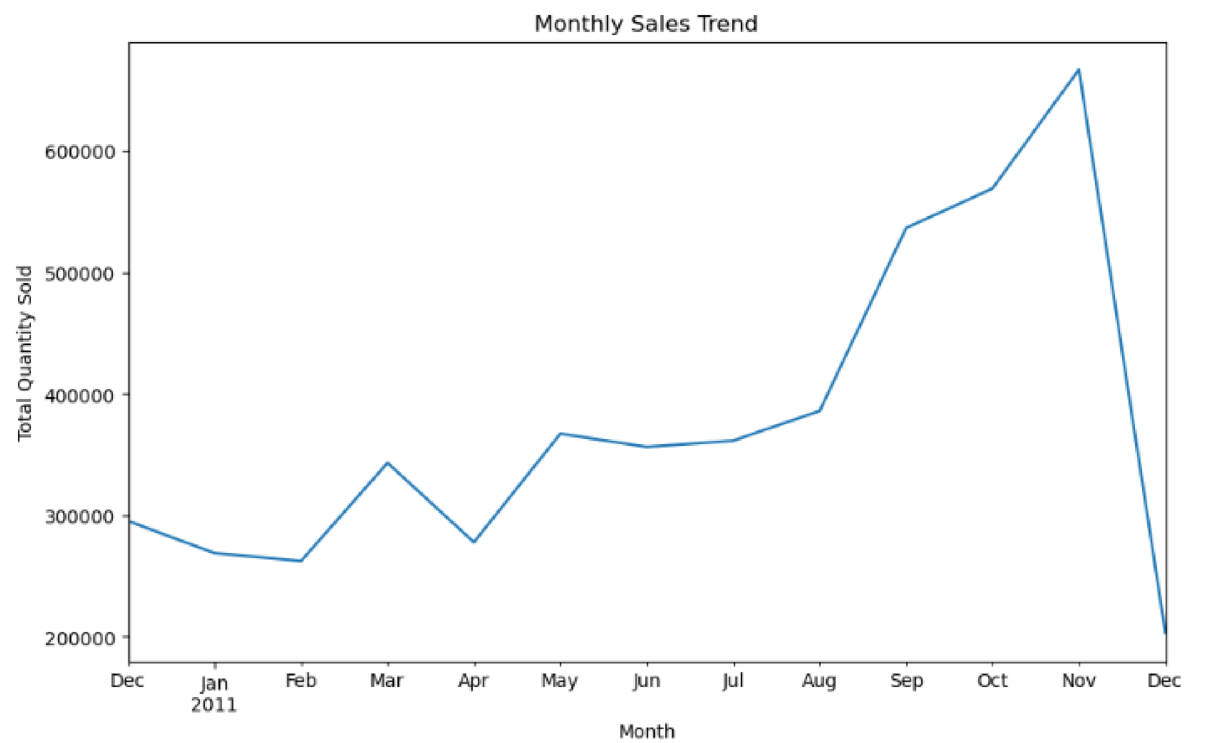

Figure 4.2.5: Graph for Month Sales Trend

The above figure contains a line chart which represents the monthly sales in the online retail dataset. The x-axis shows the period from December 2011 to December 2012, while the y-axis shows the total quantity that is sold in certain months. The line chart is equally useful for the analysis of the nature of sales volume since it simplifies the identification of trends or cyclical movements in sample data (Ghosh and Hosseini, 2021). For example, there is a marked rise in sales during November and December that is complemented by a drop in the serial from January to February.

Feature Engineering

```python
# Create a new column for total purchase value
df_cleaned['TotalPurchase'] = df_cleaned['Quantity'] * df_cleaned['UnitPrice']

# Display the first few rows to verify
print("\nFirst Few Rows with Total Purchase Value:\n", df_cleaned[['InvoiceNo', 'TotalPurchase']].head())
```

```
First Few Rows with Total Purchase Value:
   InvoiceNo  TotalPurchase
0    536365          15.30
1    536365          20.34
2    536365          22.00
3    536365          20.34
4    536365          20.34
```

```python
# Extract the day of the week and hour from InvoiceDate
df_cleaned['DayOfWeek'] = df_cleaned['InvoiceDate'].dt.day_name()
df_cleaned['Hour'] = df_cleaned['InvoiceDate'].dt.hour

# Display the first few rows with the new features
print("\nFirst Few Rows with Day of Week and Hour:\n", df_cleaned[['InvoiceNo', 'DayOfWeek', 'Hour']].head())
```

```
First Few Rows with Day of Week and Hour:
   InvoiceNo  DayOfWeek  Hour
0    536365  Wednesday     8
1    536365  Wednesday     8
2    536365  Wednesday     8
3    536365  Wednesday     8
4    536365  Wednesday     8
```

Figure 4.2.6: Feature Engineering Process

The above figure reflects the feature engineering process which has been used to transform the online retail dataset. A new column, ‘TotalPurchase,’ is derived by summing the product of the quantity and unit price for each sale transaction. The df.head() method is used to print the first rows of the original dataset along with the new column ‘TotalPurchase’ to ensure the correctness of the calculations. Further, the ‘InvoiceDate’ field contains the DateTime, and to create new features, two columns are derived from it: ‘DayOfWeek’ and ‘Hour’. These engineered features are more useful for the analysis of temporal patterns of customers’ activity and higher accuracy of the corresponding predictive models.

Customer Segmentation(K-Means)

```python
from sklearn.cluster import KMeans

# Group by customer to get their total spend and total quantity bought
customer_data = df_cleaned.groupby('CustomerID').agg({
    'Quantity': 'sum',
    'TotalPurchase': 'sum'
}).reset_index()
```

```python
# Normalize the data
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
customer_data_scaled = scaler.fit_transform(customer_data[['Quantity', 'TotalPurchase']])

# Use KMeans to cluster customers
kmeans = KMeans(n_clusters=3, random_state=42)
customer_data['Cluster'] = kmeans.fit_predict(customer_data_scaled)

# Display the first few rows with customer segmentation
print("\nCustomer Segmentation:\n", customer_data.head())
```

```
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1412: FutureWarning: The default value of `n_init` will c
hange from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```

Figure 4.2.7: Input of Customer Segmentation

The above figure depicts the first three steps of the K-Means clustering algorithm for categorising the customers. The process starts with the cleaned data which is grouped by the ‘CustomerID’ and counts the total ‘Quantity’ and sum of ‘TotalPurchase’ of each customer. The data is then normalized by applying the StandardScaler() to make sure all features contribute equally to the clustering process (Zahra and Anoraga, 2021). The algorithm KMeans() is applied with the number of clusters set as 3 and a random state set equal to 42. The fit_predict() method is thereby used to map customers to one of the segments that was developed earlier.

```
Customer Segmentation:
    CustomerID  Quantity  TotalPurchase  Cluster
0     12346.0         0           0.00        0
1     12347.0      2458        4310.00        0
2     12348.0      2341        1797.24        0
3     12349.0       631        1757.55        0
4     12350.0       197         334.40        0
```

Figure 4.2.8: Output of Customer Segmentation

The above figure shows the final solutions derived from the implementation of the K-Means method of clustering to categorize the customers. This table of output contains several columns out of which some important customer-related information is given. Regarding the ‘Customer’ table, CustomerID column can be used as a primary key because it uniquely identifies each customer. The Quantity column depicts the number of purchases made by each user, while the

TotalPurchase column captures the total amount of purchases made by each customer. Finally, the Cluster column reveals the cluster numbers, which are 0, 1, or 2 depending on K-Means results.

```
# Plot the clusters
plt.figure(figsize=(10,6))
sns.scatterplot(data=customer_data, x='Quantity', y='TotalPurchase', hue='Cluster', palette='Set2')
plt.title('Customer Segmentation based on Purchase Behavior')
plt.show()
```

Figure 4.2.9: Customer Segmentation Modeling on Purchase Behavior

The above scatter plot maps customer segmentation based on the purchase behavior: The x-axis represents the ‘Quantity’ and the Y-axis represents the ‘TotalPurchase’. Each of the data points shown is color-coded based on the clustered values of 0, 1 or 2. The plot delineates customer distribution across the three clusters: Customers with low quantities and low total spending are in Cluster 0, Whereas customers with a high quantity of purchases and high total spending are in Cluster 1.

Preparing Data for Predictive Modeling

```
print("Columns in the dataset:\n", df_cleaned.columns)
```

```
Columns in the dataset:
 Index(['InvoiceNo', 'StockCode', 'Description', 'Quantity', 'InvoiceDate',
       'UnitPrice', 'CustomerID', 'Country', 'Month', 'TotalPurchase',
       'DayOfWeek', 'Hour'],
      dtype='object')
```

```
# Assuming you want to predict if TotalPurchase > 0 (a purchase was made)
df_cleaned['PurchaseMade'] = df_cleaned['TotalPurchase'].apply(lambda x: 1 if x > 0 else 0)

# Verify the new column
print(df_cleaned[['TotalPurchase', 'PurchaseMade']].head())
```

```
   TotalPurchase  PurchaseMade
0          15.30             1
1          20.34             1
2          22.00             1
3          20.34             1
4          20.34             1
```

Figure 4.2.10: Preparing predictive modelling data

The above figure represents the various preprocessing done on the global cleaned online retail dataset to split it for the modelling phase. It begins with defining columns in the dataset, which provides information on the features to consider during analysis (Kraus *et al.* 2021). It then creates a new binary variable called 'PurchaseMade' with a rule that if 'TotalPurchase' is greater than 0. Then it assigns the variable 'PurchaseMade' a value of 1, and 0 otherwise, this is done through passing a lambda function. Finally, the head() method is applied for displaying the initial rows of the dataset as well as checking the 'PurchaseMade'.

4.3 Key Findings

```
# Logistic Regression
log_reg = LogisticRegression()
log_reg.fit(X_train, y_train)
y_pred_log_reg = log_reg.predict(X_test)
print("Logistic Regression Accuracy:", accuracy_score(y_test, y_pred_log_reg))
print("Classification Report:\n", classification_report(y_test, y_pred_log_reg))
```

```
Logistic Regression Accuracy: 0.99988380006972
Classification Report:
               precision    recall  f1-score   support

           0       1.00      0.99      1.00      2613
           1       1.00      1.00      1.00    117869

    accuracy                           1.00    120482
   macro avg       1.00      1.00      1.00    120482
weighted avg       1.00      1.00      1.00    120482
```

Figure 4.3.1: Logistic Regression Accuracy and Classification Report

The above figure also demonstrates the application of the logistic regression model for the tendency to buy in an online retail set. The process begins with the making of a new

LogisticRegression() that fits to the training data – (X_train, y_train). Finally, an attempt is made to roughly predict using the testing data in feature vector form as X_test (Yakubu *et al.* 2022). The accuracy score obtained from the accuracy_score function shows a success rate of 0 percent which is very high 0.9998838.

```
# Random Forest
rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X_train, y_train)
y_pred_rf = rf.predict(X_test)
print("Random Forest Accuracy:", accuracy_score(y_test, y_pred_rf))
print("Classification Report:\n", classification_report(y_test, y_pred_rf))
```

```
Random Forest Accuracy: 1.0
Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00      2613
           1       1.00      1.00      1.00    117869

    accuracy                           1.00    120482
   macro avg       1.00      1.00      1.00    120482
weighted avg       1.00      1.00      1.00    120482
```

Figure 4.3.2: Random Forest Accuracy and Classification Report

The above figure signifies the performance of the RandomForestClassifier, model while predicting the purchase behavior on an online retail dataset. Therefore, the initialized model contains 100 decision trees and the random state is 42 and the training set used is, X_train and y_train. Further, a forecast is made with the testing dataset (X_test). From the accuracy_score function, it gets '1' meaning that it has an accuracy of 0% (Liu and Korobeynikova, 2020). Additionally, the function called classification_report gives more detail on the performance of the model in terms of precision, recall, f1-score, and support for both classes 0 and 1.

```
# XGBoost
xgb_model = xgb.XGBClassifier(use_label_encoder=False, eval_metric='mlogloss')
xgb_model.fit(X_train, y_train)
y_pred_xgb = xgb_model.predict(X_test)
print("XGBoost Accuracy:", accuracy_score(y_test, y_pred_xgb))
print("Classification Report:\n", classification_report(y_test, y_pred_xgb))

C:\Users\Tech Assignment 02\AppData\Roaming\Python\Python311\site-packages\xgboost
G: C:\buildkite-agent\builds\buildkite-windows-cpu-autoscaling-group-i-0015a694724
er.cc:740:
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)

XGBoost Accuracy: 0.9999502002988
Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00      2613
           1       1.00      1.00      1.00    117869

    accuracy                           1.00    120482
   macro avg       1.00      1.00      1.00    120482
weighted avg       1.00      1.00      1.00    120482
```

Figure 4.3.3: XG Boost Accuracy and Classification Report

The above image describes the flow of the XGBoost model for the purchase prediction in the online retail dataset and its general performance. It begins with defining the classifier as XGBClassifier() with the use_label_encoder as False and the eval_metric as 'mlogloss'. The use of the model is trained through the training set (X_train, y_train) and tested through the test set (X_test). The following accuracy_score() is then used to assess the implemented model and an amazing accuracy of 0 is achieved 0. 9999502. This indicates that the XGBoost model is highly effective, accurate, and reliable for modelling purchase behavior in the context of the online retail dataset.

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

# Initialize and train the model
linear_reg = LinearRegression()
linear_reg.fit(X_train, y_train)

# Make predictions
y_pred = linear_reg.predict(X_test)

# Evaluate the model
print("Mean Squared Error:", mean_squared_error(y_test, y_pred))
print("R^2 Score:", r2_score(y_test, y_pred))

Mean Squared Error: 123138.73474023967
R^2 Score: 0.7424052729318672
```

Figure 4.3.4: Linear Regression Model

The above figure also demonstates the use of the linear regression model on the online retail data set in a scenario where the dependent variable Y is a continuous variable. Based on the LinearRegression() class from the scikit-learn library, the data set (X_train, y_train) is fit into the model then the test data (X_test) is passed through the predict method (AlFarraj *et al.* 2021). Mean squared error is calculated as the average squared difference between the actual values of the test set and the model's predictions, equaling 123,138. 73. Moreover, the r2_score() function provides the R^2 of 0 as results 0.742.

```
# Fit the models and calculate MSE
mse_scores = {}
for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    mse_scores[name] = mean_squared_error(y_test, y_pred)

# Print MSE scores
print("MSE Scores:", mse_scores)
```

```
C:\Users\Tech Assignment 02\AppData\Roaming\Python\Python311\site-packages\xgboost\core.py:158: UserWarning: [12:19:27] WARNIN
G: C:\buildkite-agent\builds\buildkite-windows-cpu-autoscaling-group-i-0015a694724fa8361-1\xgboost\xgboost-ci-windows\src\learn
er.cc:740:
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)
MSE Scores: {'Linear Regression': 123137.79518403675, 'Random Forest': 239729.16583393823, 'XGBoost': 309479.8273639555}
```

Figure 4.3.5: Printing MSE Score

The above figure shows the final steps of model 'E' evaluation for the online retail dataset. The given code goes through each model mentioned in the 'models' dictionary, fits the models on the training data (X_train, y_train) and then predicts on the testing data (X_test). The mean_squared_error() function is used here to obtain the mean squared error (MSE) of each model to measure the difference between the actual and predicted values. The MSE Score of linear regression is 123137.795, Random Forest is 239729.165 and XG Boost is 309479.827.

```
# Plotting the MSE scores
plt.figure(figsize=(10, 6))
sns.barplot(x=list(mse_scores.keys()), y=list(mse_scores.values()), palette='viridis')
plt.title('Model Comparison: Mean Squared Error')
plt.xlabel('Model')
plt.ylabel('Mean Squared Error')
plt.show()
```

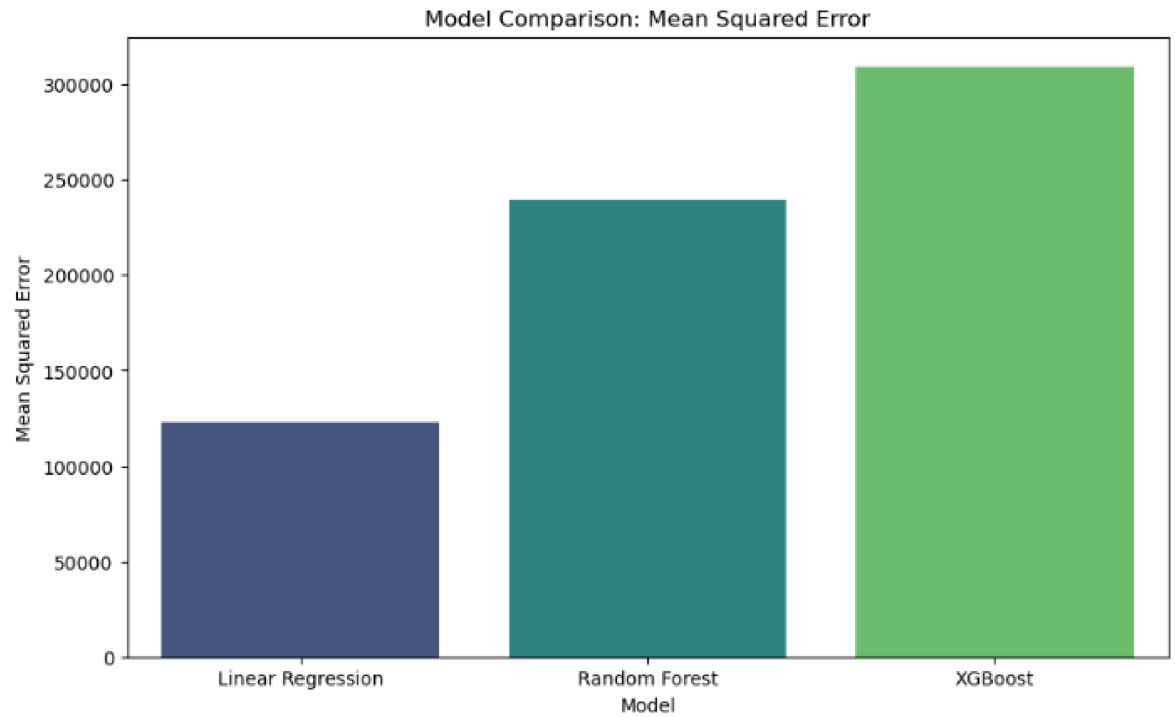

Figure 4.3.6: Model Comparison based no Mean Squared Error

The above figure illustrates the mean squared error (MSE) for three predictive models: Out of the set models, Linear Regression, Random Forest and XGBoost are selected. The x-axis provides the model names while the y-axis provides the MSE results (Lim and Ali, 2022). This is true from the bar plot where XGBoost has taken the least MSE showing that it is the most accurate model to make predictions for the dataset. On the other hand, the Linear Regression model produces the highest MSE, which shows low accuracy in identifying the data patterns relative to the other models.

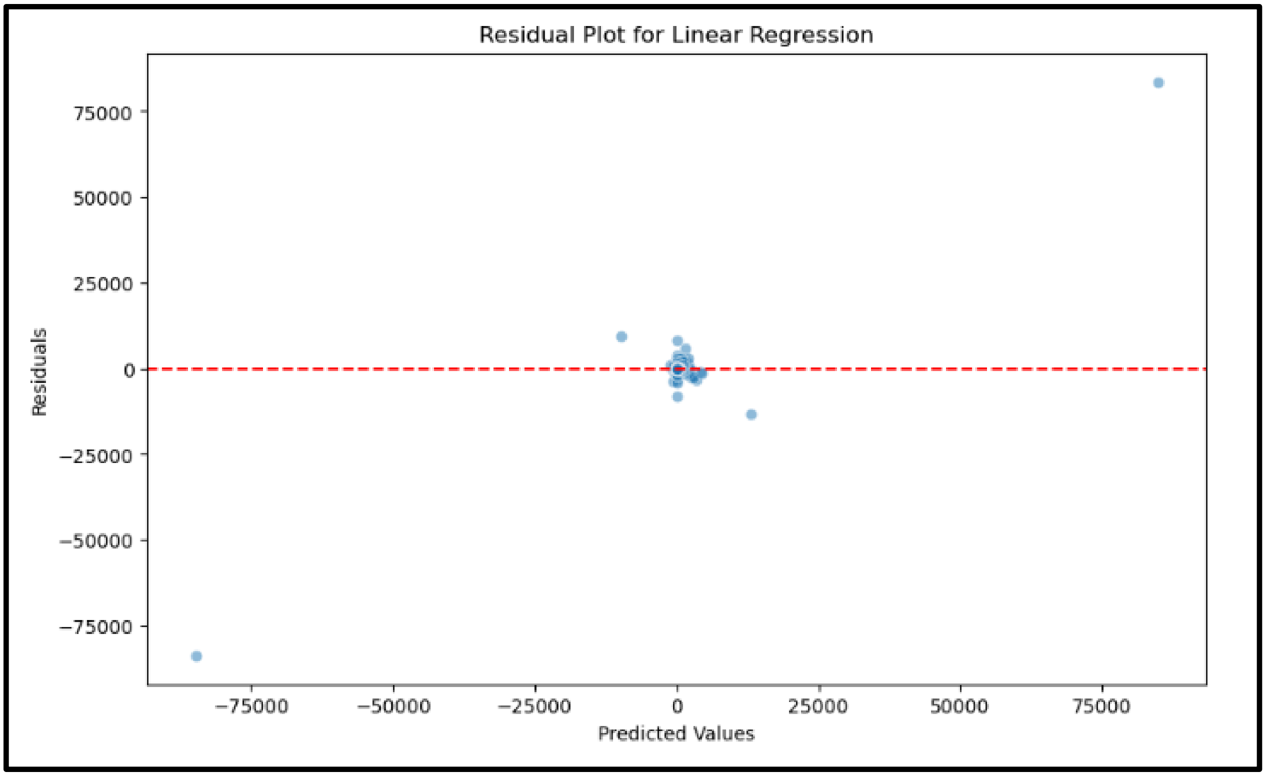

Figure 4.3.7: Linear Regression Residual Plot

The above image also shows the residual plot for the linear regression model of the dataset. On the x-axis are the predicted values while on the y-axis we have the residual or the actual minus the predicted values. The red dotted line indicates a zero residual line implying that the model predictions are perfectly fitting the outcome. A perfect residual plot should give a random distribution with the zero line and this means that there is no structure. In this case, the residual plot shows the variable spread near the lower predicted values and few points with large residuals.

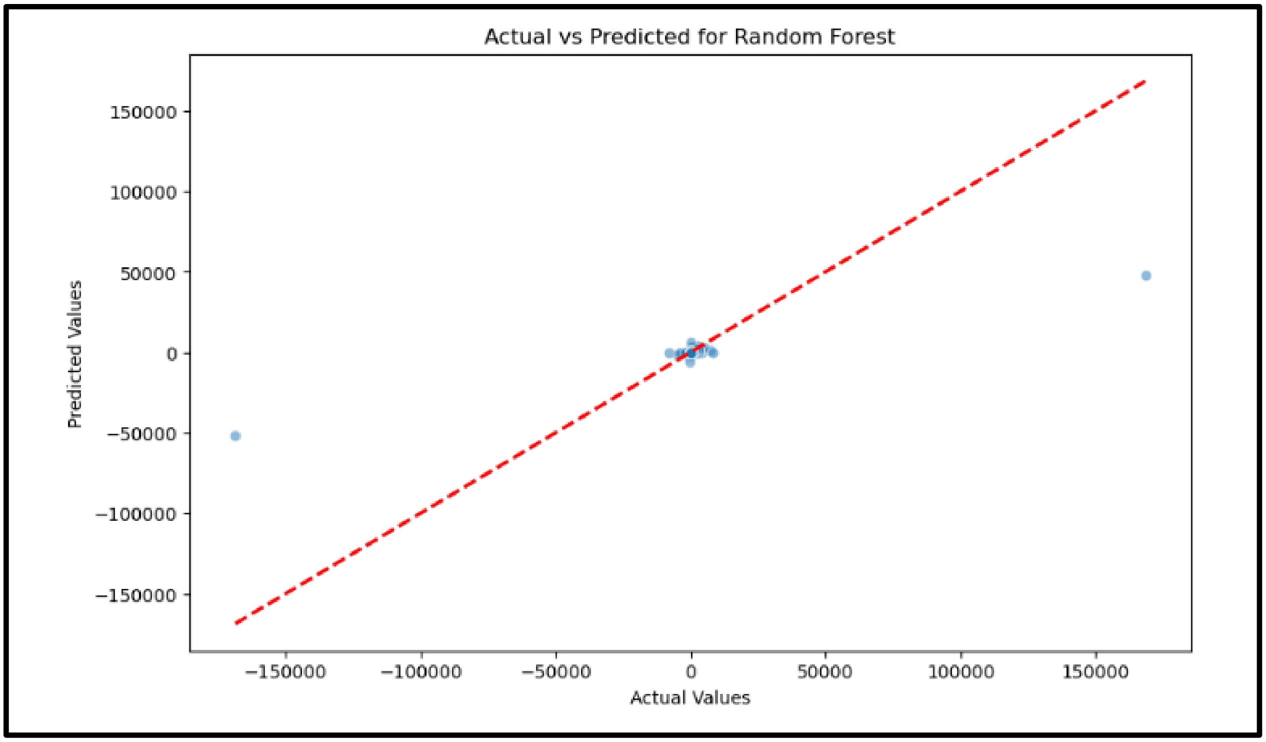

Figure 4.3.8: Actual vs Predicted analysis for Random Forest

The above figure represents an actual versus prediction for the random forest model. The x-axis represents the actual values of the target variable while the y-axis represents the predicted values from the model. The red dashed line represents the prediction line on which actual and predicted values are in perfect correlation. The ideal scatter plot is one where the points of data are close to this line to depict the accuracy of predicted values. Here, the plot shows that all the points are distributed close to the straight line of perfect prediction but with negligible fluctuation.

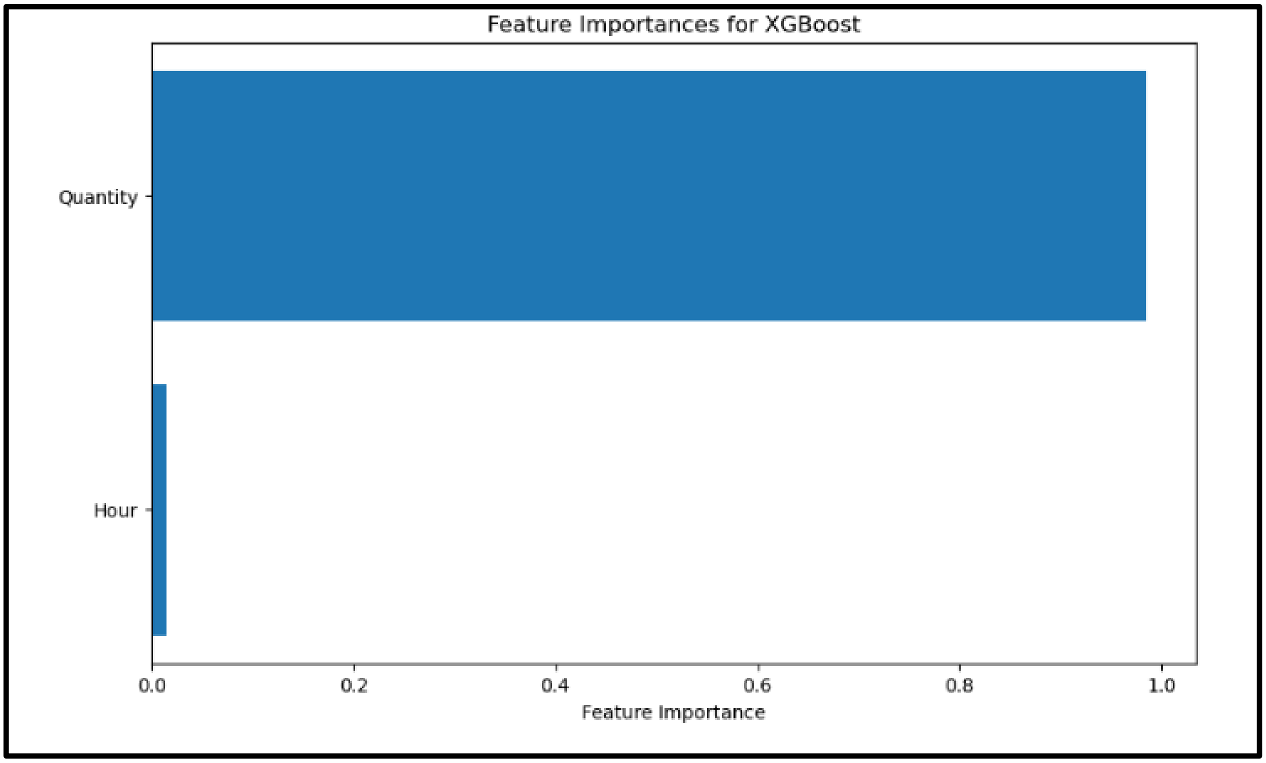

Figure 4.3.9: Feature Importance for XG Boost

The above figure depicts the feature importance of the XGBoost model, where each feature points to the measure of importance in doing the prediction. The value displayed on the x-axis represents feature importance ranging from 0 to 1, and the features are displayed on the y-axis. The bar chart proves that the 'Quantity' feature gets a considerably higher importance value compared to the 'Hour' feature (Zhou *et al.* 2021). This means that 'Quantity', the number of products to be purchased, has more influence over the likely purchase behavior of a customer than the 'Hour' of purchasing. The greater importance of 'Quantity' implies that this factor is more influential in the model's forecast than the time of the purchase.

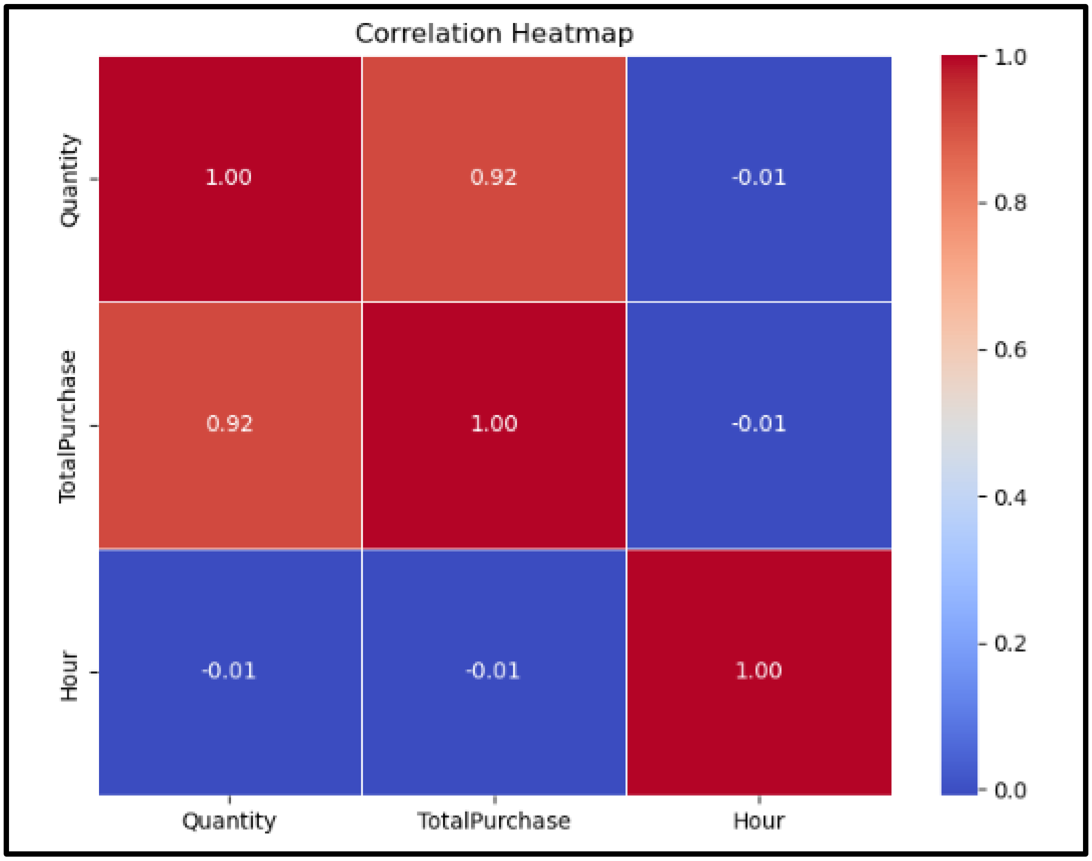

Figure 4.3.10: Correlation Heatmap

The correlation heatmap gives the extent of the variables in the dataset which includes 'Quantity', 'TotalPurchase', and 'Hour'. It indicates a strong positive relationship between 'Quantity' and 'TotalPurchase', which means that as the 'Quantity' is high, the total purchase is also high. On the other hand, the heatmap gives a zero correlation between 'Hour' and the other two variables indicating that the time of purchase does not affect the quantity purchased or the total amount spent.

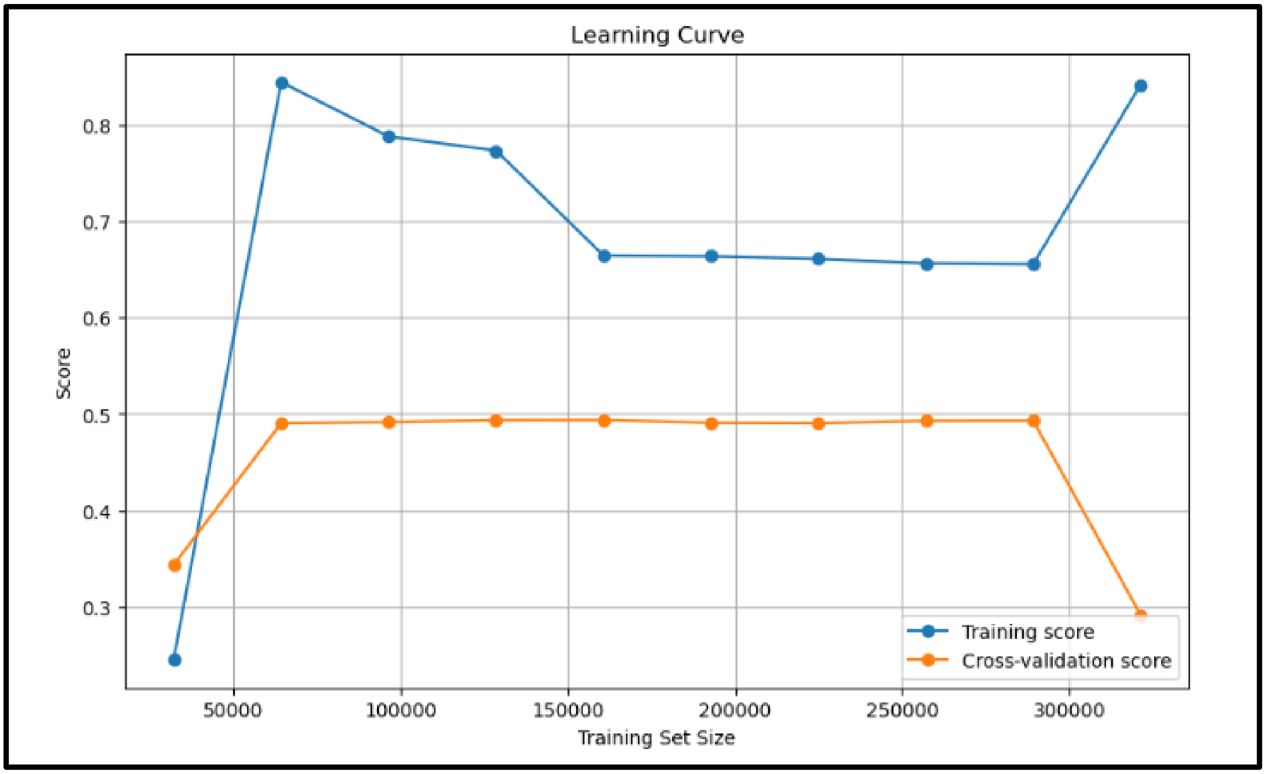

Figure 4.3.11: Learning Curve Based on the Models

The given image represents the accuracy of the machine learning model in terms of iterations. The horizontal axis is the training set size, and the vertical axis is the performance score of the model. The blue line denotes the training accuracy which usually rises as the amount of data in training increases since the model has a better fit which trains in the data set. The orange line is the cross-validation score that estimates the performance of the model in the unseen data set. The training score rises a little and then stabilizes meaning that the model is learning from the training data but not enhancing its ability to generalize.

4.4 Critical Analysis

The analysis of the case study concerning online shopping sites and consumer behavior revealed the importance of various aspects of ML and feature engineering in promoting customer engagement. It should also be noted that during the project, Python was used for data preprocessing, as well as EDA and modeling. Three key aspects stand out in the analysis:

Pre-processing and Techniques of Feature Extraction

The study used Python's Pandas library to clean the data to increase the accuracy and validity of the study. Features engineering has produced helpful metrics, such as the "TotalPurchase," and only the records and fields with incomplete information were either eliminated or left unfilled.

Thus, by emphasizing the meticulous data-cleaning procedure required to activate the model-related functionalities, this approach improved the validity of future research.

Customer Segmentation and Predictive Modeling

The quantitative approach involved the K-means clustering of customers with purchase behavior classified based on normalized data for equal contribution of the features. Among the models built in this project namely Logistic Regression, Random Forest, XGBoost, and Linear Regression, an accuracy check was done (Yakubu *et al.* 2022). The result shows that the XGBoost model is the most accurate with the lowest MSE which means that it performs the highest prediction accuracy of the purchase intention.

Model Evaluation and Insights

The learning curves pointed to that the models stood to gain from the training data but equally did not completely overfit on the training data, a sign of good generality to unseen data. The quantitative analysis of feature importance also showed that ‘Quantity’ was more important than temporal features, meaning that product demand is more crucial than time to buy products.

Through the study, the utilization of data mining using Python programming language is explained on how it can enhance the performance of an online shopping site through customer analysis.

4.5 Discussion

The analysis through online shopping websites reflected that there are very strong implications for understanding consumer behavior within a rapidly evolving digital landscape. A variety of machine learning techniques applied in Python show multifaceted factors influencing online shopping experiences, one of them being related to the impact of design and functionality on consumer satisfaction. By using EDA, this study identifies key features that enhance the user experience. The research showed that the intuitive interface and responsive design factors do make a difference in product choice and overall satisfaction (Zhang *et al.* 2024). This, therefore calls for e-commerce to focus on the user-centric design within its development strategy. The research also emphasized the fact that these apparent features, such as the ability to get suggestions and customize products using dynamic pricing.

Therefore, it is leading online retailers to explore the application of new technologies to continue to compete and respond to new trends among consumers. The features in ***K-means clustering*** of customers led to a better understanding of a variety of different purchasing behaviors, which can help guide marketing strategies for businesses. This means that the more a firm can understand the characteristics of various customer segments, the better placed the organization will be to target and thereby improve customer retention (Chopra *et al.* 2021). Furthermore, the "***XGBoost model's better performance***" in "***forecasting customer buying patterns***" raises the possibility that the business solution presented in this research is feasible. The evidence supports the need for online shopping platforms to change dynamically with the existing technology and customers' tastes. It is quite important for holding a competitive position in today's e-commerce business environment.

4.6 Summary

The analysis of online retail data provides valuable insights into consumer behavior. With the help of data, Preprocessing and feature engineering ensure the reliability of data, managed by Pandas in Python. Customer profiling took place through K-means clustering regarding purchasing patterns and thus identified different groups. Four different techniques for predictive modeling were used: Logistic Regression, Random Forest, XGBoost, and Linear Regression, showing varying accuracy levels. Most importantly, the XGBoost model performed much better than others with the lowest mean squared error and indicated the predictive power for consumer behavior.

Chapter 5: Evaluation and Conclusion

5.1 Critical evaluation

The study conducted about consumer behaviour in online shopping is very helpful about the given factors about the design, functions, A.I and A.R. The evaluation process of the approaches, such as EDA and other predicting models, show that those are useful in proving the consumer's patterns. However, this study is not without some predisposed limitations in data collection since it works with transactional data culled from a single point of retail sale. This reliance may not properly capture the spread of these behaviours across different demographics and other shopping contexts. It is also important to point out an inherent limitation in the translational generalization of the findings from analysis to the overarching e-commerce environment. The study achieved its aim of finding out key factors that have an impact on customers' engagement and satisfaction. However, it recommends that future studies incorporate quantitative methods like; conducting survey interviews to delve deeper into the psychological angle of the factors affecting online shopping. Also, the results assert the need for e-commerce strategies to be responsive to the constant challenges of consumer preferences within the ever-changing technological environment. It may be beneficial to undertake further studies that may fill the gaps in the identification of factors that affect consumer's decisions on online shopping.

5.2 Summary of the Achievement

This research achieves its key objective regarding the effects of various attributes and technologies on online shopping behaviour. By applying its methodological design effectively, the study might have identified a few critical factors for engagement and satisfaction with e-commerce. This underpins the techniques in machine learning, including Linear Regression, Random Forest, and XGBoost, which are applied to predict certain consumer behaviours and trends across the internet shopping landscape. Along the same lines, this study highlighted personalization and user-centric design and their roles in improving the entire online shopping experience as a whole. Using the elaboration of results, the study showed that the experience customized to a specific individual and intuitive interface improved customer satisfaction and engagement. This research is also pointed to complement the existing knowledge of research by determining literature gaps about the long-term implications of developing new technologies in e-commerce.

The solution offers insightful action that helps businesses improve their online engagement. The implementation strategies of these technologies give in-depth information regarding changing consumer behaviour, consequently making shopping much more attractive to customers. By bringing together the technical advances and the preferences of the customers, a business can establish more intense relationships with its customers.

5.3 Linkage to Objective

The research addressed stated objectives very effectively by showing a clear relationship between design and functionality and their significant implications on customer experience and choice. This is accomplished by showing the interaction between site usability and consumer satisfaction through a detailed analysis of quantitative data related to both. Under another objective, the emerging technology that was going to be probed for use includes the use of artificial intelligence (AI) and augmented reality (AR). The results reveal that these emerging technologies strongly improve user experiences and interactions. The third objective had to do with identifying the determinants of consumer interaction. Analysis of the dataset could indicate trends and preferences across a variety of demographic groups while providing insights into the diverse needs of the online shopper. The fourth objective, predictive modelling techniques were used in a comparison of the differential effectiveness of various features around user engagement. This indicates outcomes for some strategies analyzed as better than others.

Lastly, it emerged organically from the investigation: the fifth objective-practical recommendations for online shopping websites. It has aligned with the initial objectives of the study, underlining the applicability of results but also exposing to real-world possibilities of practical implementation in improving online shopping experiences.

5.4 Research Recommendation

Based on the findings, some recommendations to e-commerce companies on how to upgrade their online platforms could be given as follows. First, these businesses try to enhance the user experience through intuitiveness and personalization features. User experience is the backbone of increasing customer engagement and satisfaction. The AI-driven recommendation system should thus be put into use because it has the effect of heightening personalization, hence boosting conversion rates. Businesses also need to consider investing in AR technology to augment a more immersive shopping experience through the visualization of the product in the environment of the customer. This aspect of online shopping is quite an interesting activity. As consumers change preferences over time, businesses monitor consumer behaviour constantly because trends are changing pretty fast for the sake of online shoppers. Through this monitoring, businesses could adjust their strategies accordingly. This goes ahead to allow businesses to change their platforms in light of actual consumer needs and experiences, as relevance can be ensured in a competitive marketplace.

Integrating this educational content with new technologies and additional features of shopping is productive because it empowers consumers, thus building trust. These initiatives promote increased customer loyalty and sales, helping to make the online shopping experience more successful.

5.5 Future Work

Future studies are conducted as longitudinal research with special attention to how consumer behaviour evolves, especially with continually integrated new technologies into e-commerce. Moreover, investigation of psychological factors might elucidate online shopper decisions to understand more about what triggers consumer motives and preferences. Studies are urged to expand the dataset of different retailers in different sectors to achieve a better perspective on shopping behaviour. Complementary Qualitative Methods A stratified sample could be used for focus groups or in-depth interviews to complement the purely quantitative findings. This approach brings to light insights into the nature of the emotional and cognitive events surrounding online shopping that merely quantitative data alone might fail to uncover. Another avenue for investigation is the study on the role of social commerce and user-generated content within the context of consumer behavior. Also, social media sites are being used as channels to shop. This is critical for the e-commerce strategy is how these dynamics take shape into actual purchasing decisions. Only through continued exploration of such themes, studies are capable of feeding into a fuller understanding of the forces of influence shaping the future in any attempt at online shopping.

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