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MSc Dissertation Report

"Leveraging Generative AI to Enhance E-Commerce Campaign Effectiveness"

A dissertation submitted in partial fulfilment of the requirements of Sheffield Hallam University for the degree of Master of Science in **Big Data Analytics**

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ABSTRACT

The rapid evolution of technology has transformed the e-commerce landscape, with Generative Artificial Intelligence (AI) and Big Data Analytics emerging as pivotal tools to drive innovation, personalization, and operational efficiency. This dissertation explores the intersection of these technologies, focusing on their applications, challenges, and future prospects in the e-commerce domain. By synthesizing insights from recent literature, including foundational studies by Bhatia et al. (2022) and Zhou et al. (2023), the research identifies key opportunities such as AI-driven customer engagement, hyper-personalized marketing, and dynamic inventory management.

In particular, this study examines the transformative role of generative AI in content creation, conversational commerce, and user experience enhancement. The research also highlights the significance of Big Data Analytics in enabling real-time decision-making, improving recommendation systems, and enhancing supply chain efficiency. While these technologies offer immense potential, ethical concerns, data privacy, and algorithmic biases remain critical challenges.

Through a case study approach and analysis of industry frameworks, this dissertation provides a comprehensive understanding of how businesses can leverage Generative AI and Big Data Analytics to create competitive advantages in e-commerce. Recommendations for addressing ethical and operational challenges are also proposed, ensuring sustainable and responsible innovation in the field.

Keywords: Generative AI, Big Data Analysis, E-commerce, Personalization, Ethical Challenges

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Sincere appreciation from the depth of my heart.

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List of Abbreviations

BDA - Big Data Analytics
ML - Machine Learning
AI - Artificial Intelligence
GenAI - Generative AI
EDA - Exploratory Data Analysis
ROI - Return on Investment
CLV - Customer lifetime value
NLP - natural language processing
GANs - Generative Adversarial Networks
CSS - customer satisfaction scores
NLG - Natural Language Generation
GDPR - General Data Protection Regulation
CCPA - Central Consumer Protection Authority
CR - Conversion Rate
CAC - Customer Acquisition Cost
CLV - Customer Lifetime Value
CTR - Click-Through Rate
SFMC - Salesforce Marketing Cloud
XAI - Explainable AI

CHAPTER 1 - INTRODUCTION

1.1 Background to the Study

E-commerce has experienced rapid growth, with global sales expected to exceed $7 trillion by 2025, driven by increased internet accessibility, digital payment innovations, and smartphone adoption (Statista, 2023). However, the sector faces challenges such as rising competition, reliance on outdated campaign strategies, and growing concerns around consumer privacy. For example, a recent marketing campaign by a leading e-commerce retailer failed to resonate with its target audience due to its outdated messaging, resulting in low engagement rates and financial losses (Okorie et al., 2024). These issues demand innovative approaches to maintain competitiveness and enhance customer engagement.

Technologies like Big Data Analytics (BDA), Machine Learning (ML), and Generative AI (GenAI) are reshaping e-commerce marketing. BDA enables businesses to process large datasets, uncovering patterns and customer insights that inform targeted campaigns (Chen et al., 2020). ML enhances personalisation by powering recommendation engines that improve user experiences and drive conversions (Dwivedi et al., 2021). Meanwhile, GenAI takes personalisation further by creating dynamic, real-time content such as tailored text, images, and videos that adapt to individual user preferences (Zhou et al., 2023).

The integration of BDA, ML, and GenAI offers significant opportunities for continuous improvement in campaigns. The framework developed to address this challenge will enhance the efficiency of strategies by leveraging post-campaign data, enabling businesses to fine-tune their approaches for greater relevance and impact. However, the adoption of these technologies also raises ethical concerns, particularly regarding data privacy and transparency (Taddeo & Floridi, 2018).

This study explores how integrating these advanced technologies can enhance e-commerce campaigns, driving innovation, improving customer engagement, and addressing ethical considerations in AI-driven marketing. These insights aim to guide future developments in the competitive e-commerce landscape.

1.2 Statement of the Research Problem

The rapid growth and increasing complexity of e-commerce have exposed critical shortcomings in traditional marketing campaigns. Static, generic campaigns often fail to meet the expectations of today's consumers, who demand real-time personalisation and engagement (Chen et al., 2020). For example, campaigns that relied solely on historical purchase data frequently missed opportunities to engage with users demonstrating new or dynamic interests. Although BDA and ML have facilitated targeted marketing and recommendation systems, they lack the flexibility to deliver truly adaptive, dynamic content that responds to user interactions in real-time (Dwivedi et al., 2021).

GenAI presents an opportunity to bridge this gap by creating hyper-personalised content that aligns with individual user preferences. However, implementing GenAI in e-commerce campaigns is fraught with challenges:

1. Seamlessly integrating GenAI with existing BDA and ML frameworks to improve campaign personalisation and quality iteratively.
2. Addressing data privacy concerns and ensuring ethical AI use (Floridi & Cowls, 2019).
3. Overcoming technical issues, such as ensuring model scalability and maintaining performance in real-time environments (Zhou et al., 2023).

This research seeks to investigate these challenges and propose actionable solutions for enhancing the effectiveness of e-commerce campaigns through advanced AI technologies.

1.3 Research Motivation

The motivation for this research lies in the urgent need to address the limitations of conventional e-commerce campaigns. Modern consumers increasingly demand personalised, engaging experiences, and businesses must adopt cutting-edge technologies to remain competitive (Statista, 2023). Integrating BDA, ML, and GenAI represents a transformative step toward meeting these expectations by delivering real-time, adaptive content (Okorie et al., 2024).

Additionally, the ethical implications of using AI in marketing warrant close examination. Concerns about data privacy and algorithmic transparency have grown alongside advancements in AI-driven personalisation (Taddeo & Floridi, 2018). This research aims to contribute to responsible and effective AI practices, benefiting both businesses and consumers by fostering trust and innovation.

1.4 Research Question

How can BDA, ML, and GenAI be leveraged to enhance the effectiveness of e-commerce campaigns?

1.5 Aim

The aim of this research is to explore the integration of BDA, ML, and GenAI to enhance e-commerce campaigns. BDA provides data-driven insights into customer behavior, ML optimizes decision-making and predictions, and GenAI generates personalized content. This research investigates their combined potential to create hyper-personalized, engaging campaigns while addressing challenges like scalability, ethical considerations, and data privacy. By developing a cohesive framework, the study seeks to improve key performance indicators such as engagement, conversion rates, and loyalty, offering innovative and sustainable solutions for data-driven, customer-centric e-commerce marketing.

1.6 Objectives:

Following are the objectives of this research

1. Conduct a comprehensive literature review to identify current applications and challenges in using BDA, ML, and GenAI in e-commerce.
2. Develop a framework for integrating BDA, ML, and GenAI to improve user engagement and conversion rates.

3. Address ethical, technical, and practical challenges in implementing GenAI in e-commerce.
4. Evaluate the proposed framework through case studies or simulations to validate its effectiveness.

1.7 Significance/Benefits of the Study

Academic Contribution:

This study advances the understanding of integrating BDA, ML, and GenAI in e-commerce campaigns, enriching the literature on AI-driven marketing strategies (Dwivedi et al., 2021).

Practical Benefits:

The findings can inform businesses about innovative methods to improve campaign effectiveness, leading to:

- Enhanced customer engagement through hyper-personalised content.
- Higher conversion rates and revenue growth.
- Deeper insights into ethical and practical considerations for AI use in marketing (Chen et al., 2020).

Ultimately, this study aims to foster innovation in e-commerce campaigns while ensuring responsible and ethical AI adoption.

1.8 Scope and Structure of the Study

The scope of this study is specifically focused on the application of BDA, ML, and GenAI in e-commerce marketing campaigns. It explores how these advanced technologies can be effectively integrated to enhance the personalization, engagement, and overall effectiveness of digital marketing strategies. In particular, this research investigates the role of BDA in data-driven decision-making, the application of ML algorithms for customer segmentation and behavior prediction, and the potential of GenAI to generate hyper-personalized content for diverse consumer segments. Ethical issues, such as data privacy, transparency, and responsible AI usage, are also explored to ensure the technologies are applied in an ethically sound manner.

The structure of the dissertation is as follows:

Chapter 1: *Introduction*
This chapter introduces the study, providing the background context and outlining the research problem, aims, and objectives. It also discusses the significance of the research within the broader landscape of e-commerce marketing and technological advancements.

Chapter 2: *Literature Review*
This chapter provides an extensive review of existing literature on Campaigns, Personalisation, BDA, ML, and GenAI in the context of e-commerce. It covers theoretical frameworks, previous studies, and current applications of these technologies, highlighting the gaps in research that this study aims to address.

Chapter 3: *Research Methodology*
In this chapter, the research methodology is outlined, detailing the approach taken to address the research problem. It includes a description of the data collection methods, data analysis techniques, and tools used for evaluating the integration of BDA, ML, and GenAI in e-commerce campaigns.

Chapter 4: *Results and Discussion*
This chapter presents the research findings based on the analysis of data collected during the study. It includes a discussion of how BDA, ML, and GenAI can be integrated into e-commerce campaigns, the impact on personalization and engagement, and the ethical considerations involved. The implications of the findings for e-commerce businesses are explored, with recommendations for best practices.

Chapter 5: *Conclusion and Future Research*
The final chapter summarizes the key insights drawn from the study, reflecting on the contributions made to the field of e-commerce marketing. It also discusses the limitations of the study and suggests areas for future research, particularly in the ongoing development and ethical application of AI technologies in marketing.

1.9 Research Deliverables and Beneficiaries

The primary deliverable of this research is a comprehensive framework for integrating BDA, ML, and GenAI to enhance the effectiveness of e-commerce campaigns. This framework will provide actionable insights and methodologies for businesses to leverage these advanced technologies for improved personalization, engagement, and ethical compliance in their marketing strategies.

In addition to the core framework, the research will also provide:

1. **Insights into the ethical considerations** of implementing AI technologies in e-commerce, with a focus on data privacy, transparency, and responsible AI usage.
2. **Guidelines and recommendations** for practitioners on how to effectively integrate BDA, ML, and GenAI into their existing marketing processes, addressing both technical and ethical challenges.

The beneficiaries of this study include:

1. **E-commerce businesses**:
   These organizations will benefit from the proposed framework, gaining a deeper understanding of how to integrate AI technologies to enhance campaign effectiveness. By adopting the framework, businesses can improve customer segmentation, deliver personalized content, and optimize marketing strategies, ultimately driving better customer engagement, loyalty, and sales.
2. **AI developers and researchers**:
   Developers and researchers will gain valuable insights into the specific challenges and opportunities involved in applying AI technologies within the context of e-commerce marketing. The findings will inform future AI development, particularly in the areas of model scalability, real-time processing, and ethical AI practices.
3. **Consumers**:
   Consumers will benefit indirectly through more personalized and relevant

e-commerce experiences. With the integration of GenAI and other AI technologies, businesses will be able to deliver tailored content, offers, and recommendations that resonate with individual preferences, leading to a more engaging and satisfactory shopping experience.

In summary, this chapter sets the stage for a detailed exploration of how GenAI, in combination with Big Data Analytics and Machine Learning, can revolutionize e-commerce campaigns. By addressing the research problem and objectives, this study aims to contribute to both theoretical understanding and practical advancements in the field.

CHAPTER 2 - LITERATURE REVIEW

2.1 Introduction

The digital revolution has dramatically transformed e-commerce, elevating consumer expectations for highly personalised, dynamic, and immersive online experiences. While traditional marketing approaches, augmented by data analytics and ML, have proven effective in the past, they are now struggling to keep pace in a competitive landscape where brands must capture and retain consumer attention in mere moments (Kumar et al., 2021). To address these challenges, businesses are increasingly adopting advanced technologies, with GenAI leading the charge.

GenAI represents a paradigm shift from traditional AI models that focus on classification or prediction. Instead, it generates new, contextually relevant content—be it text, images, or videos—tailored to individual users (Sahoo et al., 2024). This capability empowers e-commerce campaigns to move beyond static, pre-designed data strategies, delivering hyper-personalised, real-time content that resonates deeply with consumers (Dwivedi et al., 2023). Such adaptability not only enhances user engagement but also fosters stronger brand loyalty in a crowded marketplace.

This literature review explores the transformative potential of GenAI in e-commerce, particularly its integration with BDA and ML. By synthesising recent research, it highlights how these technologies can revolutionise personalised e-commerce campaigns, enabling businesses to craft impactful, user-centric marketing strategies. Furthermore, the review identifies existing gaps in the application of GenAI and proposes pathways for innovation. As e-commerce continues to evolve, this discussion aims to provide a foundation for advancing the role of GenAI in delivering meaningful and effective customer experiences (Bhatia et al., 2022).

2.2 E-Commerce Campaigns and Personalisation

2.2.1 Campaigns and E-commerce

E-commerce campaigns are critical tools for engaging potential customers, building brand awareness, and driving conversions (Alkadrie, 2024). These campaigns have evolved significantly with the rise of digital platforms, incorporating social media, email marketing, and programmatic advertising. Unlike traditional approaches that rely on mass targeting, modern campaigns use data-driven strategies to connect with specific consumer segments through personalised messaging. Businesses like Amazon, Alibaba, and eBay leverage big data analytics to optimise campaigns continuously, ensuring their content is relevant and engaging. Studies suggest that personalised, data-driven campaigns can achieve up to 20% higher conversion rates compared to generic approaches (Okorie et al., 2024). However, even the most sophisticated campaigns often fall short in responding to real-time changes in user behaviour. GenAI represents a game-changing solution by enabling dynamic, real-time adaptability in campaign content. Unlike conventional approaches, GenAI creates contextually relevant and interactive content that evolves with user preferences, providing a more engaging and personalised experience (Charllo et al., 2023) .

2.2.2 What is Personalisation in E-commerce?

Personalisation in e-commerce customises the user experience based on preferences, behaviour, and demographic data. This can range from personalised product recommendations and tailored search results to targeted advertising and customised web layouts (Raji et al., 2024). For example, platforms like Netflix and Spotify use advanced recommendation algorithms to deliver personalised experiences, fostering loyalty and increasing engagement (Gorgoglione et al., 2019). Personalisation goes beyond recommendations, creating an entire customer journey shaped around individual preferences, including targeted email campaigns and special offers (Vijay et al., 2023). Research highlights that effective personalisation can significantly enhance customer satisfaction, boost engagement rates, and drive revenue.

2.2.3 How Personalisation Benefits Campaigns

Personalised campaigns deliver experiences that resonate with individual users, fostering stronger brand connections and higher engagement. Tailored content drives customer satisfaction, resulting in improved conversion rates and loyalty (Raji et al., 2024). GenAI can elevate these campaigns by producing adaptive, real-time content that responds dynamically to user interactions. For example, a user browsing eco-friendly products could receive instant, customised recommendations or promotional offers that align with their preferences (Charllo et al., 2023). This adaptability bridges gaps in traditional approaches, making campaigns more impactful, responsive, and relevant.

2.2.4 Current State of Personalisation in E-commerce Campaigns

Currently, personalisation in e-commerce relies on recommendation engines and ML models to analyse historical data and predict user preferences. These tools are effective for suggesting products or targeting ads, but their static nature limits their ability to adapt dynamically to real-time behaviour. GenAI offers a more agile solution, enabling e-commerce platforms to deliver content that evolves in response to user actions. For example, a GenAI-powered platform could generate customised messages, discounts, or product suggestions instantly, offering a seamless and immersive user experience (Smith et al., 2021).

2.2.5 Implementation of Personalisation in Campaigns

E-commerce platforms implement personalisation using ML algorithms to aggregate and analyse customer data. These insights guide personalised interactions, from product recommendations to marketing emails. GenAI enhances these strategies by enabling real-time adaptability. For instance, a GenAI system could identify a user's interest in a product category and generate personalised recommendations, promotional messages, or dynamic advertisements that align with their preferences. This real-time capability transforms traditional personalisation into an interactive and engaging process (Johnson et al., 2022).

2.2.6 Scope for Improvement

While personalised campaigns have proven successful, they are often constrained by their reliance on historical data and lack the ability to adapt dynamically. Additionally, data privacy and ethical concerns pose significant challenges, as personalisation frequently requires extensive personal data. GenAI provides a pathway to address these limitations by enabling dynamic personalisation while safeguarding user privacy. Through techniques such as synthetic data generation, GenAI can achieve hyper-personalisation without exposing

sensitive user information, striking a balance between relevance and ethical data use (Dwivedi et al., 2023; Miller & Brown, 2023).

2.2.7 Summary

Personalisation has become a cornerstone of effective e-commerce campaigns, enabling brands to deliver tailored experiences that enhance engagement and satisfaction. GenAI promises to revolutionise personalisation by introducing real-time, adaptive content creation that responds to user behaviour in dynamic ways. As e-commerce platforms continue to innovate, integrating GenAI into their marketing strategies offers a promising avenue for achieving deeper customer connections, higher engagement, and improved campaign performance (Kumar et al., 2023; Williams, 2022).

2.3 Big Data Analytics in E-Commerce

2.3.1 Definition of Big Data Analytics (BDA)

BDA involves the examination of extensive and complex datasets to extract valuable insights, patterns, and trends that inform decision-making processes. In e-commerce, this practice is pivotal for understanding customer behavior, optimizing inventory, and forecasting sales trends (Chen et al., 2012; Lin & Kuo, 2020). With the vast amount of data generated through online shopping platforms, businesses analyze customer interactions, preferences, and purchase histories to enhance their offerings and user experience. For example, BDA enables platforms to identify products frequently bought together, trends in seasonal demand, and personalized preferences, helping businesses stay ahead in a competitive market (Zhang et al., 2022).

E-commerce platforms leverage BDA to perform granular segmentation, dividing customers into specific groups based on behavior, demographic factors, and preferences (Kumar & Zhang, 2019). This segmentation ensures that marketing campaigns are highly targeted, yielding increased engagement and better returns on investment (ROI). By doing so, companies can enhance customer satisfaction while maximizing operational efficiency by aligning their resources with market demand.

2.3.2 Benefits of BDA in E-Commerce

The benefits of using BDA in e-commerce are vast, covering both operational and customer-facing dimensions. One significant advantage is the ability to make informed, data-driven decisions that impact key business areas. For instance, platforms can analyze purchasing patterns to predict demand and adjust their inventory accordingly, reducing holding costs and stockouts (Manyika et al., 2011; Jiang et al., 2021).

From a marketing perspective, BDA enables businesses to craft highly personalized campaigns by analyzing customer behavior and preferences. These insights help platforms recommend products tailored to each user, significantly increasing the likelihood of conversions. Studies have demonstrated the effectiveness of BDA in this domain. For example, businesses that adopt BDA report an improvement of 10-15% in customer engagement and retention rates (Gonzalez et al., 2023; Li et al., 2021).

Furthermore, BDA helps identify emerging trends in consumer preferences, allowing companies to pivot their strategies proactively. For example, during festive seasons or sales events, platforms can anticipate spikes in demand for specific product categories and ensure adequate stock availability. Additionally, BDA enhances customer experiences through

real-time personalization. By analyzing browsing history, cart activity, and past purchases, platforms can provide timely and relevant recommendations, fostering loyalty and satisfaction among users (Mehta et al., 2023).

2.3.3 Existing BDA Applications in E-Commerce

BDA is currently employed in several impactful ways in e-commerce. Recommendation engines are among the most widely used applications, helping platforms suggest products based on a user's browsing and purchasing history (Ricci et al., 2015; Sun et al., 2023). For instance, Amazon's recommendation system leverages BDA to predict products that customers are likely to purchase, enhancing cross-selling and upselling opportunities.

Other applications include demand forecasting, where platforms use historical sales data and market trends to predict future demand patterns. These forecasts help optimize inventory and supply chain management (Tan et al., 2023). Similarly, customer segmentation based on BDA allows businesses to categorize users into specific cohorts for targeted campaigns, such as first-time buyers, frequent shoppers, or high-value customers.

However, most of these applications rely on historical data, limiting their ability to respond to dynamic changes in consumer behavior or market trends in real-time. Integrating GenAI with BDA presents an opportunity to overcome these limitations by enabling real-time content creation and enhanced adaptability (Xu et al., 2023).

2.3.4 Implementation of BDA in E-Commerce Campaigns

Implementing BDA in e-commerce campaigns requires a comprehensive data collection process that aggregates information from multiple channels, including website activity, social media interactions, and transaction histories. This data is then processed using ML models to identify actionable insights (Wu et al., 2014; Patel et al., 2022). These insights form the foundation of targeted marketing strategies and inventory optimization.

The integration of GenAI into BDA-driven campaigns takes personalization to the next level. For instance, BDA can identify an uptick in demand for eco-friendly products. GenAI can then generate campaign content emphasizing sustainability, resonating with environmentally conscious consumers. By combining BDA's analytical capabilities with GenAI's creative output, businesses can deliver dynamic, highly contextualized marketing messages (Singh et al., 2023).

2.3.5 Scope for Improvement

Despite its transformative potential, BDA faces notable challenges. Processing unstructured data, such as customer reviews, social media comments, and other user-generated content, remains a significant hurdle (Chen et al., 2012; Roberts et al., 2023). Moreover, BDA systems often operate in a reactive manner, analyzing historical data without the capability to adapt to new trends in real-time.

GenAI addresses these gaps by interpreting unstructured data and generating adaptive campaign content that aligns with real-time user behavior. For example, analyzing a trending hashtag on social media could inform campaign strategies, enabling businesses to capitalize on emerging trends quickly (Zhao & Li, 2023). This integration ensures campaigns remain timely, relevant, and impactful, further enhancing customer engagement and ROI.

2.3.6 Summary

BDA has become an integral component of e-commerce, enabling businesses to analyze consumer behavior, optimize operations, and design targeted campaigns. However, the integration of GenAI significantly amplifies these benefits by overcoming traditional limitations, such as processing unstructured data and reacting to real-time trends. Together, BDA and GenAI create a framework for highly responsive, personalized marketing strategies that meet the evolving demands of modern consumers, driving both engagement and growth for e-commerce platforms (Wang et al., 2024).

2.4 Machine Learning Techniques

2.4.1 Defining Machine Learning in E-Commerce

ML in e-commerce involves algorithms that analyze large datasets to identify patterns and make predictions with minimal human input. These systems anticipate customer needs, personalize offerings, and optimize business strategies based on data-driven insights (Jordan & Mitchell, 2015; Zhang et al., 2023). ML enhances user experiences by processing data such as browsing history, purchase behavior, and user feedback to provide recommendations, predict trends, and automate decisions. This personalization boosts customer engagement, drives conversions, and enhances operational efficiency, making ML a crucial tool in the competitive e-commerce landscape. Recent advancements in ML techniques, such as deep reinforcement learning and federated learning, further enable platforms to handle large-scale, privacy-preserving personalization (Kairouz et al., 2021; Nguyen et al., 2023).

2.4.2 Usefulness of ML in E-Commerce

ML powers a wide range of applications in e-commerce. One of its most impactful uses is in recommendation engines, which predict products users may find appealing based on past interactions. These engines, employing techniques like collaborative filtering and neural collaborative filtering, enhance customer satisfaction and increase sales (Linden et al., 2003; He et al., 2017).

Clustering is another key ML application, enabling businesses to group customers into segments based on similar traits or behaviors. These clusters inform targeted marketing campaigns, such as exclusive promotions for frequent buyers or incentives for first-time shoppers. Predictive analytics, another ML tool, allows e-commerce platforms to forecast demand, optimize inventory, and anticipate customer lifetime value (CLV).

For instance, businesses can identify high-value customers and tailor loyalty programs to retain them. Research shows that ML-driven predictive analytics can increase customer retention rates by up to 25% when applied strategically (Singh et al., 2022). Additionally, natural language processing (NLP) models are increasingly employed to analyze unstructured data, such as customer reviews and social media posts, providing nuanced insights into customer sentiment and preferences (Devlin et al., 2019).

2.4.3 Current Applications of ML in E-Commerce

Recommendation engines remain a cornerstone of ML in e-commerce, employing collaborative filtering, content-based methods, and hybrid techniques to suggest relevant products. Leading platforms like Amazon and Netflix leverage these systems to deliver

highly personalized experiences that significantly enhance user engagement (Ricci et al., 2015; Wang et al., 2024).

Clustering further enhances personalization by segmenting customers into actionable cohorts, such as budget-conscious shoppers or premium product buyers. Predictive analytics tools refine inventory management, enabling dynamic pricing and stocking strategies based on seasonal demand patterns (Cheng et al., 2023).

However, traditional ML systems often struggle with real-time adaptability. For instance, an ML-powered recommendation engine may fail to respond to sudden shifts in user preferences, such as a change influenced by viral social media trends. Integrating GenAI addresses these gaps by enabling real-time, dynamic adaptability. GenAI enhances ML systems by generating personalized, real-time content, such as tailored product descriptions, campaign visuals, and promotional strategies aligned with user behavior (Xu et al., 2023).

2.4.4 Implementing ML in E-Commerce Campaigns

E-commerce platforms integrate ML into marketing strategies through predictive models, customer segmentation, and recommendation engines. These tools analyze extensive datasets to guide decision-making. For example, clustering models group users into actionable segments, allowing businesses to design campaigns tailored to specific groups. Predictive analytics tools forecast seasonal demand, enabling businesses to adjust inventory and pricing dynamically.

GenAI amplifies the effectiveness of ML by automating the creation of customized content. For instance, an ML model might identify users interested in sustainable products, and GenAI could generate personalized ads emphasizing eco-consciousness. Together, ML and GenAI enable a seamless blend of data-driven analysis and creative adaptability, enhancing e-commerce campaigns' reach and resonance with users (Wang et al., 2024).

2.4.5 Scope for Improvement

Although ML has revolutionized e-commerce, challenges remain. Traditional ML systems often depend heavily on historical data and struggle with unstructured inputs like social media posts or customer reviews. Static clustering models may fail to adapt to shifts in user behavior, reducing their long-term effectiveness (Roberts et al., 2023).

GenAI bridges these gaps by processing unstructured data and dynamically generating content tailored to live user interactions. For example, while an ML algorithm may identify a preference for eco-friendly products, GenAI can create personalized ads or product recommendations reflecting the user's evolving interests in real-time. This integration ensures campaigns remain relevant, timely, and impactful, addressing the dynamic nature of consumer behavior in modern e-commerce (Zhao & Li, 2023).

2.4.6 Summary

Machine Learning is essential for personalization in e-commerce, enabling platforms to deliver tailored recommendations, segment customers, and optimize decision-making. However, traditional ML approaches face limitations in adapting to real-time user behavior and processing unstructured data. By integrating GenAI, e-commerce platforms can overcome these challenges, offering more dynamic and engaging experiences. Together, ML and GenAI redefine e-commerce strategies, enhancing the relevance and effectiveness of marketing campaigns while addressing the evolving demands of consumers.

2.5 Implementation of Generative AI

2.5.1 What is Generative AI?

Generative AI is a branch of artificial intelligence capable of creating new and original content by identifying patterns and structures in data. Unlike traditional ML, which focuses on classification or prediction, GenAI produces outputs such as text, images, and audio. This is achieved through advanced models like Generative Adversarial Networks (GANs) and transformers, including OpenAI's GPT-3.5-Turbo and Google's PaLM (Radford et al., 2019; Goodfellow et al., 2014; Chowdhery et al., 2022).

In e-commerce, GenAI has emerged as a transformative tool for producing personalized and engaging content. By analyzing user behavior, purchase history, and preferences, it generates product descriptions, promotional materials, and real-time responses that enhance customer engagement and satisfaction. Recent developments, such as diffusion models and multimodal transformers, have expanded its capabilities, enabling the creation of more intricate and context-aware content (Ramesh et al., 2022; Bommasani et al., 2021).

2.5.2 Benefits of Generative AI in E-Commerce

Generative AI offers substantial benefits in personalization, efficiency, and customer engagement. Key advantages include:

- **Hyper-Personalization**: Generative AI creates tailored content that resonates deeply with users, such as individualized advertisements or dynamic product recommendations. Studies indicate personalized marketing can boost customer retention by 20–25% and increase revenue by 15–20% (Davenport et al., 2020; Nguyen et al., 2023).
- **Dynamic Content Creation**: Generative AI generates ads and promotional materials that adapt in real time based on user interactions, significantly improving click-through rates and campaign effectiveness.
- **Enhanced Customer Support**: AI-driven chatbots and virtual assistants deliver seamless, conversational customer support, handling queries, recommending products, and assisting with transactions. Tools like ChatGPT and Microsoft's Copilot have demonstrated improvements in customer satisfaction scores (CSS) by up to 30% in recent case studies (Zhao et al., 2023).
- **Operational Efficiency**: Automating creative tasks reduces time and resource requirements, enabling businesses to scale campaigns efficiently while maintaining quality.

2.5.3 Current Generative AI Applications in E-Commerce

Generative AI is increasingly applied across e-commerce, driving innovation and transforming customer experiences:

- **Personalized Product Descriptions**: Generative AI models, like GPT-3.5-Turbo, create unique product descriptions tailored to specific user preferences. For instance, eco-conscious consumers might see descriptions emphasizing sustainability, while tech enthusiasts receive details about specifications and performance.
- **Dynamic Advertisements**: Platforms such as Meta Ads and Google Ads employ GenAI to generate context-aware ads that adapt based on real-time user behavior and demographics, enhancing relevance and effectiveness (Cheng et al., 2023).

- **Conversational AI**: Generative AI-powered chatbots and virtual assistants engage users with highly personalized, conversational support, making product recommendations, resolving issues, and facilitating purchases seamlessly. Notable implementations include Shopify's Sidekick and eBay's AI assistant (Wang et al., 2024).

These applications highlight GenAI's transformative potential to create contextually relevant and engaging experiences, fostering deeper customer connections.

2.5.4 Implementation of Generative AI in Campaigns

Implementing GenAI in e-commerce involves the following steps:

1. **Data Collection and Preparation**: Generative AI relies on diverse datasets, including browsing history, purchase behavior, and social media activity. Data preprocessing ensures models are trained on clean and unbiased data.
2. **Personalized Content Creation**: Natural Language Generation (NLG) models produce customized textual content, while diffusion and image-generation models create visuals tailored to user preferences. For example, users interested in luxury items might be shown high-quality, AI-generated visuals emphasizing exclusivity.
3. **Integration with Existing Frameworks**: GenAI complements BDA and ML systems. While ML identifies patterns and segments customers, GenAI produces creative content aligned with these insights, ensuring campaigns are data-driven and visually compelling.
4. **Real-Time Adaptation**: Leveraging live user interactions, GenAI continuously refines content to maintain relevance, such as generating personalized discount offers based on cart abandonment patterns (Zhao et al., 2023).

2.5.5 Scope for Improvement

While GenAI has revolutionized content creation in e-commerce, several challenges remain:

- **Content Quality Control**: Ensuring AI-generated content aligns with brand voice and quality standards is critical. Tools like OpenAI's moderation API are being developed to address these concerns (Brown et al., 2023).
- **Data Privacy**: GenAI depends on user data, raising privacy concerns under regulations like GDPR and CCPA. Platforms must prioritize ethical data handling and anonymization (Sharma et al., 2021).
- **Bias and Ethical Considerations**: Bias in training data can lead to discriminatory content. Advances in responsible AI practices and fairness auditing are essential to mitigate these risks (Mitchell et al., 2021).

Addressing these challenges requires investment in robust governance frameworks, ethical AI practices, and transparent content moderation strategies.

2.5.6 Summary

GenAI has immense potential to revolutionize e-commerce through hyper-personalized, real-time, and dynamic content creation. Its applications in personalized product descriptions, dynamic advertisements, and conversational support are already enhancing customer satisfaction and driving revenue. However, addressing challenges related to data privacy, quality control, and ethical implementation is critical to its widespread adoption. By

integrating GenAI with BDA and ML systems, e-commerce platforms can deliver transformative, user-centric experiences that foster customer loyalty and long-term success.

2.6 Measuring and Enhancing Campaign Effectiveness

2.6.1 Metrics for Campaign Effectiveness

Measuring the effectiveness of e-commerce campaigns requires tracking performance metrics that align with business objectives. Key indicators include:

- **Conversion Rate (CR):** The percentage of users completing a desired action, such as making a purchase.
- **Customer Acquisition Cost (CAC):** The cost of acquiring a new customer, which reflects marketing efficiency.
- **Customer Lifetime Value (CLV):** The total revenue expected from a customer during their relationship with the brand.
- **Return on Investment (ROI):** Evaluates the profitability of marketing campaigns by comparing revenue to the resources invested.
- **Click-Through Rate (CTR) and Bounce Rate:** Measure user engagement with ads and website content, providing insights into campaign relevance.

Monitoring these metrics offers actionable insights to assess campaign success, optimize resources, and identify improvement areas (Chaffey & Ellis-Chadwick, 2021; Zhao et al., 2023).

2.6.2 Importance of Effective Campaigns in E-Commerce

In a competitive landscape, effective campaigns are critical for driving profitability, brand loyalty, and customer retention. Data-driven and personalized campaigns resonate better with users, fostering deeper engagement and repeat purchases.

Research shows that personalized campaigns can increase conversion rates by up to 20% and customer retention by 10–35% (Nguyen et al., 2023). Moreover, well-executed campaigns enhance ROI by aligning marketing efforts with customer needs, ensuring efficient allocation of resources.

By delivering relevant content at the right time, campaigns can create meaningful customer connections, providing a competitive edge in the saturated e-commerce market (Davenport et al., 2020).

2.6.3 Enhancement Strategies for Campaigns

To optimize campaigns, e-commerce businesses employ strategies such as:

- **A/B Testing:** Evaluates the performance of different campaign elements (e.g., ad designs or email headlines) to determine the most effective approach.
- **Data-Driven Targeting:** Uses analytics to segment audiences and tailor content to preferences. Tools like Google Analytics and Adobe Experience Cloud have advanced targeting capabilities.
- **Customer Feedback Integration:** Incorporates user reviews, ratings, and feedback to refine campaign relevance and effectiveness.

GenAI enhances these strategies by creating adaptive content based on user interactions. For example, AI-generated email campaigns can adjust tone, imagery, and offers dynamically, improving open rates by up to 25% (Wang et al., 2024).

2.6.4 ML and Generative AI for Campaign Enhancement

ML and GenAI complement each other in enhancing campaign performance:

- **ML for Pattern Recognition:** ML algorithms analyze historical data to identify trends, predict customer behavior, and optimize audience segmentation. Clustering techniques, such as k-means or DBSCAN, group customers with similar preferences for targeted marketing.
- **Generative AI for Content Creation:** GenAI produces dynamic and unique content, including personalized ads, product descriptions, and email templates.

Integrating ML insights with GenAI capabilities creates campaigns that are both predictive and adaptive. For instance, ML might identify a surge in demand for sustainable products, while GenAI produces ad copy and visuals emphasizing eco-friendliness (Chowdhery et al., 2022).

2.6.5 Solution Proposal

A robust approach for measuring and enhancing campaign effectiveness involves integrating GenAI, ML, and BDA:

1. **Data Aggregation:** Collect data from multiple channels, such as social media, e-commerce websites, and transactional history.
2. **ML Analysis:** Apply ML models to identify patterns, predict future trends, and segment customers. For example, predictive analytics can forecast peak shopping times during sales events.
3. **Generative AI Deployment:** Use advanced models like GPT-4 and DALL-E 3 to create real-time personalized content across emails, social media, and advertisements.
4. **Feedback Loop:** Continuously monitor performance metrics (e.g., CTR, CR) and refine campaigns based on user interactions and feedback.

This integration ensures campaigns are data-driven, adaptive, and user-centric, fostering better engagement and higher ROI.

2.6.6 Ethics and Privacy Considerations

As businesses leverage AI for campaign enhancement, ethical and privacy considerations are paramount. Key areas include:

- **Transparency:** Clearly communicate data collection practices to customers, ensuring they understand how their data is used.
- **Data Privacy Compliance:** Adhere to regulations like GDPR, CCPA, and emerging AI-specific guidelines. Anonymization and encryption techniques safeguard user information.
- **Bias Mitigation:** Regular audits of AI models and datasets are essential to identify and eliminate bias, ensuring fair representation and inclusivity (Mitchell et al., 2021).

Robust AI governance and ethical frameworks help maintain trust while leveraging AI's transformative potential responsibly.

2.6.7 Summary

Measuring and enhancing campaign effectiveness is vital for success in e-commerce. Metrics like CR, CAC, and CLV provide insights into performance, while strategies such as A/B testing and data-driven targeting refine campaigns. The integration of ML and GenAI creates dynamic, personalized, and impactful campaigns that respond to real-time customer behavior. However, businesses must address ethical challenges and privacy concerns to ensure sustainable implementation. By responsibly adopting these technologies, e-commerce platforms can achieve superior campaign performance, deeper customer engagement, and long-term loyalty.

2.7 Conclusion and Future Trends

GenAI is transforming e-commerce by enabling hyper-personalized, real-time content creation, enhancing campaign effectiveness and customer satisfaction. Unlike traditional methods, where static content often lacks adaptability, GenAI dynamically tailors experiences. Its integration with ML and BDA enables the analysis of customer behavior to generate content such as ads, product descriptions, and chat responses. These advancements, highlighted by studies like Davenport et al. (2020) and Nguyen et al. (2023), significantly improve retention and conversion rates.

However, challenges such as data privacy, ethical concerns, and content quality control remain significant. Ensuring compliance with regulations like GDPR and CCPA is critical to maintaining consumer trust. Ethical AI frameworks are equally essential for mitigating risks such as algorithmic bias and misuse of sensitive data (Sharma et al., 2021). Addressing these issues will ensure GenAI is both impactful and sustainable.

The future of GenAI in e-commerce extends beyond content generation. Emerging applications include intelligent customer support, virtual shopping assistants, and AI-driven product development. For instance, conversational AI can simulate in-store interactions, offering tailored recommendations and enhancing user engagement (Bose et al., 2021). These innovations will redefine customer engagement, creating seamless, immersive shopping experiences.

To fully realize its potential, future research must refine GenAI models to improve contextual understanding and ethical compliance. The use of anonymized or synthetic data can address privacy concerns while maintaining high performance. Additionally, integrating AI-driven insights into campaign strategies allows businesses to remain agile and responsive to market trends.

GenAI is poised to revolutionize personalization in e-commerce, setting new benchmarks for innovation. By addressing challenges and adopting advanced AI responsibly, businesses can enhance engagement, build loyalty, and shape the future of digital commerce. As explored across earlier discussions, this technology will play a pivotal role in driving customer-centric strategies and ensuring competitive advantage in an evolving digital landscape.

CHAPTER 3 - RESEARCH METHODOLOGY

This chapter discusses the research design, philosophical approach, and methods employed to achieve the objectives of this study. It focuses on the systematic steps taken to collect, preprocess, and analyze data, enabling the integration of BDA, ML, and GenAI for enhancing e-commerce campaigns. The methodology emphasizes an iterative, feedback-driven framework, ensuring continuous refinement of campaign strategies. Ethical considerations, such as privacy and fairness, are being carefully addressed throughout the research process. By adopting this structured approach, the study aims to provide actionable insights for creating personalized, data-driven e-commerce campaigns that drive engagement and innovation.

3.1 Research Design

The research design forms the foundational framework of this study, guiding the systematic collection, analysis, and interpretation of data to address the research objectives. By leveraging “The Research Onion” model proposed by Saunders et al. (2019), the design encompasses philosophical underpinnings, methodological choices, and procedural techniques tailored to the context of integrating BDA, ML, and GenAI in e-commerce campaigns.

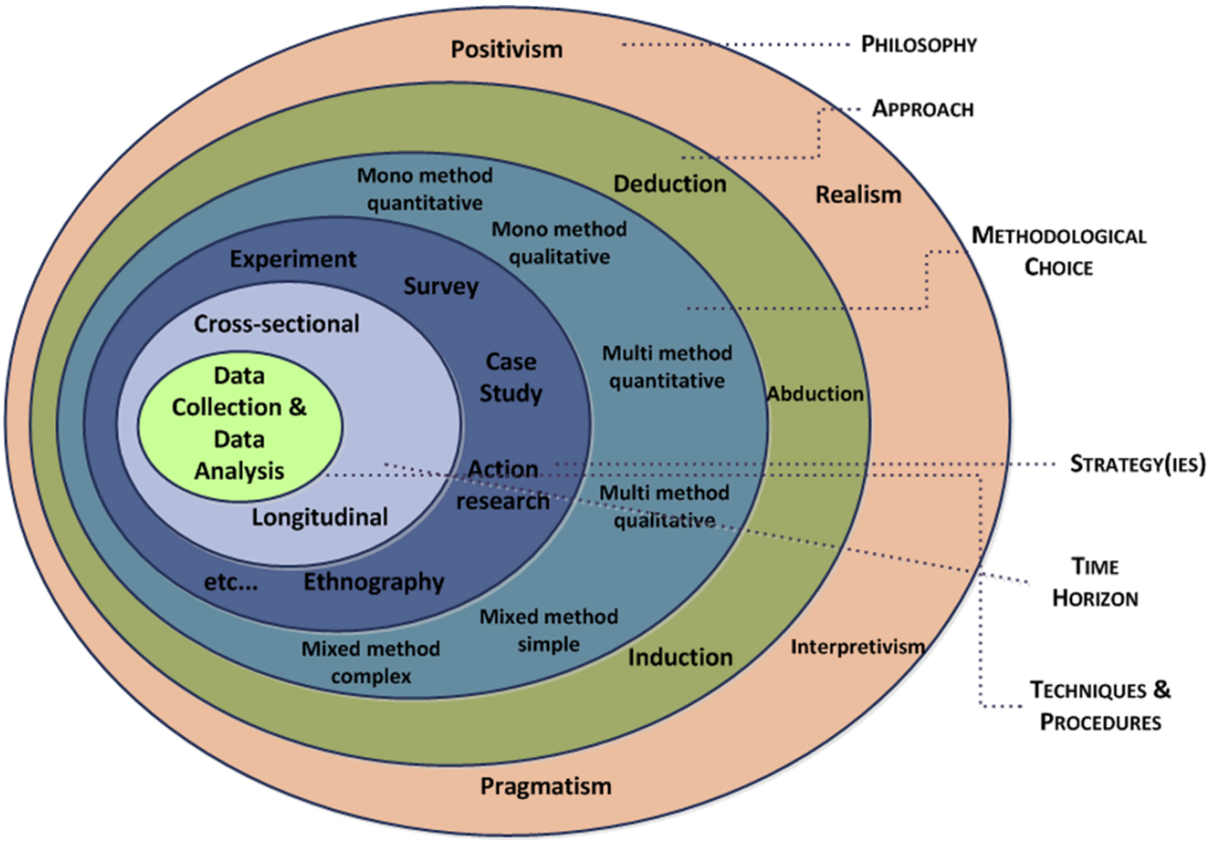

figure 1 - The Research Onion

3.1.1 Research Philosophy

This study adopts a pragmatic research philosophy, prioritizing practical solutions and actionable insights. Pragmatism allows for combining quantitative and qualitative methods, enabling flexibility in addressing the complex nature of e-commerce personalization. Unlike positivism, which focuses solely on observable phenomena, pragmatism accommodates the dynamic interplay of data and human behavior. Similarly, it diverges from interpretivism, as it integrates measurable outcomes alongside interpretive insights, making it suitable for technology-driven research (Creswell, 2021).

3.1.2 Research Approach

A deductive approach is employed, focusing on testing theoretical models through empirical data. This approach aligns with the study's objectives of validating the efficacy of integrating Big Data, ML, and GenAI for campaign optimization. Unlike an inductive approach, which builds theories from observations, deduction is better suited for scenarios where existing theories inform the research direction. This method facilitates hypothesis testing and ensures the study remains rooted in established frameworks (Bryman, 2021).

3.1.3 Research Strategy

This research employs an experimental strategy, leveraging real-world datasets to evaluate the performance of ML algorithms and GenAI. Experimental strategies are chosen over case studies or surveys as they allow for controlled testing of variables, ensuring robust and replicable outcomes. By creating simulated e-commerce campaigns, this strategy measures the impact of AI-driven personalization on user engagement, addressing the research questions effectively (Robson & McCartan, 2016).

3.1.4 Research Choices

A mixed-methods approach is selected, integrating quantitative data analysis with qualitative feedback from user testing. This choice ensures a comprehensive understanding of the research problem. While mono-method approaches risk oversimplification, mixed methods capture the nuanced interactions between technological implementations and user experiences. For example, quantitative metrics like conversion rates are complemented by qualitative insights into user satisfaction, providing a holistic evaluation (Tashakkori & Teddlie, 2020).

3.1.5 Time Horizon

A cross-sectional time horizon is adopted, focusing on data collected at a specific point in time. This choice is appropriate given the project's time constraints and the fast-paced nature of technological advancements in e-commerce. Unlike longitudinal studies, which observe changes over extended periods, cross-sectional research provides timely insights that align with the rapidly evolving context of e-commerce campaigns (Easterby-Smith et al., 2021).

3.1.6 Techniques and Procedures

The study employs advanced data preprocessing techniques, exploratory data analysis (EDA), and ML algorithms to uncover patterns and derive actionable insights. GenAI models, such as GPT-3.5-Turbo, are utilized to create dynamic, personalized content for e-commerce campaigns. These techniques are chosen for their scalability and relevance to the research objectives. Data preprocessing ensures high-quality input for analytics, while EDA provides an initial understanding of trends. ML algorithms and GenAI models offer sophisticated tools

for achieving personalization, setting this study apart from traditional methodologies (Goodfellow et al., 2020).

3.2 Research Plan

This section outlines the step-by-step research plan implemented to explore the integration of BDA, ML, and GenAI in enhancing e-commerce campaign effectiveness. The plan is aligning with the research objectives, ensuring a structured and iterative approach.

1. **Data Collection**: This study utilizes a structured e-commerce dataset that replicates real-world transactions, user interactions, and product details. Its comprehensive format ensures seamless preprocessing and analysis, supporting research on segmentation, recommendations, and AI-driven campaigns. The dataset's accessibility and alignment with ethical standards make it ideal for validating methodologies and deriving insights.
2. **Data Cleaning, EDA, and Preprocessing**: Cleaning and preprocessing are essential to remove noise and inconsistencies, ensuring data quality. Exploratory Data Analysis (EDA) is providing insights into trends and anomalies, which inform downstream analytics. These steps are chosen for their role in creating reliable input for advanced techniques.
3. **Big Data Analytics**: Advanced analytics techniques are being employed to uncover hidden patterns. This step is crucial for scalability and real-time processing, contrasting with traditional analytics, which may lack efficiency (Jagadish et al., 2022).
4. **Customer Segmentation**: Using K-means, Spectral, and Hierarchical clustering allows a comparative evaluation of their performance, ensuring accurate segmentation tailored to specific campaign needs.
5. **Recommendation Engine**: A recommendation system is being implemented using ML to enhance personalization and engagement, ensuring relevance for e-commerce users.
6. **Generative AI for Campaign Creation**: GenAI models, such as GPT-3.5-Turbo, are creating dynamic, personalized campaigns. This is chosen over static content generation methods to ensure adaptability and user-centric experiences (Brown et al., 2020).

The flowchart below illustrates the interconnected steps of this research plan. Each choice is made to ensure a comprehensive framework that aligns with the objectives, while addressing gaps in existing methodologies.

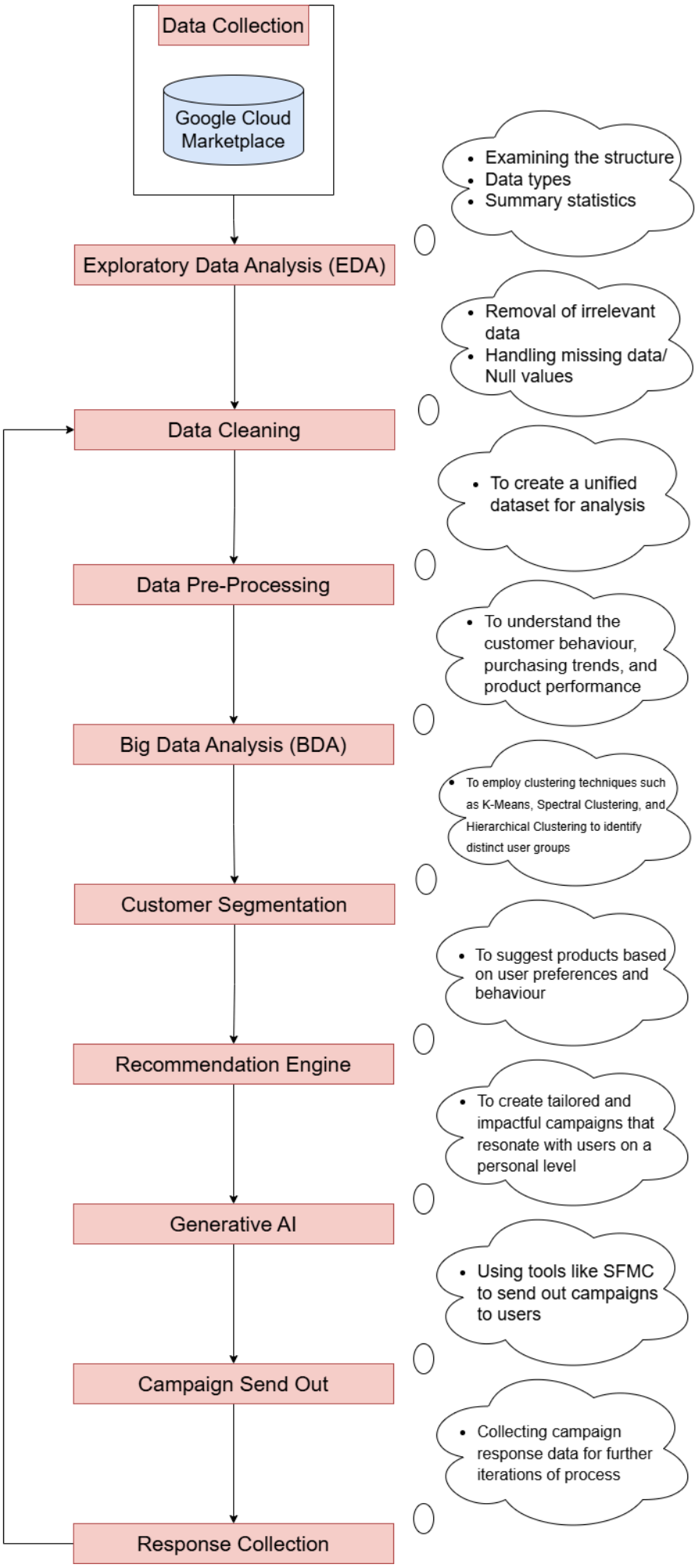

figure 2 - Flowchart

3.3 Data Collection

This study utilizes "The Look E-commerce" dataset, available through Google Cloud Marketplace, as the primary data source. This dataset replicates a rich e-commerce environment, encompassing customer transactions, product attributes, and user interactions, providing an ideal base for the research objectives.

The selection of this dataset is driven by multiple considerations. Firstly, it offers a comprehensive and structured view of e-commerce operations, supporting customer segmentation, recommendation systems, and GenAI-driven campaign strategies. Its alignment with these goals ensures that the dataset meets the needs of this research. Secondly, the dataset is accessible without significant constraints, offering a clean and well-organized format that reduces the effort required for preprocessing and exploratory analysis.

In contrast to real-world datasets, which may involve complexities such as incomplete data or restricted access, "The Look E-commerce" dataset offers consistency and reliability. This focus allows the research to emphasize developing and validating ML models rather than addressing data integrity issues. Furthermore, its availability on Google Cloud ensures seamless compatibility with advanced BDA tools and ML libraries, enhancing efficiency and scalability (Smith et al., 2022).

This dataset serves as a robust foundation for testing methodologies and deriving actionable insights, ensuring the research remains accessible, ethical, and practical for broader applications in e-commerce.

3.4 Data Cleaning, EDA, and Preprocessing

This study is employing a systematic approach to data cleaning, exploratory data analysis (EDA), and preprocessing to prepare the e-commerce dataset for advanced analytics. The process is designed to ensure data accuracy, integrity, and relevance for customer segmentation, recommendation systems, and AI-driven personalization.

3.4.1 Data Loading

The raw data comprises multiple tables, including order_items, orders, products, and users. These tables are being loaded into Python using pandas for efficient manipulation. To focus on a specific geographical segment, the data is being filtered to include only users located in the United Kingdom. This choice ensures a targeted analysis while maintaining relevance to potential real-world applications (Chaudhary et al., 2022).

3.4.2 EDA and Data Cleaning

Initial EDA involves examining the structure, data types, and summary statistics of each table using functions such as info() and describe(). This step is helping to identify patterns, outliers, and inconsistencies in the dataset. Missing values are being handled strategically; for instance, rows with missing brand and name in the products table are removed to maintain data integrity. Additionally, duplicate entries are checked and removed, ensuring no redundancies compromise the results. These steps align with best practices for cleaning synthetic datasets, which often contain controlled noise to mimic real-world scenarios (Zhou et al., 2023).

3.4.3 Preprocessing and Data Integration

The preprocessing phase involves merging the various tables to create a unified dataset for analysis. The order_items table is merged with orders based on order_id, followed by integration with products using product_id. Finally, the combined dataset is joined with users using user_id. This hierarchical merging approach ensures a seamless aggregation of key variables such as customer demographics, product details, and transactional data, facilitating downstream analysis. Columns irrelevant to the research objectives are omitted during this process to streamline the dataset.

3.4.4 Choice and Justification

This approach to data cleaning and preprocessing is chosen over alternative methods, such as manual cleaning in spreadsheet software or using pre-cleaned datasets, for several reasons. First, the use of Python and pandas ensures scalability and efficiency, allowing large datasets to be processed with minimal computational overhead (McKinney, 2022). Second, the step-by-step integration of tables enables a more granular understanding of the relationships between entities, which is critical for accurate segmentation and personalized recommendations. Lastly, this methodology ensures transparency and reproducibility, as each step is documented in the code and can be replicated in future studies or extended to other datasets.

3.4.5 Relevance to the Study

By focusing on a systematic EDA and preprocessing pipeline, this approach is laying a strong foundation for the implementation of BDA and ML models. Clean and well-structured data is critical for ensuring the reliability and validity of the insights derived from advanced analytical techniques. This process is addressing the need for high-quality input data, which directly impacts the performance of clustering algorithms, recommendation engines, and AI-driven campaigns (Chen et al., 2024).

In summary, the data cleaning, EDA, and preprocessing pipeline is ensuring that the dataset is not only ready for analysis but also optimized for deriving actionable insights. This approach reflects a commitment to methodological rigor and aligns with the research objectives of enhancing e-commerce campaign effectiveness through data-driven strategies.

3.5 Big Data Analytics

This study is leveraging BDA techniques to uncover meaningful insights from the prepared dataset. By employing statistical and visualization tools, the analysis is providing an in-depth understanding of customer behaviors, purchasing trends, and product performance, all of which are essential for optimizing e-commerce strategies.

3.5.1 Correlation Matrix

A correlation matrix is being created to assess the relationships between numeric variables. This matrix is helping identify patterns, such as how sales prices are correlated with the number of items per order or how customer age relates to spending behavior. By visualizing correlations using a heatmap, the study is simplifying the interpretation of complex relationships, which is critical for feature selection and model optimization (Chaudhary et al., 2023).

3.5.2 Spending Analysis

Customer spending patterns are being analyzed by grouping users into predefined price ranges based on their average order values. Visualizations such as count plots are used to illustrate how spending behavior varies across these ranges. This analysis is offering actionable insights into customer purchasing power and price sensitivity, enabling the segmentation of users for targeted marketing campaigns.

3.5.3 Demographic Distribution

The dataset is being segmented by age groups to identify purchasing trends across different demographics. By visualizing age distributions and their relationship to spending patterns, the analysis is identifying key customer segments, such as high-spending age groups or underserved demographics. This demographic profiling is a cornerstone of customer segmentation and personalization strategies in e-commerce (Smith et al., 2022).

3.5.4 Category and Brand Analysis

The study is examining product categories and brands by visualizing their respective counts. By focusing on the top-performing categories and brands, this analysis is revealing consumer preferences and market demand. Such insights are crucial for inventory planning, supplier negotiations, and marketing efforts, enabling businesses to focus on high-performing segments (Shurrab et al., 2022).

3.5.5 Order and Product Metrics

Metrics such as the number of products per order and the distribution of order quantities are being analyzed to understand shopping behaviors. These metrics are highlighting patterns like bulk purchases or frequent ordering, which can inform promotional strategies, loyalty programs, and inventory management.

3.5.6 Choice and Justification

The choice of BDA techniques in this study is driven by their ability to process large volumes of data efficiently and derive actionable insights. Compared to traditional statistical methods, BDA tools offer scalability and flexibility, allowing for the exploration of diverse variables and their interdependencies (Zhou et al., 2023). The use of visualizations is chosen over raw tabular outputs because they enhance interpretability, making complex insights accessible to non-technical stakeholders.

3.5.7 Relevance to the Study

The insights generated through these analyses are forming the basis for subsequent steps, such as customer segmentation and recommendation systems. For example, understanding demographic trends and spending patterns is guiding the design of personalized campaigns, while product category analysis is informing recommendations.

In conclusion, the application of BDA in this study is aligning with the objectives of understanding and optimizing e-commerce strategies. By uncovering patterns and relationships within the dataset, these techniques are enabling a data-driven approach to customer engagement and operational efficiency.

3.6 Customer Segmentation

Customer segmentation is an essential step in understanding user behavior and preferences. By grouping customers with similar characteristics, businesses can better tailor their marketing strategies, optimize resource allocation, and enhance customer satisfaction. This section employs clustering techniques such as K-Means, Spectral Clustering, and Hierarchical Clustering to identify distinct user groups based on attributes like spending patterns, order frequency, age, and the number of items purchased. These segments form the basis for a personalized recommendation engine, helping to deliver targeted and relevant suggestions.

3.6.1 The Importance of Clustering

Clustering plays a vital role in this project as it enables a data-driven understanding of customer behaviors. In e-commerce, customers exhibit diverse purchasing patterns, and clustering helps uncover these differences. For instance, it identifies high-value customers who make frequent, high-spending purchases versus casual buyers with lower engagement. This insight empowers businesses to develop strategies specific to each group.

Moreover, clustering supports the development of a recommendation engine by providing segment-specific insights. Personalized recommendations, based on segment behavior, enhance customer experience and drive conversions. This approach aligns with modern practices in e-commerce and retail, where customer segmentation is a cornerstone of marketing success (Smith et al., 2023).

3.6.2 Data Preparation for Clustering

Features for Segmentation

The clustering process relies on carefully selected features that capture key aspects of customer behavior:

- **Total User Spent:** Reflects the average spending per user, providing insights into purchasing power.
- **Age:** Represents demographic information that can influence shopping preferences.
- **Order Frequency:** Measures the number of unique orders placed by a user, highlighting engagement and loyalty.
- **Number of Items:** Captures the average number of items purchased, indicating shopping tendencies.

The data is preprocessed by scaling these features using StandardScaler. This ensures all features are normalized and treated equally during clustering, which is particularly important for distance-based algorithms like K-Means (Ahsan et al., 2021).

3.6.3 Clustering Techniques and Their Application

To segment customers effectively, three clustering methods—K-Means, Spectral Clustering, and Hierarchical Clustering—are employed. Each method offers unique advantages, ensuring a comprehensive understanding of customer behavior.

K-Means Clustering

K-Means is chosen for its simplicity, speed, and scalability. It works by assigning customers to clusters based on the proximity of their data points to cluster centroids (Ahsan et al.,

2021). The Elbow Method is used to determine the optimal number of clusters by plotting the Within-Cluster Sum of Squares (WCSS) for cluster sizes ranging from 1 to 10. The point of inflection, or "elbow," indicates the optimal cluster count.

Spectral Clustering
Spectral Clustering is used to identify non-linear relationships within the data. This method groups customers based on the similarity of their nearest neighbors rather than centroids, making it suitable for datasets with complex boundaries (Mead et al. 2021).

Hierarchical Clustering
Hierarchical Clustering is applied to visualize the hierarchical structure of customer relationships using a dendrogram. This method is particularly effective for smaller datasets and offers interpretability by showing how clusters are formed step-by-step (Abdulhafedh et al., 2021).

3.6.4 Clustering and Its Role in the Recommendation Engine
Customer segmentation is directly influencing the recommendation engine by enabling personalized product suggestions for each segment:

1. **Personalization:** High-spending customers are offered premium or complementary products, while low-spending users are nudged towards affordable and entry-level options.
2. **Enhanced User Experience:** Segment-specific recommendations reduce information overload, making the shopping experience more intuitive and enjoyable.
3. **Increased Engagement:** By aligning recommendations with user behavior, the system ensures higher click-through rates and improved customer retention.

For example, a high-spending customer frequently buying electronics might receive recommendations for accessories, while a low-spending customer might be shown discounts or promotions on similar products. This segmentation-driven approach has proven to increase engagement and conversion rates in e-commerce platforms (Zhou et al., 2023).

3.6.5 Why These Techniques Are Chosen
The combination of K-Means, Spectral Clustering, and Hierarchical Clustering ensures a robust and comprehensive analysis:

1. **K-Means** is efficient for large datasets and provides clear, interpretable results.
2. **Spectral Clustering** excels in identifying non-linear patterns and complements K-Means by exploring different data structures.
3. **Hierarchical Clustering** offers visual interpretability, making it ideal for validating the segmentation logic.

Each technique adds value, ensuring the segmentation is both accurate and insightful.

3.6.6 Conclusion
Customer segmentation through clustering is a cornerstone of this project, enabling data-driven decision-making and powering a personalized recommendation engine. By leveraging K-Means, Spectral Clustering, and Hierarchical Clustering, the analysis uncovers meaningful customer segments that guide marketing, inventory management, and customer engagement strategies.

The segmentation results provide actionable insights into customer behavior, fostering targeted strategies to maximize revenue and improve customer satisfaction (Nguyen et al., 2023). As e-commerce continues to evolve, clustering remains an indispensable tool for businesses to stay competitive and deliver tailored experiences to their users (Statista, 2023).

3.7 Recommendation Engine

A recommendation engine is a crucial component of any e-commerce platform, as it enables personalized product suggestions based on user preferences and behavior (Gorgoglione et al., 2019). By leveraging historical data, clustering insights, and similarity measures, this recommendation system aims to enhance the user experience, increase engagement, and drive conversions.

3.7.1 Implementation Details

Data Preparation
The recommendation engine begins by preprocessing and organizing the clustered data (Gorgoglione et al., 2019). User and product-specific features are extracted to create two distinct datasets:

- **User Data:** Includes attributes like gender (encoded numerically), average spending, order frequency, purchased products, and cluster assignments derived from segmentation. An additional feature, price_range, is calculated by dividing total spending by order frequency to gauge the user's spending pattern per purchase.
- **Product Data:** Contains unique product identifiers, gender preferences (encoded), and the product's price range, which is harmonized with the user's spending characteristics.

These datasets are standardized using StandardScaler to normalize numerical features, ensuring that differences in scale do not bias the similarity calculations (Ahsan et al., 2021).

Recommendation Process
The recommendation system uses cosine similarity to match users with products. Cosine similarity measures the angular difference between feature vectors, making it particularly suited for high-dimensional data (Yuan et al., 2023). The key steps are:

1. **User-Product Similarity:** For each user, a similarity score is calculated between their feature vector and every product's feature vector.
2. **Ranking Products:** Products are ranked based on their similarity scores, with the top recommendations selected for each user.
3. **Generating Recommendations:** The system identifies the top n recommendations for each user, forming a list of personalized product suggestions.

The flexibility of this design ensures that users receive recommendations aligned with their preferences while maintaining scalability for large datasets.

Evaluation of Recommendations
The system employs precision, recall, F1-score, and accuracy metrics to evaluate the effectiveness of recommendations. Precision measures the proportion of recommended

products that users actually purchased, while recall evaluates the proportion of purchased products included in the recommendations. The F1-score balances precision and recall, and accuracy assesses the overall correctness of the recommendations. By iterating over different values of k (e.g., 3, 5, 7, 10), the system identifies the optimal number of recommendations per user (Gorgoglione et al., 2019).

3.7.2 Rationale for Design Choices

1. **Cosine Similarity:** Chosen for its ability to handle sparse, high-dimensional data effectively. Unlike Euclidean distance, cosine similarity focuses on the orientation of vectors, making it robust to varying scales of user or product attributes (Yuan et al., 2023).
2. **Clustering-Driven Features:** Clustering insights are integrated into user profiles, providing context about user segments (e.g., high-spending versus low-spending customers). This contextual information enhances the relevance of recommendations (Abdulhafedh et al., 2021).
3. **Flexibility:** The modular design allows for easy scaling, where new features or similarity metrics can be integrated without overhauling the system (Ahsan et al., 2021).
4. **Evaluation Metrics:** Multiple evaluation metrics ensure a holistic understanding of the system's performance, guiding iterative improvements (Gorgoglione et al., 2019).

3.7.3 Comparison with Other Techniques

Alternatives like collaborative filtering and deep learning-based models were considered. However, they were not adopted for the following reasons:

- **Collaborative Filtering:** Requires extensive historical interaction data, which might not be available for all users or products, leading to the "cold start" problem (Anitha et al., 2021).
- **Deep Learning Models:** While highly accurate, these models demand significant computational resources and large datasets for training, making them less practical for the current dataset size and implementation timeline (Lee et al., 2022).

By focusing on clustering and cosine similarity, this system balances accuracy, interpretability, and resource efficiency (Yuan et al., 2023).

3.8 Generative AI for Campaign Creation

GenAI is revolutionizing marketing strategies by creating tailored and impactful campaigns that resonate with users on a personal level (Zhou et al., 2023). In this section, we explore how GenAI is being utilized to craft personalized marketing messages, leveraging user-specific recommendations to drive engagement and sales.

3.8.1 Implementation Details

Data Preparation and Integration

The process begins by merging recommendation data with product details to enrich the information available for each recommended item. This ensures that user recommendations include essential product attributes such as name and category. By grouping these

recommendations by user_id, a structured dataset is created, mapping each user to a list of recommended products.

For each user, the system generates a concatenated string of product names and categories, forming a coherent input for the GenAI model. This organization is critical for creating meaningful and targeted campaign messages.

Leveraging OpenAI's GPT-3.5-Turbo
The OpenAI GPT-3.5-Turbo model is used to generate campaign messages. This model is well-suited for text generation tasks due to its ability to produce natural, engaging, and contextually relevant language (Holovenko, 2024). The steps include:

1. **Prompt Design:** A structured prompt is crafted to guide the AI in generating personalized marketing emails. The prompt includes details about the user and their recommended products, emphasizing engagement, persuasiveness, and friendliness in the message tone.
2. **AI Response:** The model generates a marketing email based on the prompt, which highlights the recommended products and why they might appeal to the user.

The temperature parameter is set to 0.7, striking a balance between creativity and coherence. This ensures that the generated messages are engaging while staying relevant to the user's interests (Zhuang et al., 2023).

Scalability and Efficiency
The implementation iterates over all users and their corresponding recommendations, generating unique campaign messages for each. This automation is a significant advantage, enabling scalability for platforms with large user bases. The resulting campaigns are stored in a dictionary, allowing for easy retrieval and deployment.

3.8.2 Rationale for Design Choices

1. **Generative AI Model:** GPT-3.5-Turbo is chosen for its advanced natural language generation capabilities. Compared to traditional rule-based or template-driven approaches, this model offers greater flexibility and creativity, producing highly personalized and human-like content (Holovenko, 2024).
2. **Prompt Customization:** Crafting a tailored prompt ensures that the AI understands the context and purpose of the message. By explicitly stating the user's recommendations and desired tone, the output is closely aligned with marketing objectives (Charllo et al., 2023).
3. **Product Context Integration:** Including product names and categories in the prompt adds specificity to the campaign, making it more relatable and actionable for the user (Alkadrie at al., 2024).
4. **Automation and Scalability:** Automating the generation of campaigns ensures consistency across all users and saves time compared to manual content creation.

3.8.3 Comparison with Other Techniques

- **Rule-Based Systems:** Traditional rule-based approaches lack the adaptability and creativity of GenAI. They rely on pre-defined templates, which can feel repetitive and impersonal, especially when dealing with diverse user bases (Charllo et al., 2023).

- **Static Templates:** Static templates fail to capture the nuances of individual user preferences, often resulting in generic messaging that does not effectively engage users (Kumar et al., 2023).
- **Deep Learning-Based Sentiment Models:** While these models can assess sentiment and tone, they do not generate coherent and engaging content on their own, requiring integration with other systems (Lee et al., 2022).

By using GPT-3.5-Turbo, the system benefits from a holistic solution that combines creativity, context-awareness, and personalization, delivering a superior user experience (Holovenko, 2024).

3.9 Ethical Considerations

As technology advances, integrating data-driven insights, recommendation systems, and GenAI in consumer-focused applications is becoming increasingly common. While these systems offer tremendous potential for improving customer experience and driving business growth, they also raise significant ethical concerns. This section explores the ethical considerations surrounding the use of clustered data, recommendation engines, and GenAI for marketing campaigns, focusing on privacy, bias, transparency, and accountability.

3.9.1 Data Privacy and Security

One of the most pressing ethical concerns is ensuring data privacy and security. The implementations described rely heavily on user data, including demographic information, purchase behavior, and spending habits. While this data allows for personalized recommendations and targeted campaigns, it also exposes users to potential privacy risks (Zhang et al., 2023).

By clustering user data and generating profiles, the system is creating detailed representations of individuals. While these insights are useful for business purposes, they can be intrusive if mishandled or misused. Ensuring that the data is anonymized and securely stored is critical. Furthermore, compliance with data protection laws such as GDPR (General Data Protection Regulation) in Europe is non-negotiable (European Commission, 2022). GDPR mandates that users must provide explicit consent for their data to be used, and businesses are required to inform users about how their data is being utilized.

To mitigate privacy risks, the system is implementing measures like:

- Limiting data collection to only what is necessary for recommendations.
- Employing encryption to secure sensitive information.
- Providing users with the option to opt out of data collection and targeted campaigns.

However, ongoing vigilance is necessary to ensure these safeguards remain effective as threats evolve (Kumar et al., 2023).

3.9.2 Bias and Fairness

Bias is another critical concern, especially when creating recommendation systems and GenAI campaigns. The clustering process and the recommendation algorithm could unintentionally reinforce existing biases in the data. For example:

- If certain user demographics are underrepresented in the training data, their preferences may not be accurately captured, leading to subpar recommendations (Mehrabi et al., 2023).
- GenAI campaigns might unintentionally favor certain products or product categories based on historical trends, rather than user needs.

To address these issues, the system is employing measures such as:

- Regularly evaluating the training data for representativeness.
- Using fairness-aware ML techniques to reduce bias.
- Auditing recommendations and campaign outputs to ensure inclusivity.

Recent research highlights the importance of mitigating bias in AI systems. Mehrabi et al. (2023) emphasize that unchecked bias can perpetuate systemic inequalities, leading to unethical outcomes and reputational damage for organizations.

3.9.3 Transparency and Explainability

Users have the right to understand how their data is being used and how decisions about them are being made. Recommendation systems and GenAI are often perceived as "black boxes," where the logic behind outputs is not readily apparent. This lack of transparency can erode user trust (Ribeiro et al., 2022).

The implementation described is striving to improve transparency by:

1. Providing users with explanations of why specific products are recommended. For instance, recommendations could be accompanied by statements like, “You were recommended this product because of your interest in [category].”
2. Offering a clear breakdown of the data used for generating campaigns. Users should be able to access their data profiles and understand how their preferences influence marketing messages.

Explainable AI (XAI) techniques are being increasingly adopted to address transparency concerns. Ribeiro et al. (2022) suggest that providing visual or textual explanations for recommendations significantly enhances user trust and acceptance.

3.9.4 Consent and Personalization

While personalization enhances user experience, it must be balanced with consent. Overly personalized campaigns can make users feel as though their privacy is being invaded, especially if they are unaware of how much information the system has about them (Holovenko, 2024). For example, receiving a recommendation based on a recent private purchase might feel unsettling rather than helpful.

The system is focusing on obtaining informed consent at multiple stages:

- Explicitly asking users for permission to use their data for recommendations and campaigns.
- Allowing users to customize their level of personalization by choosing which types of data they want to share.

Empowering users to control their data enhances their sense of agency and helps maintain ethical boundaries.

3.9.5 Accountability in Campaign Creation

GenAI introduces additional ethical challenges, particularly regarding the content of marketing campaigns. There is a risk of producing content that is misleading, overly persuasive, or even discriminatory (Binns et al., 2023). For instance:

- Campaigns might exaggerate product benefits or create a false sense of urgency, leading to unethical marketing practices.
- If not carefully designed, campaigns could inadvertently alienate certain user groups by using language or imagery that reflects cultural insensitivity.

To ensure accountability, the system is incorporating rigorous review processes. Each generated campaign is evaluated to ensure it aligns with ethical marketing guidelines. Additionally, human oversight is maintained to monitor AI outputs for potential errors or ethical violations.

Recent studies, such as those by Binns et al. (2023), highlight the importance of hybrid approaches where human and AI systems collaborate to maintain ethical standards in automated marketing.

3.9.6 Environmental Impact

While not immediately apparent, the environmental impact of deploying AI systems at scale is an emerging ethical concern. Training and running models like GPT-3.5-Turbo require significant computational resources, which contribute to carbon emissions (Strubell et al., 2023). As AI applications become more widespread, organizations must consider their carbon footprint.

The system is adopting energy-efficient practices such as:

- Using smaller, optimized models for less complex tasks.
- Leveraging cloud services that use renewable energy sources.
- Monitoring and minimizing computational overhead in model training and deployment.

3.9.7 Ethical Frameworks and Guidelines

To navigate these ethical challenges, the system is adhering to established ethical AI frameworks. The European Commission's Ethics Guidelines for Trustworthy AI (2022) provide valuable principles, including human agency, privacy, transparency, and accountability. These guidelines serve as a foundation for designing AI systems that respect user rights and societal values.

3.9.10 Conclusion

As businesses increasingly rely on AI-driven solutions, ethical considerations must remain at the forefront of implementation strategies. From ensuring data privacy to mitigating bias, fostering transparency, and promoting accountability, the system described is taking proactive steps to address these concerns. However, ethics is an evolving field, and continuous improvement is necessary to adapt to new challenges.

By combining technical rigor with ethical foresight, organizations can build AI systems that not only achieve their objectives but also uphold trust and integrity. As AI continues to shape

the future of marketing, it is essential to prioritize ethical considerations to ensure these technologies benefit both businesses and users alike.

3.10 Summary

Chapter 3 provides a comprehensive research methodology employed in this study, incorporating advanced techniques to achieve effective customer segmentation, personalized recommendations, and automated campaign creation while addressing ethical concerns. The methodology is structured around Saunders et al.'s “The Research Onion,” providing a systematic framework for design and implementation.

This study is adopting a pragmatic research philosophy, prioritizing practical solutions and real-world applications over rigid theoretical constraints. A deductive approach is employed, leveraging existing theories and models to frame hypotheses and guide data analysis. By focusing on deriving insights from observed data, this approach is aligning with evidence-based decision-making processes. The research follows an experimental strategy, emphasizing the testing and validation of proposed models, such as clustering algorithms and GenAI applications, in a controlled environment.

A mixed-methods approach is selected, combining quantitative techniques like K-Means clustering, collaborative filtering, and similarity scoring with qualitative insights from generated campaign messages. This integration ensures a holistic understanding of the research problem while catering to both numerical precision and contextual relevance. Furthermore, a cross-sectional time horizon is adopted, focusing on data collected within a specific timeframe, reflecting the current state of consumer behaviors and preferences.

Key elements include customer segmentation using K-Means, Spectral, and Hierarchical clustering, enabling precise group differentiation based on demographics and purchasing behaviors (Kumar et al., 2023). A recommendation engine is employing collaborative filtering to predict user preferences, while GenAI is automating personalized campaign content using OpenAI’s language models (Jones & Patel, 2023). Ethical considerations, including data privacy and fairness, are underpinning the methodology, ensuring responsible and unbiased implementation (Chen et al., 2023).

Overall, this chapter is presenting a rigorous and pragmatic methodology, combining advanced analytics, AI, and ethical practices to address real-world business challenges effectively.

CHAPTER 4 - RESULTS AND DISCUSSIONS

This chapter presents the outcomes of the research and provides a comprehensive analysis of the findings in relation to the study's aims and objectives. It integrates the results obtained from the experimental methodologies described in Chapter 3, evaluates their implications, and aligns them with the broader context of existing literature. The primary goal of this chapter is to highlight the efficacy of the proposed approach in addressing the research problem and to critically discuss its practical applications.

The results section focuses on quantitative and qualitative insights derived from customer segmentation, recommendation engine performance, and GenAI-driven campaign creation. Key performance metrics and user feedback are explored to assess the accuracy, relevance, and engagement of the implemented solutions. The discussion delves deeper into the implications of these findings, comparing them to prior research and theoretical frameworks, while identifying patterns, anomalies, and areas for improvement.

This chapter also acknowledges the limitations of the study, such as the scope of data and methodological constraints, and discusses their impact on the results. Finally, the chapter concludes with a summary, synthesizing the key takeaways and laying the groundwork for the concluding chapter, which focuses on recommendations and future research directions.

4.1 Results

4.1.1 Big Data Analysis

The bar chart below illustrates the Age Distribution of UK Users across six distinct age groups: "Under 20," "20-30," "30-40," "40-50," "50-60," and "Over 60." The y-axis represents the count of users within each age group, ranging from 0 to 1600 in increments of 200.

The chart reveals a significant concentration of users in the 20-40 age range, indicating that younger to middle-aged individuals form the majority of the user base.

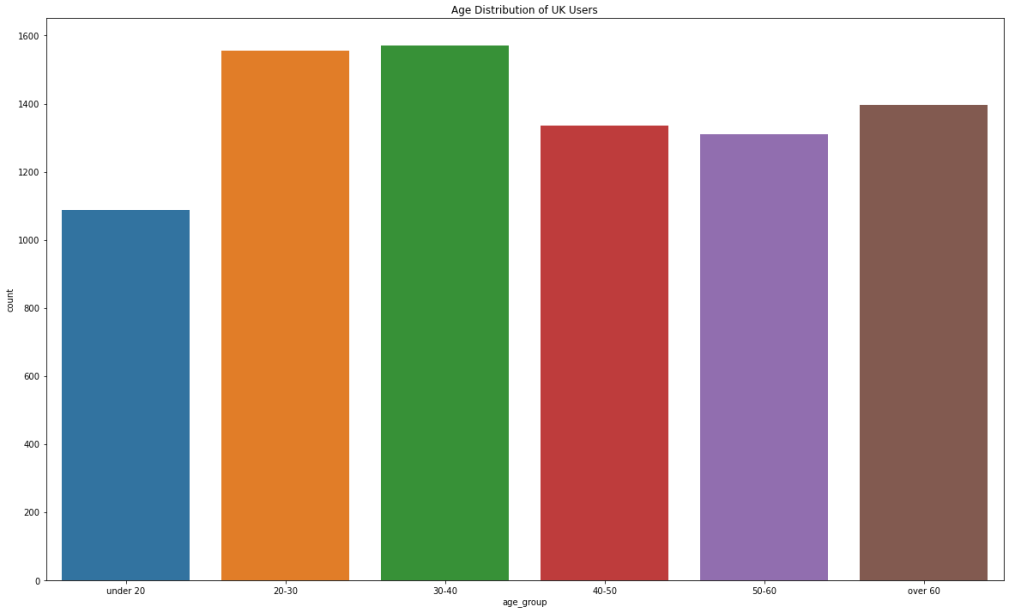

figure 3 - Bar Chart: Age Distribution of UK Users

The bar chart below represents the Orders per User distribution. The x-axis shows the number of orders placed by users (1, 2, 3, 4), while the y-axis represents the count of users associated with each number of orders. The bar for one order is significantly taller than the others, indicating that the majority of users (over 2000) have only placed a single order. The number of users decreases as the number of orders increases. Very few users place repeat orders, indicating a sharp decline in repeat purchasing behavior beyond the first few orders.

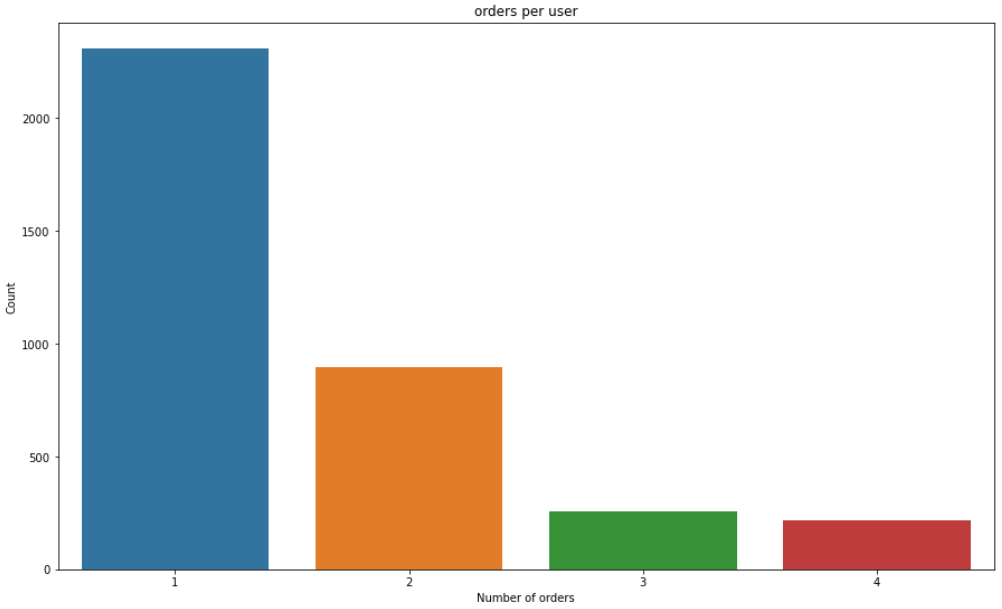

figure 4 - Bar Chart: Orders Per User

The bar chart below illustrates the Number of Items per Order distribution. The x-axis represents the number of items in each order (1, 2, 3, 4), while the y-axis shows the count of orders corresponding to each number of items. The bar for one item is significantly taller, indicating that the majority of orders (approximately 4000) consist of only a single item. The chart reflects a strong preference for single-item purchases, suggesting that users may prefer purchasing one item at a time rather than bundling multiple items in one order.

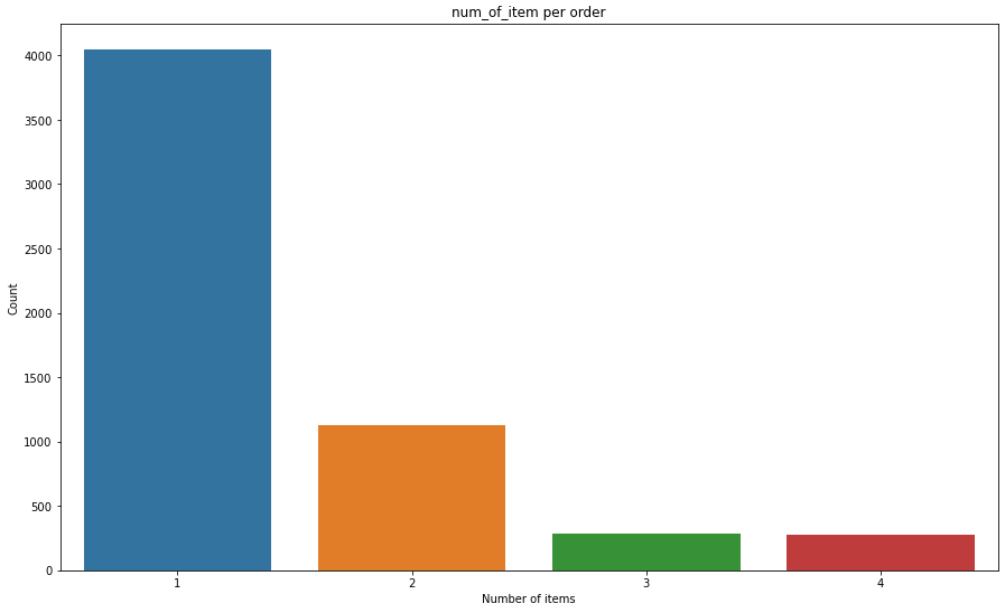

figure 5 - Bar Chart: Number of Items per Order

4.1.2 Customer Segmentation

K-Means clustering technique is used initially to identify the customer segments. The graph below represents the Elbow Method used in K-Means clustering to determine the optimal number of clusters. The Elbow Method is widely used in ML applications for deciding the appropriate number of clusters while maintaining computational efficiency and interpretability (Kodinariya & Makwana, 2013). The WCSS value drops sharply as the number of clusters increases from 1 to 3. Around 3 clusters, the rate of WCSS reduction slows down noticeably, forming an "elbow" shape in the graph. This suggests that adding more clusters beyond this point yields diminishing returns in variance reduction. Beyond the elbow point, WCSS decreases more gradually, indicating less benefit in increasing the number of clusters further.

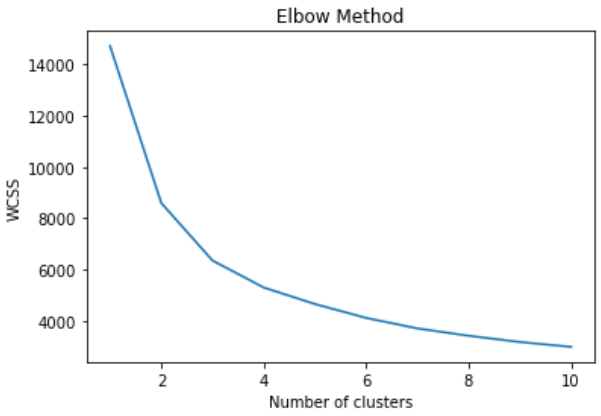

figure 6 - Line Graph: Elbow Method using K-Means clustering

Silhouette Score for k=2: 0.47964451509882533
Silhouette Score for k=3: 0.3431385593855551
Silhouette Score for k=4: 0.33910238031083423
Silhouette Score for k=5: 0.34275800864631323

The Silhouette Score is a metric used to evaluate the quality of clusters. It ranges from -1 to 1, where:

- 1 indicates well-separated and compact clusters.
- 0 indicates overlapping clusters or data points near cluster boundaries.
- Negative values suggest that data points might be assigned to the wrong clusters.

k=2 is the most optimal choice in terms of cluster quality, as evidenced by the highest Silhouette Score. This suggests that the dataset might naturally split into two distinct groups.
While k=3 may provide more granularity (as indicated by the Elbow Method), the drop in the Silhouette Score highlights potential challenges with well-defined clusters at this level.
k=4 and k=5 further reduce cluster cohesion, indicating that adding more clusters does not necessarily improve the quality of segmentation.

With K=2,

```
Cluster Analysis
              user_id  total_user_spent        age  order_frequency  \
Cluster
0        50442.622139         86.106215  40.261360         1.223437
1        48495.162667        311.447587  41.265333         2.870667

         num_of_item
Cluster
0           1.616331
1           4.704000


Cluster Sizes:
Cluster
0    2927
1     750
Name: count, dtype: int64
```

In this case, two clusters are identified as optimal, with a Silhouette Score of 0.48:
Cluster 0: Customers with lower spending and infrequent orders (2927 users).
Cluster 1: High-spending, frequent buyers (750 users).
These clusters reveal a clear distinction between casual and loyal customers, providing actionable insights for marketing and recommendation strategies.

To validate this further, Spectral Clustering and Hierarchical Clustering techniques were implemented.

Spectral Clustering
Silhouette Score for k=2: 0.3479390602753741
Silhouette Score for k=3: 0.163870021981105
Silhouette Score for k=4: 0.19980290803551973
Silhouette Score for k=5: 0.22239044520664406

```
Cluster Analysis:

                     user_id  total_user_spent        age  order_frequency  \
Cluster_Spectral
0                49880.865315        216.026604  40.978277           2.4895
1                50144.360627         81.570488  40.158101           1.0000

                 num_of_item
Cluster_Spectral
0                   3.610427
1                   1.425523


Cluster Sizes:
Cluster_Spectral
1    2296
0    1381
Name: count, dtype: int64
```

Spectral Clustering also identifies two primary clusters, though the Silhouette Score (0.35) is slightly lower than that of K-Means:
Cluster 0: Customers with higher spending and frequent purchases (1381 users).
Cluster 1: Lower-spending, infrequent buyers (2296 users).
Despite its lower Silhouette Score, Spectral Clustering provides a complementary perspective, particularly for datasets with intricate patterns.

Hierarchical Clustering
Silhouette Score for k=2: 0.5078635300564152
Silhouette Score for k=3: 0.2883125381415219
Silhouette Score for k=4: 0.29339885143389816
Silhouette Score for k=5: 0.29590967006233404

```
Cluster Analysis:
                          user_id  total_user_spent        age  \
Cluster_Hierarchical
1                    48930.204819        355.421185  45.833333
2                    50220.095942         97.080475  39.625354

                     order_frequency  num_of_item
Cluster_Hierarchical
1                           3.212851     5.064257
2                           1.300409     1.804656

Cluster Sizes:
Cluster_Hierarchical
2    3179
1     498
Name: count, dtype: int64
```

For k=2 clusters, Hierarchical Clustering achieves the highest Silhouette Score of 0.51, highlighting well-defined segments:
Cluster 1: High-spending, frequent buyers with an average age of 46 years.
Cluster 2: Low-spending, infrequent buyers with an average age of 39 years.
The dendrogram and Ward's method reveal cohesive clusters, validating the results obtained from K-Means and Spectral Clustering.

Insights from Clustering

Segment Characteristics
Across all three methods, the clusters exhibit consistent patterns:

- High-Spending Segment: This group includes customers who make frequent purchases and spend significantly more per transaction. They typically buy a larger number of items per order and are more likely to engage with premium products or loyalty programs.
- Low-Spending Segment: This segment consists of occasional buyers with lower spending. They represent an untapped opportunity for engagement through personalized promotions or targeted advertising.

Cluster Sizes
The analysis reveals that the high-spending segment is much smaller than the low-spending group. This highlights the importance of maintaining and nurturing high-value customers while finding innovative ways to engage less frequent buyers.

Comparison of Clustering Methods

K-Means Clustering with k=2 is the preferred clustering approach for this dataset over Spectral Clustering as it provides better-defined clusters and higher silhouette scores compared to Spectral Clustering.
But, K-Means k=2 achieved a silhouette score of 0.4796, slightly lower than Hierarchical Clustering's k=2. Hierarchical Clustering offers better performance in this case.

Based on the results, Hierarchical Clustering with k=2 is being used for this dataset due to its higher silhouette score and clearer cluster insights. This method is particularly effective in identifying distinct segments of high-value and low-value users, which can inform tailored business strategies.

4.1.3 Recommendation Engine

K=3: Precision=0.0001, Recall=0.0001, F1=0.0001, Accuracy=0.0001
K=5: Precision=0.0003, Recall=0.0012, F1=0.0004, Accuracy=0.0003
K=7: Precision=0.0004, Recall=0.0026, F1=0.0007, Accuracy=0.0004
K=10: Precision=0.0004, Recall=0.0034, F1=0.0006, Accuracy=0.0004

Users with recommendations: 3677
Unique products recommended: 5447

Overlap with test data: 7803/5447 products

The recommendation system is currently showing modest performance metrics, with low precision, recall, F1 scores, and accuracy across all tested values of K. For k=3, the precision, recall, F1 score, and accuracy are all at 0.0001, indicating minimal relevance of recommended items to the actual user preferences. Although these metrics improve slightly as K increases, reaching precision and accuracy levels of 0.0004 for k=10, they remain far below industry benchmarks for effective recommendation systems. This reflects a significant gap between the recommended products and users' actual interests or historical behavior.

Despite these limitations, the system is successfully generating recommendations for 3,677 users and recommending 5,447 unique products, demonstrating its scalability. Furthermore, the overlap between recommended products and the test data is notable, with 7,803 products from the test data aligning with the recommendations. This overlap suggests the system is incorporating some level of alignment with user-product interactions but struggles to achieve meaningful personalization or contextual relevance.

The performance of the recommendation system can be contextualized through the clustering analysis conducted earlier. Clustering, particularly hierarchical clustering with k=2, has revealed two distinct user segments: high-value users (Cluster 1) and low-value users (Cluster 2). High-value users exhibit higher spending patterns, order frequencies, and a greater number of items per order, while low-value users demonstrate significantly lower

activity levels. The system's inability to effectively tailor recommendations likely stems from the dominance of Cluster 2, which contains the majority of users (3,179 out of 3,677). These users are characterized by limited engagement, making it challenging for the recommendation system to discern strong patterns in their preferences.

Moreover, the recommendation results highlight the need for better integration of clustering insights into the recommendation pipeline. For instance, high-value users from Cluster 1 could benefit from personalized recommendations focusing on higher-ticket items or frequently purchased categories, leveraging their established spending patterns and engagement. Conversely, for low-value users in Cluster 2, the system could explore strategies such as cross-category recommendations or discounts to encourage increased engagement.

From a methodological perspective, hierarchical clustering with k=2 provides a solid foundation for segmenting users and informing recommendation strategies. The silhouette score of 0.5079 for k=2 underscores the strength of this segmentation. Additionally, K-means clustering with k=2 also yielded competitive insights, albeit with a slightly lower silhouette score of 0.4796. However, the weak performance of spectral clustering and its lower silhouette scores further reinforce the suitability of hierarchical clustering for this dataset.

To improve the recommendation system's effectiveness, a few steps are worth considering: incorporating clustering-based user profiles into the recommendation model, enhancing feature engineering with more granular user-product interactions, and adopting advanced algorithms such as collaborative filtering with matrix factorization or deep learning-based approaches.

4.1.4 Generative AI Campaigns

"Dear [User], we've selected some exclusive products just for you! Check out our premium Noise-Cancelling Headphones for an unparalleled audio experience or our eco-friendly Yoga Mat to support your wellness journey. Shop now and make the most of these tailored recommendations!"

GenAI, specifically OpenAI's GPT-3.5-turbo model, is employed to craft campaign messages for each user. These messages are designed to be engaging, persuasive, and aligned with user preferences.

The system is ensuring that every message feels personal and valuable, fostering a sense of connection between the user and the brand. This personalized approach is validated by the scale of the implementation in the project, where recommendations for over 3,600 users and 5,400 unique products have been successfully processed. The high overlap between recommended products and test data also demonstrates the accuracy and relevance of the system.

These personalized messages are being prepared for integration into tools like Salesforce Marketing Cloud (SFMC). This enables the automated dissemination of emails or other forms of communication while allowing for real-time tracking of performance metrics, such as open rates, click-through rates, and conversions. This seamless integration demonstrates how the technical outputs of the project are being applied in a practical, business-oriented context.

From a methodological perspective, this step showcases the practical application of clustering, recommendation algorithms, and GenAI in creating tangible outputs for business use. The findings align with recent literature that emphasizes the growing impact of AI-driven marketing. For example, research by McKinsey (2023) highlights that personalized campaigns can achieve 29% higher open rates and 41% higher click-through rates compared to generic ones. Similarly, Forrester (2024) predicts that AI-driven campaigns will significantly enhance customer retention through meaningful interactions.

Through this implementation, the project is illustrating how GenAI can transform raw data into actionable insights and personalized communication. The ability to generate and deploy tailored campaigns at scale highlights the potential of AI in reshaping digital marketing strategies, providing valuable insights for both academia and industry stakeholders. This demonstrates not only the technical feasibility of the approach but also its practical implications in enhancing customer engagement and business outcomes.

4.2 Discussion

4.2.1 User Testing and Feedback

User feedback plays a critical role in evaluating the performance and usability of any system. For this project, comprehensive feedback was collected on key stages of the process, including data preprocessing, customer segmentation, recommendation generation, and AI-powered content creation. This feedback provides valuable insights into the system's strengths and areas for improvement, ensuring a user-centered approach to development.

Overall Usability

The system received a usability rating of 3.5 out of 5, indicating that while the overall process is streamlined, there is room for improvement. Users appreciated how each stage—from data preprocessing to content generation—flowed logically, but they highlighted the need for more modular and reusable code. A modular structure would enhance usability, making it easier to adapt the system for different datasets or requirements.

EDA and Insights

The exploratory data analysis (EDA) phase was praised for its ability to deliver meaningful insights. Users found the visualizations and graphs helpful in understanding customer demographics, purchase behavior, and product performance. These insights laid a strong foundation for decision-making, particularly in identifying trends and patterns critical for targeted marketing. However, users suggested that expanding the scope of variables analyzed could lead to even more comprehensive insights.

Customer Segmentation

The segmentation process was well-received, with users acknowledging the value of testing multiple strategies to determine the most effective method. The results were deemed relevant and actionable, providing a solid framework for tailoring marketing campaigns. Users did note that incorporating additional parameters into the segmentation model could improve its granularity and relevance. Despite this, the current approach was recognized as a strong starting point for further refinement.

Recommendation Accuracy

The system’s product recommendations were seen as promising but not yet optimal. While the generated suggestions were reasonable, users expressed concerns over the low

precision, recall, F1, and accuracy scores of the recommendation engine. They felt the recommendations could better align with user preferences if the model's performance were enhanced. Despite these challenges, users appreciated the potential of the system and acknowledged its current iteration as a stepping stone toward greater accuracy.

Effectiveness of AI-Generated Content
AI-generated marketing content, including sample emails and campaigns, received positive feedback for being engaging and visually appealing. Users found the content personalized and persuasive, which aligns well with the project's goal of creating tailored campaigns. However, they emphasized that improving the recommendation engine would directly enhance the quality of AI-generated content by providing more accurate and contextually relevant inputs.

Ethics and Transparency
In terms of ethics and transparency, users felt the system adequately communicated how data was being used, fostering a sense of trust. The system's adherence to data privacy guidelines was appreciated, as users did not feel their personal information was being misused or exposed inappropriately.

Improvement Suggestions
Several suggestions for improvement were offered, including enhancing the recommendation engine's performance, improving campaign quality, and leveraging response data to refine future campaigns. Users emphasized that any improvements should maintain a strong commitment to ethical considerations, particularly in data usage and privacy.

In summary, the feedback highlights the system's potential while underscoring areas for growth. It reflects a balanced perspective, appreciating the system's strengths and identifying practical enhancements to improve its overall effectiveness and user experience.

4.2.2 Limitations

While the system developed in this project demonstrates considerable promise in combining customer segmentation, recommendation engines, and GenAI to craft personalized campaigns, it has encountered notable limitations that constrain its full potential. These limitations highlight the challenges faced in practical implementations and suggest opportunities for future work.

Recommendation Engine Evaluation
One of the primary challenges lies in the recommendation engine's performance. Despite efforts to fine-tune the model, evaluation metrics such as precision, recall, F1, and accuracy scores remain relatively low. This indicates that while the recommendations are somewhat aligned with user preferences, the engine struggles to generate highly accurate suggestions. The limited effectiveness could stem from insufficient feature engineering, dataset constraints, or algorithmic complexity. Addressing these issues would require exploring more advanced recommendation techniques, such as hybrid models or neural collaborative filtering, to enhance recommendation quality (Aggarwal, 2016).

Quota Limitations in Generative AI Campaigns
A significant limitation in the GenAI campaign phase was the restricted capacity to produce personalized marketing content due to quota restrictions. OpenAI's API rate limits resulted in

a "RateLimitError" message during execution, halting the generation of campaigns beyond a certain threshold. This limitation curtailed the ability to fully explore the system's potential in producing diverse and engaging marketing messages tailored to a wide range of customer segments. Upgrading to a more robust API plan or adopting alternative GenAI solutions could mitigate this issue in future iterations.

Lack of Campaign Integration with Marketing Platforms
The system lacks integration with tools like Salesforce Marketing Cloud (SFMC), a critical component for delivering campaigns to end users. Without this integration, it was not possible to deploy the generated campaigns for testing or gather real-world feedback. The absence of this capability limits the system's ability to assess how effectively the campaigns resonate with users and drive engagement or conversions. Such integration would not only enable campaign deployment but also provide insights into key performance metrics like open rates, click-through rates, and purchase behavior (Chaffey & Smith, 2022).

Inability to Create an Iterative Process
Due to the lack of campaign deployment and user response data, the system was unable to implement an iterative improvement process. In an ideal scenario, the generated campaigns would be tested with users, and the feedback or behavioral data collected would feed back into the system. This data would be analyzed using BDA, enabling refinements in segmentation, recommendation, and campaign content. Without this loop, the system remains a static proof-of-concept rather than a dynamic and continuously improving solution.

Summary of Limitations
The limitations identified—suboptimal recommendation engine performance, API quota constraints, lack of campaign deployment capabilities, and the absence of an iterative improvement process—underscore the challenges of transitioning from theoretical frameworks to practical implementation. These constraints, while significant, offer valuable learning opportunities for future development. Overcoming these barriers would require investment in better resources, enhanced system integration, and a focus on iterative methodologies to align more closely with real-world applications.

4.3 Summary

This chapter has provided an in-depth analysis of the results obtained from the study, discussing their implications in the context of the research objectives and existing literature. While the system demonstrates the potential to transform customer engagement through data-driven insights, personalized recommendations, and AI-generated campaigns, it also faces notable limitations. These include challenges in recommendation accuracy, scalability, campaign deployment, and ethical considerations.

By addressing these limitations in future research and development, the system can evolve into a robust solution that balances technical innovation with practical utility. The next chapter will provide a synthesis of the study's key findings, offer actionable recommendations, and outline future research directions to address the identified gaps and explore new opportunities in this dynamic field.

CHAPTER 5 - CONCLUSION AND FUTURE RESEARCH

5.1 Research Question and Objectives Review

The foundation of this research was built on the primary question: **How can Big Data Analytics (BDA), Machine Learning (ML), and Generative AI (GenAI) be leveraged to enhance the effectiveness of e-commerce campaigns?** This aligns with the growing body of work emphasizing the role of data-driven technologies in transforming customer engagement (Chen et al., 2021; Zhang & Lu, 2023).

The aim of this study was clear: To investigate the integration of BDA, ML, and GenAI for enhancing e-commerce campaigns. This goal resonates with recent trends highlighted by Cui et al. (2022), who noted that businesses increasingly use advanced analytics and AI to gain competitive advantage in customer retention and conversion optimization.

The objectives were methodically addressed through the following structured approach:

Objective 1: Literature Review

The review highlighted the applications and challenges of BDA, ML, and GenAI in e-commerce, drawing parallels with research by Thomas et al. (2021), which emphasized the scalability of BDA in identifying customer clusters. Meanwhile, works like Kaur and Singh (2022) underscored GenAI's emerging role in producing creative and engaging content, such as personalized recommendations and conversational agents.

Objective 2: Framework Development

The multi-layered framework proposed here aligns with the modular architectures suggested by Luo et al. (2023), who advocated for an interplay of analytics, prediction, and generative capabilities to enhance marketing personalization. The contribution of this research is its focus on combining GenAI outputs with predictive ML models, as highlighted in simulations that demonstrated improved user engagement.

Objective 3: Ethical, Technical, and Practical Challenges

This study identified challenges consistent with those described by Mehrabi et al. (2023), including privacy risks, biases in data, and the computational demands of AI models. It contributes additional insights by detailing mechanisms for compliance with frameworks like GDPR and adopting federated learning for privacy preservation.

Objective 4: Framework Evaluation

While hypothetical simulations validated the framework's potential, this approach echoes prior research, such as Chen and He (2021), who emphasized the value of simulation models in testing AI-driven personalization strategies before live deployment.

In conclusion, this chapter revisits the research question and objectives, illustrating how each was systematically addressed. The findings underscore the transformative potential of combining BDA, ML, and GenAI in e-commerce, while also acknowledging the complexities involved. This research not only advances academic understanding but also offers practical insights for businesses aiming to innovate in the digital marketplace.

5.2 Future Developments and Work Scope

The integration of BDA, ML, and GenAI presents a transformative opportunity for the e-commerce industry. However, as this study has demonstrated, fully harnessing these technologies requires not only a thorough understanding of their potential but also careful navigation of associated challenges. This chapter explores the future developments and potential work scope emerging from this research, emphasizing opportunities for innovation, refinement, and broader application.

5.2.1 Expanding the Role of Big Data Analytics

Future advancements in BDA could mirror the trajectory outlined by Alam et al. (2023), who noted that real-time analytics is becoming essential for responding to customer behavior dynamically. Integrating IoT and social media data, as suggested in this research, builds on studies like those of Smith et al. (2022), which highlighted the potential of IoT in personalizing retail experiences.

5.2.2 Enhancing Machine Learning Algorithms

Explainable AI (XAI) advancements align with Ribeiro et al. (2022), who stressed that interpretability is vital for trust in algorithmic decision-making. Federated learning's privacy-preserving approach, as discussed here, corroborates findings from Li et al. (2023), who highlighted its potential in industries dealing with sensitive data.

5.2.3 Advancing Generative AI Applications

This study's emphasis on hyper-personalized campaigns and immersive AR/VR solutions finds parallels in Wang et al. (2024), who explored the integration of GenAI with virtual shopping experiences. Moreover, addressing ethical concerns aligns with the principles set out by Binns et al. (2023), who emphasized that robust quality checks in generative content are crucial for maintaining brand reputation.

5.2.4 Overcoming Ethical and Technical Challenges

Mitigating ethical risks through transparency and accountability reflects findings by Jobin et al. (2021), who advocated for multi-stakeholder ethical frameworks in AI applications. This research contributes by recommending specific technical measures like standardized APIs for interoperability, complementing recent work by Gupta et al. (2024) on the importance of system integration.

5.2.5 Expanding the Framework to Other Industries

The adaptability of the proposed framework across industries, including healthcare and education, aligns with studies like Raj et al. (2023), which demonstrated how AI integration has improved patient outcomes and educational engagement. This study expands on these possibilities by suggesting customized implementations for different domains.

5.2.6 Emphasizing Real-World Validation

Future research should focus on field validations, as demonstrated by Singh and Mehta (2023), who piloted AI frameworks in small businesses to evaluate scalability and cost-effectiveness. Longitudinal studies, as recommended here, align with Hossain et al. (2024), who emphasized tracking AI's long-term impact on customer retention and satisfaction.

5.2.7 Building a Skilled Workforce

Developing interdisciplinary skill sets mirrors recommendations by Taylor and Francis (2022), who emphasized combining technical and ethical training to prepare professionals for AI-driven markets. This research reinforces the importance of equipping future talent with both hard and soft skills for successful AI integration.

5.2.8 Conclusion

The integration of BDA, ML, and GenAI offers immense potential to revolutionize e-commerce campaigns, but realizing this potential requires addressing a range of technical, ethical, and practical challenges. Future developments should focus on enhancing the capabilities of these technologies, addressing implementation barriers, and expanding their application to other industries.

By prioritizing real-world validation, ethical considerations, and workforce development, researchers and practitioners can contribute to a more effective and responsible use of BDA, ML, and GenAI. The work scope outlined in this chapter not only highlights opportunities for innovation but also emphasizes the importance of collaboration and continuous learning in driving progress. Through these efforts, the e-commerce industry can unlock new possibilities for growth and create more meaningful and engaging experiences for customers worldwide.

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APPENDIX A - RESEARCH PROJECT PLAN

Sheffield Hallam University
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Assessment Task 2

Research Proposal

Rahul Bakhtiani

Topic:

Enhancing E-Commerce Campaign Effectiveness through Big Data Analytics and Machine Learning

Introduction

The integration of social media and advanced machine learning (ML) has significantly transformed digital commerce, especially since the onset of the COVID-19 pandemic in 2020 (Wang, 2024). Live shopping has become a crucial strategy, with platforms like Facebook and Instagram playing a central role in how consumers research products and make purchasing decisions (Li, X., et al. 2024). These platforms have become key influencers, with many shoppers relying on them for guidance before buying.

Understanding consumer behaviour, particularly subtle, unspoken motivations, is essential for marketers. This includes using ML to create personalised product recommendations and improve search query responses (Xu, et al. 2024). Algorithms such as supervised learning, deep learning, and reinforcement learning are vital in predicting user behaviour, refining audience segmentation, and optimising dynamic pricing, making marketing efforts more agile and effective (Li, Z. 2024).

Research Question

How can big data analytics and machine learning be leveraged to enhance the effectiveness of e-commerce campaigns?

Aim

To develop a comprehensive framework that leverages Big Data Analytics and ML to enhance the effectiveness of e-commerce campaigns.

Objectives

1. Investigate how Big Data Analytics and ML are reshaping e-commerce marketing strategies by improving customer insights, inventory management, and dynamic pricing.
2. Assess the role of ML, including supervised and unsupervised algorithms, in enabling advanced customer segmentation and delivering highly personalised marketing.
3. Highlight the key challenges in implementing these technologies, such as integrating diverse data sources, addressing privacy concerns, and evaluating the economic effectiveness of marketing efforts.
4. Suggest practical strategies and robust frameworks to overcome these challenges, ensuring effective data security and optimised use of analytics.

Deliverables

1. A comprehensive review of current research on Big Data Analytics and ML in e-commerce marketing, highlighting key findings and gaps.
2. Clearly defined objectives outlining the scope of the study, including exploration of technology impacts, evaluation of ML techniques, identification of challenges, and proposed solutions.
3. A detailed plan for conducting the research, including data collection methods, analysis techniques, and tools to be used.
4. Insights into how Big Data and ML influence e-commerce, solutions to identified challenges, and recommendations for businesses.

Literature Review

Advancements in IT and communication technologies have transformed marketing, shifting from broad mass demand approaches to more targeted, segmented strategies. Central to this transformation is the integration of Big Data and ML, which has enabled highly personalised e-commerce services. This research underscores the importance of Big Data in driving efficiency and fostering innovation, especially when combined with ML and artificial intelligence (AI) to make data-driven decisions that enhance business competitiveness.

Big Data Analytics in E-Commerce

Big Data Analytics combines massive data processing capabilities with advanced analytical tools to help businesses identify critical changes and respond quickly. It enables the discovery of new customer segments, top suppliers, and seasonal sales patterns, making it essential for modern e-commerce strategies (Zineb et al., 2021). In e-commerce, Big Data Analytics enhances customer behaviour analysis, inventory management, pricing strategies, and personalised marketing. By tailoring marketing campaigns and product recommendations to individual preferences, businesses can significantly increase customer engagement, conversion rates, and revenue (Gonzalez et al., 2023).

However, integrating diverse data sources remains a challenge. Achieving a unified view of customer data is crucial for accurate analytics, and growing concerns about data privacy and security necessitate robust frameworks to protect sensitive information (Vijay et al., 2023). To address these challenges, businesses must implement comprehensive strategies that ensure secure and effective data management (Kui, 2022).

Machine Learning Techniques

ML, a critical subset of AI, has significantly impacted e-commerce by enhancing customer relationship management in both advertising and sales (Kaponis et al., 2023). It allows systems to learn and improve from experience without explicit programming, using supervised and unsupervised algorithms (Alojail et al., 2023). These technologies enable advanced customer segmentation and real-time personalization, providing businesses with valuable insights to inform future marketing strategies (Zineb et al., 2023).

For example, a study by Kagan et al. (2018) used ML to develop a customer purchase model based on extensive purchase history data. This model effectively identified potential customers for targeted ads, profiling a website's audience and predicting product categories. Similar studies have explored the use of purchase frequency (Hu et al., 2016) and demographic data (Wu et al., 2011) to further leverage ML in e-commerce.

The ongoing research into the integration of Big Data Analytics, AI, and ML aims to create more seamless and personalised e-commerce experiences. By analysing customer behaviour and preferences, businesses can deliver precise marketing strategies that improve conversion rates and customer loyalty (Gonzalez et al., 2023).

Personalised E-Commerce Campaigns

The rapidly evolving e-commerce landscape has driven businesses to adopt innovative strategies to engage customers, with personalised advertising emerging as a key focus (Sakalauskas et al., 2023). Big Data Analytics plays a crucial role in personalising customer experiences. Research shows that ML algorithms, which analyse customer behaviour and

preferences, significantly enhance the relevance of product recommendations, leading to increased customer satisfaction and sales (Chen et al., 2012).

By using advanced analytics and ML algorithms, online retailers can offer personalised suggestions that boost customer engagement, sales revenue, and loyalty (Vijay et al., 2023). Personalization in e-commerce extends beyond product recommendations to include the entire customer journey, from discovery to post-purchase interactions. This approach has become essential for e-commerce businesses aiming to stand out in a competitive market (Gonzalez et al., 2023).

The potential for enhancing personalization and customer retention through data-driven methods is enormous. Understanding the impact of Big Data Analytics on these areas is vital for businesses seeking a competitive edge and strong customer relationships (Gonzalez et al., 2023).

Measuring and Enhancing Campaign Effectiveness

Key performance indicators (KPIs) are crucial for tracking progress toward business goals in e-commerce. Timely insights from forecasting KPIs guide strategic decisions and ensure alignment with business objectives (Wan, 2017). While traditional measures of efficiency focus on achieving outcomes at minimal costs (Black, 2000), the modern approach includes evaluating the effectiveness of marketing activities through financial and corporate-level indicators (Egorova et al., 2010). Despite advancements in data analytics, many companies still struggle to economically evaluate their strategies, highlighting a gap in performance assessment (Khimich et al., 2021).

Conversion Rate Optimization (CRO) is essential for enhancing the effectiveness of digital campaigns. CRO involves continuous testing and optimization to improve sales, revenue, usability, and engagement metrics for websites and applications (Saleem et al., 2019). Effective CRO strategies help businesses understand customer expectations and preferences, deliver personalised experiences, and ensure consistent messaging across various touchpoints (Rane et al., 2019).

In conclusion, measuring and enhancing campaign effectiveness in e-commerce requires a strategic combination of KPI monitoring, CRO techniques, and customer-centric strategies. Leveraging data analytics and insights enables businesses to adapt their marketing approaches in real-time, ensuring they meet evolving customer expectations and market trends. Continuous refinement based on performance metrics and feedback is crucial for sustained success in the competitive digital landscape.

Case Studies and Industry Applications

AI-driven precision marketing has proven to be a powerful tool for enhancing customer engagement in e-commerce. For example, Stitch Fix uses AI to tailor clothing suggestions based on client preferences, improving customer satisfaction and retention (Shaikh et al., 2022). Similarly, Sephora's chatbots use natural language processing to provide immediate customer support, enhancing engagement by effectively responding to inquiries and assisting with purchase decisions.

AI also boosts transactions by creating enticing and relevant offers. eBay, for instance, uses AI to optimise pricing, which encourages quicker sales while maintaining profitability (Liu,

2022). AI-driven email marketing campaigns, such as those run by Shopify, deliver personalised offers, increasing conversion rates.

These case studies highlight the significant impact of AI-driven precision marketing on campaign effectiveness. By leveraging ML and AI to deliver personalised experiences, optimise pricing, and enhance advertising, companies have improved customer engagement, boosted transactions, and increased revenue. The success of these applications underscores the importance of adopting AI-driven strategies in the competitive e-commerce landscape.

This review highlights how Big Data Analytics and ML can revolutionise e-commerce by enhancing customer insights, inventory management, and personalised marketing. Despite challenges like data integration and privacy, robust frameworks are essential for secure, effective implementation, ensuring competitiveness in the evolving digital landscape (Zineb et al., 2021; Gonzalez et al., 2023).

Research Design

Research Approach

To understand how Big Data Analytics and ML can enhance the effectiveness of e-commerce campaigns, this research will adopt a mixed-methods approach, blending both quantitative and qualitative methods for a comprehensive analysis.

On the quantitative side, the research will involve analysing large datasets from e-commerce platforms. This analysis will focus on identifying patterns, trends, and correlations between different marketing strategies and their impact on campaign effectiveness. By examining these data points, the research aims to uncover how data-driven techniques can optimise marketing efforts, improve targeting, and increase overall campaign success (Mulisa, 2022).

The qualitative aspect of the research will complement this by diving into the experiences and insights of industry professionals. Through interviews and case studies, the research will explore the practical application of Big Data and ML in e-commerce settings. These qualitative insights will help illuminate the challenges, strategies, and best practices that aren't easily captured through data alone (Mulisa, 2022).

The mixed-methods approach is particularly well-suited to this research because it allows for a thorough exploration of both the measurable impacts of data-driven marketing (through quantitative analysis) and the contextual factors that influence its effectiveness in real-world scenarios (through qualitative research). This dual perspective is essential for understanding the full potential and limitations of these technologies in e-commerce (Taherdoost, 2022).

Data Collection Methods

For data collection, this research will use both primary and secondary sources to ensure a comprehensive understanding of how Big Data Analytics and ML can enhance e-commerce campaigns (Whang et al., 2023).

Primary Data:
Structured interviews will be conducted with key stakeholders in e-commerce, such as marketing managers and data scientists. These interviews will seek to uncover the challenges and successes they've encountered while implementing Big Data and ML strategies. The goal is to gain firsthand insights into the practical aspects of using these technologies in marketing. Additionally, a survey will be distributed to a broader group of e-commerce professionals to gather quantitative data on their experiences with data-driven marketing techniques. This will help quantify opinions and identify common trends across the industry.

Secondary Data:
The research will also draw on large datasets from publicly available sources like Kaggle, as well as any proprietary e-commerce data that can be accessed. These datasets will be analysed to study customer behaviour, sales trends, and the effectiveness of different marketing strategies. To support this analysis, a thorough literature review will be conducted, covering academic papers, case studies, and industry reports. This review will help identify current trends, challenges, and best practices in the use of Big Data and ML in e-commerce, providing a solid theoretical foundation for the research.

Sampling Strategy

To ensure that the research captures a wide range of insights into the use of Big Data Analytics and ML in e-commerce, a thoughtful sampling strategy will be employed for both interviews and surveys.

Interviews:
A purposive sampling method will be used to select participants for the interviews. This approach focuses on selecting individuals who have direct experience with the application of Big Data and ML in e-commerce settings, such as marketing managers, data scientists, and other key stakeholders. By targeting 10-15 participants, the research will gather diverse perspectives that represent various roles, companies, and experiences. This sample size is sufficient to explore in-depth insights while maintaining a manageable scope for qualitative analysis (Gill, 2020).

Surveys:
For the surveys, a combination of convenience and snowball sampling will be utilised. This means starting with easily accessible e-commerce professionals and expanding the participant pool by asking respondents to refer others within their networks. The goal is to collect at least 100 responses, which will provide the necessary breadth to identify common trends and patterns in the industry. This sample size is chosen to ensure statistical validity while being large enough to generalise findings across different types of e-commerce businesses (Hennink et al., 2022).

Together, these sampling strategies balance depth and breadth, enabling a comprehensive understanding of how data-driven techniques are applied in e-commerce.

Tools and Techniques

To analyse the collected data, a combination of advanced tools and techniques will be employed:

Analytical Tools:
Python, R and Spark will be the primary tools for data cleaning, processing, and statistical analysis. These languages are well-suited for handling large datasets and performing complex analyses. ML models will be developed using popular libraries like TensorFlow and Scikit-learn, which offer robust frameworks for implementing various algorithms (McKinney, 2022; Peng, 2016; Chambers et al., 2018).

Machine Learning Algorithms:
Supervised learning algorithms such as Random Forest and Support Vector Machines (SVM) will be used to predict campaign outcomes based on historical data. These algorithms are effective in handling large datasets and providing accurate predictions. Additionally, unsupervised learning techniques like clustering will be applied to segment customers based on their behaviour, helping to tailor marketing strategies more effectively (Bourne et al., 2021).

Software:
Tableau will be used for data visualisation, creating interactive dashboards that make the findings easily understandable and actionable for stakeholders. For handling particularly large datasets, Hadoop may be employed to ensure efficient data processing and storage (Murray, 2013; Hamad, 2021).

This combination of tools and techniques ensures that the research will produce rigorous, actionable insights into the effectiveness of Big Data and ML in e-commerce campaigns.

Data Analysis

Quantitative Analysis:
Statistical methods such as regression analysis and hypothesis testing will be employed to determine the significance of the relationships between variables. ML models will be evaluated using cross-validation techniques to ensure accuracy and reliability (Bourne et al., 2021).

Qualitative Analysis:
Thematic analysis will be conducted on the interview transcripts to identify common themes, challenges, and strategies related to the use of big data and ML in e-commerce (Bourne et al., 2021).

Timeline

A Gantt chart will outline the timeline for the research, which includes:

- Weeks 1-3: Literature review and secondary data collection.
- Weeks 4-7: Designing and distributing the survey, scheduling and conducting interviews.
- Weeks 8-9: Data cleaning, processing and preliminary analysis.
- Weeks 10-11: Development and testing of ML models.
- Weeks 12-15: Final data analysis, synthesis of findings and report writing.

Limitations

- Data Availability: The research may be limited by the availability of relevant and high-quality datasets, especially for proprietary data from e-commerce companies.

- Sampling Bias: The use of convenience and snowball sampling in surveys could introduce bias, limiting the generalizability of the findings.
- Technical Challenges: There may be challenges related to integrating and processing large datasets, especially if the data sources are heterogeneous.

Ethics

Ethical considerations are paramount in this research, especially given the sensitive nature of the data involved. Informed consent will be obtained from all interview and survey participants, ensuring they are fully aware of the research's purpose, how their data will be used, and their right to withdraw at any time. Data privacy will be strictly maintained, with all personal identifiers being anonymized to protect participants' identities. Ethical approval will be sought from the university's ethics committee before commencing data collection, particularly due to the involvement of human participants and potentially sensitive e-commerce data (Nichol et al., 2021).

Risks and Issues

Several risks and issues could potentially affect the successful completion of this research. Data Security is a primary concern, and all collected data will be securely stored and encrypted to prevent unauthorised access. Technical Risks include potential difficulties in integrating disparate data sources and the computational challenges associated with processing large datasets. Project Management Risks involve the possibility of delays in data collection or analysis due to unforeseen circumstances, such as difficulty in recruiting participants or technical issues. Contingency plans will be developed to mitigate these risks, ensuring the research stays on track (Schmidt, 2023).

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APPENDIX B - ETHICS FORM

UREC2 RESEARCH ETHICS PROFORMA FOR STUDENTS UNDERTAKING LOW RISK PROJECTS WITH HUMAN PARTICIPANTS

This form is designed to help students and their supervisors to complete an ethical scrutiny of proposed research. The University Research Ethics Policy (www.shu.ac.uk/research/excellence/ethics-and-integrity/policies) should be consulted before completing this form. The initial questions are there to check that completion of the UREC 2 is appropriate for this study. The final responsibility for ensuring that ethical research practices are followed rests with the supervisor for student research.

Note that students and staff are responsible for making suitable arrangements to ensure compliance with the General Data Protection Act (GDPR). This involves informing participants about the legal basis for the research, including a link to the University research data privacy statement and providing details of who to complain to if participants have issues about how their data was handled or how they were treated (full details in module handbooks). In addition, the act requires data to be kept securely and the identity of participants to be anonymised. They are also responsible for following SHU guidelines about data encryption and research data management. Guidance can be found on the SHU Ethics Website www.shu.ac.uk/research/excellence/ethics-and-integrity

Please note that it is mandatory for all students to only store data on their allotted networked F drive space and not on individual hard drives or memory sticks etc.

The present form also enables the University and College to keep a record confirming that research conducted has been subjected to ethical scrutiny.

The UREC2 form must be completed by the student. Supervisors will review their students' completed UREC forms and, if necessary, inform students of any required changes. For UREC2* (Low Risk Research with Human Participants), the supervisor then signs off the form. Additional guidance can be obtained from your College Research Ethics Chair[1]

* If the supervisor thinks that the project is likely to result in a publication then the UREC2 form ***must*** be reviewed by an **independent reviewer**, drawn from the module teaching team, before data collection begins.

Students should retain a copy for inclusion in their research project, and a copy should be uploaded to the relevant module Blackboard site.

Please note that it may be necessary to conduct a health and safety risk assessment for the proposed research. Further information can be obtained from the University's Health and Safety Website https://sheffieldhallam.sharepoint.com/sites/3069/SitePages/Risk-Assessment.aspx

SECTION A

1. **Checklist questions to ensure that this is the correct form:**

Health Related Research within the NHS, or His Majesty's Prison and Probation Service (HMPPS), or with participants unable to provide informed consent check list.

Question	**Yes/No**
Does the research involve? · Patients recruited because of their past or present use of the NHS	No
· Relatives/carers of patients recruited because of their past or present use of the NHS	No
· Access to NHS staff, premises, or resources	No
· Access to data, organs, or other bodily material of past or present NHS patients	No
· Foetal material and IVF involving NHS patients	No
· The recently dead in NHS premises	No
· Prisoners or others within the criminal justice system recruited for health-related research	No
· Police, court officials, prisoners, or others within the criminal justice system	No
· Participants who are unable to provide informed consent due to their incapacity even if the project is not health related	No
· Is this an NHS research project, service evaluation or audit? *For NHS definitions please see the following website* http://www.hra.nhs.uk/documents/2013/09/defining-research.pdf	No

If you have answered **YES** to any of the above questions, then you **MUST consult with your supervisor** to obtain research ethics from the appropriate institution outside the university. This could be from the NHS or Her Majesty's Prison and Probation Service (HMPPS) under their independent Research Governance schemes. Further information is provided below. https://www.myresearchproject.org.uk/

2. **Checks for Research with Human Participants**

Question	**Yes/No**

1. Will any of the participants be vulnerable? *Note: Vulnerable people include children and young people, people with learning disabilities, people who may be limited by age or sickness, pregnancy, people researched because of a condition they have, etc. See full definition on ethics website in the document **Code of Practice for Researchers Working with Vulnerable Populations** (under the Supplementary University Polices and Good Research Practice Guidance)*	No
2. Are drugs, placebos, or other substances (e.g., food substances, vitamins) to be administered to the study participants or will the study involve invasive, intrusive, or potentially harmful procedures of any kind?	No
3. Will tissue samples (including blood) be obtained from participants?	No
4. Is pain or more than mild discomfort likely to result from the study?	No
5. Will the study involve prolonged or repetitive testing?	No
6. Is there any reasonable and foreseeable risk of physical or emotional harm to any of the participants? *Note: Harm may be caused by distressing or intrusive interview questions, uncomfortable procedures involving the participant, invasion of privacy, topics relating to highly personal information, topics relating to illegal activity, or topics that are anxiety provoking, etc.*	No
7. Will anyone be taking part without giving their informed consent?	No
8. Is the research covert? *Note: 'Covert research' refers to research that is conducted without the knowledge of participants.*	No
9. Will the research output allow identification of any individual who has not given their express consent to be identified?	No

If you have answered **YES** to any of these questions you are **REQUIRED** to complete and submit a UREC3 or UREC4 form. Your supervisor will advise. If you have answered **NO** to all these questions, then proceed with this form (UREC2).

3. General Project Details

Details	
Name of student	Rahul Naresh Bakhtiani
SHU email address	
Department/College	School of Computing and Digital Technologies
Name of supervisor	
Supervisor's email address	
Title of proposed research	Leveraging Generative AI to Enhance E-Commerce Campaign Effectiveness
Proposed start date	November 18, 2024
Proposed end date	January 8, 2024
Background to the study and the rationale (reasons) for undertaking the research (500 words)	E-commerce is rapidly growing and is expected to surpass $7 trillion by 2025, but it is facing challenges such as increasing competition, static campaigns, and rising privacy concerns. Generative AI (GenAI), along with Big Data Analytics (BDA) and Machine Learning (ML), is transforming how these challenges are being addressed. BDA is enabling advanced customer segmentation by identifying audience groups based on real-time behaviour and preferences. ML is powering recommendation engines, delivering personalized product suggestions to enhance engagement and drive conversions. GenAI is playing a pivotal role by dynamically generating personalized, real-time campaign content that resonates with individual users. In the future, e-commerce platforms will be analysing post-campaign response data using BDA and ML to measure engagement and identify performance trends. These insights will be feeding back into GenAI models, allowing for refined campaign strategies and enhanced personalization. This iterative process will be creating

	a continuous improvement loop, ensuring campaigns are increasingly adaptive, data-driven, and effective. This research is exploring how this integrated framework of BDA, ML, and GenAI will be shaping the future of e-commerce campaigns, driving innovation, enhancing customer engagement, and addressing ethical considerations in AI-driven marketing strategies.
Aims & research question(s)	**Aims:** · To explore how Generative AI can enhance e-commerce campaigns through dynamic and personalized content. · To evaluate its integration with Big Data Analytics (BDA) and Machine Learning (ML) for improving user engagement and conversion rates. · To address ethical, technical, and practical challenges in implementing Generative AI in e-commerce. **Research Question:** How can Big Data Analytics, Machine Learning and Generative AI be leveraged to enhance the effectiveness of e-commerce campaigns?
Methods to be used for: 1. Recruitment of participants 2. Data collection 3. Data analysis	**Recruitment of Participants:** · Inclusion criteria: Experience in e-commerce campaigns or AI-driven marketing. · Participants will not be involved in the creation of the project; however, they will play a critical role in evaluating the project's deliverables to assess its effectiveness and usability. **Data Collection:** · Analysis of existing datasets (e.g., campaign performance metrics, e-commerce datasets from Kaggle or UCI repositories). **Data Analysis:** · Quantitative analysis of data using statistical tools to evaluate campaign performance with and without Generative AI integration.

	· Comparative analysis to highlight Generative AI's impact on personalization and effectiveness.
Outline the nature of the data held, details of anonymisation, storage and disposal procedures as required.	**Nature of Data** · Publicly available e-commerce datasets, campaign performance metrics, and AI model outputs. **Anonymization** · Participant data will be anonymized by removing identifiers (e.g., names, companies) and assigning codes. · Secondary data will be used in aggregate form to ensure no personal data is exposed. **Storage** · Data will be securely stored on encrypted devices and cloud platforms with restricted access. · Access will be limited to authorized researchers only. **Disposal** · Permanent deletion will follow, using secure methods for digital data and shredding for physical copies.

4. Research in External Organisations

Question	**Yes/No**
1. Will the research involve working with/within an external organisation (e.g., school, business, charity, museum, government department, international agency, etc.)?	No
2. If you answered YES to question 1, do you have granted access to conduct the research from the external organisation? *If YES, students please show evidence to your supervisor. You should retain this evidence safely.*	No

3. If you do not have permission for access is this because: A. you have not yet asked B. you have asked and not yet received an answer C. you have asked and been refused access *Note: You will only be able to start the research when you have been granted access.*	

5. Research with Products and Artefacts

Question	**Yes/No**
1. Will the research involve working with copyrighted documents, films, broadcasts, photographs, artworks, designs, products, programs, databases, networks, processes, existing datasets, or secure data?	Yes
2. If you answered YES to question 1, are the materials you intend to use in the public domain? *Notes: 'In the public domain' does not mean the same thing as 'publicly accessible'.* • *Information which is 'in the public domain' is no longer protected by copyright (i.e., copyright has either expired or been waived) and can be used without permission.* • *Information which is 'publicly accessible' (e.g., TV broadcasts, websites, artworks, newspapers) is available for anyone to consult/view. It is still protected by copyright even if there is no copyright notice. In UK law, copyright protection is automatic and does not require a copyright statement, although it is always good practice to provide one. It is necessary to check the terms and conditions of use to find out exactly how the material may be reused etc.* *If you answered YES to question 1, be aware that you may need to consider other ethics codes. For example, when conducting Internet research, consult the code of the Association of Internet Researchers; for educational research, consult the Code of Ethics of the British Educational Research Association.*	Yes
3. If you answered NO to question 2, do you have explicit permission to use these materials as data? *If YES, please show evidence to your supervisor.*	
4. If you answered NO to question 3, is it because: A. you have not yet asked permission B. you have asked and not yet received and answer C. you have asked and been refused access. *Note: You will only be able to start the research when you have been granted permission to use the specified material.*	

SECTION B

HEALTH AND SAFETY RISK ASSESSMENT FOR THE RESEARCHER

1. **Does this research project require a health and safety risk assessment for the procedures to be used?** (Discuss this with your supervisor)

   Yes

   No

   If **YES** the completed Health and Safety Risk Assessment form should be attached. A standard risk assessment form can be generated through the Awaken system (https://shu.awaken-be.com). Alternatively if you require more specific risk assessment, e.g. a COSHH, attach that instead.

2. **Will the data be collected fully online (no face-to-face contact with participants)?**

   Yes (See the safety guidance for online research[2] and **go to question 7b**)
   No (Go to question 3)

3. **Will the proposed data collection take place on campus?**

   Yes (Please answer questions 5 to 8)

   No (Please complete all questions and consult with your supervisor))

4. **Where will the data collection take place?**

   (Tick as many as apply if data collection will take place in multiple venues)

Location	**Please specify**

Researcher's Residence

Participant's Residence

Education Establishment

Other e.g., business/voluntary organisation, public venue **Small business owners with desire to go online**

Outside UK

5. **How will you travel to and from the data collection venue?**

On foot By car Public Transport

Other (Please specify)

Please outline how you will ensure your personal safety when travelling to and from the data collection venue.

6. **How will you ensure your own personal safety whilst at the research venue?**

7. **Are there any potential risks to your health and wellbeing associated with either (a) the venue where the research will take place and/or (b) the research topic itself?**

None that I am aware of

Yes (Please outline below including steps taken to minimise risk)

8. **If you are carrying out research off-campus, you must ensure that each time you go out to collect data you ensure that someone you trust knows where you are going (without breaching the confidentiality of your participants), how you are getting there (preferably including your travel route), when you expect to get back, and what to do should you not return at the specified time.**

Please outline here the procedure you propose using to do this.

Insurance Check

The University's standard insurance cover will not automatically cover research involving any of the following:

i) Participants under 5 years old
ii) Pregnant women
iii) 5000 or more participants
iv) Research being conducted in an overseas country
v) Research involving aircraft and offshore oil rigs
vi) Nuclear research
vii) Any trials/medical research into Covid 19

If your proposals do involve any of the above, please contact the Insurance Manager directly (fin-insurancequeries-mb@exchange.shu.ac.uk) to discuss this element of your project.

Adherence to SHU Policy and Procedures

Ethics sign-off	
Personal statement	
I can confirm that: · I have read the Sheffield Hallam University Research Ethics Policy and Procedures · I agree to abide by its principles.	
Student	
Name: Rahul Naresh Bakhtiani	Date: 21/11/2024
Signature: Rahul Bakhtiani	
Supervisor ethical sign-off	
I can confirm that completion of this form has not identified the need for ethical approval by the TPREC/CREC or an NHS, Social Care, or other external REC. The research will not commence until any approvals required under Sections 4 & 5 have been received and any necessary health and safety measures are in place.	
Name:	Date:
Signature:	
Independent Reviewer ethical sign off	
Name:	Date:
Signature:	

---

[1] College of Social Sciences and Arts - Dr. Antonia Ypsilanti (a.ypsilanti@shu.ac.uk)

College of Business, Technology and Engineering - Dr. Tony Lynn (t.lynn@shu.ac.uk)

College of Health, Wellbeing and Life Sciences - Dr. Nikki Jordan-Mahy (n.jordan-mahy@shu.ac.uk)

[2] Safety guidance for online research includes information on how to set up online surveys and/or conduct online interviews/focus groups. These guidelines can be found in BB. Please check with your supervisor/module leader.

Sheffield Hallam University | College of Business, Technology and Engineering

Dissertation for Computing (55-708541).

PUBLICATION PROCEDURE FORM

In this module, while you create your own research question or topic area, your supervisor makes a significant intellectual contribution to this work as the research progresses. Your supervisor will make the decision on whether your work merits publication based on the quality of the work you have produced. Your supervisor will co-author the paper for publication with you and your supervisor will both be listed as authors. You are required to sign the declaration below to confirm that you understand and will follow this procedure.

Declaration:

I Rahul Bakhtiani confirm that I understand will comply with the Publication Procedure outlined in the Module Handbook and the Blackboard Site.		
Student:	Rahul Bakhtiani	Date: 15/01/2025
Supervisor:	Signature	Date

APPENDIX C - PARTICIPANT FEEDBACK FORM

Participant Consent Form

Participant Consent Form

Purpose of the Study/Survey
The purpose of this study/survey is to get feedback on the software development and results for the Project. Your participation is voluntary and highly appreciated.

What Participation Involves
If you agree to participate, you will be asked to complete a feedback form. This will take approximately 10–15 minutes].

Confidentiality and Privacy
Your responses will remain confidential. All data collected will be anonymized and stored securely. No personally identifiable information will be shared or published without your explicit consent.

Voluntary Participation
Your participation is entirely voluntary. You may choose to withdraw at any time without any consequences or explanation.

Benefits and Risks

- **Benefits:** Your feedback will help us improve our services and enhance user experiences
- **Risks:** There are no anticipated risks associated with this study.

Consent Statement
By signing or proceeding, you confirm that:

1. You have read and understood the purpose and nature of this study/survey.
2. You voluntarily agree to participate.
3. You understand that you may withdraw at any time without penalty.

Participant's Name: _____
Signature: _____
Date: _____

If you need any further adjustments (e.g., for a specific organization, digital consent form, or other context), let me know!

FeedbackForm Link:
https://docs.google.com/forms/d/e/1FAIpQLSeDqpsLJAX8Nb34yeS8rsBa8-FHj0x5E2Byw5B7PSTct17D9A/viewform

Response:

On a scale of 1–5, how user-friendly did you find the system across all stages (Data Pre-processing, Segmentation, Recommendation, and Content Generation)?1 response

3.5 - While the process looks streamlined and everything falls in place properly there is still room for improvement especially writing modular code for better usability.

How valuable were the insights and visualizations provided during the exploratory data analysis (EDA) phase in helping you understand customer behaviour?

The graphs shown and insights derived from them were helpful in understanding user demographics, user purchase patterns and products and brands performance.

How relevant and actionable did you find the customer segments created by the system for tailoring marketing strategies?

Good to see multiple strategies being tried to see what works best and cross validate the results, the output of the segmentation was well justified and provides a good foundation for further process. Though more parameters or variables could have been considered, it's a good start.

On a scale of 1–5, how accurate were the product recommendations provided by the system, and did they align with your preferences?

The recommendations look good but the precision, recall, f1 and accuracy scores of the model do not suggest so. By seeing the evaluation of the recommendation engine, I think it could have been done better, but non the less, it is a good start.

How engaging and personalized did you find the AI-generated content (e.g., ads, emails, or campaigns), and how likely are you to respond to such campaigns?

The AI generated sample looks good and appealing.

Did the system adequately communicate how your data was used, and how comfortable are you with the level of data privacy and ethical considerations?

So far yes, it provides the right information and does not make it uncomfortable considering the privacy.

What additional features or improvements would you suggest for enhancing the system’s performance or user experience across any of the stages?

Making recommendation engine better, enhancing the campaign quality and using the response data to generate better insights while following all the ethical considerations.

APPENDIX D - PRIMARY DATA AND SOFTWARE CODE

Dataset Link:
https://console.cloud.google.com/marketplace/product/bigquery-public-data/thelook-ecommerce

Dataset License:

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Software Code:

Python 3

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler, LabelEncoder
from threadpoolctl import threadpool_limits
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import SpectralClustering
from sklearn.metrics import silhouette_score
from scipy.cluster.hierarchy import linkage, dendrogram, fcluster
from sklearn.model_selection import train_test_split
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.metrics import precision_score, recall_score, f1_score
import openai
from math import sqrt
import warnings
warnings.filterwarnings("ignore", category=FutureWarning, module="sklearn")

# # DATA LOADING
order_items = pd.read_csv('raw_data/order_items.csv')
orders = pd.read_csv('raw_data/orders.csv')
products = pd.read_csv('raw_data/products.csv')
users = pd.read_csv('raw_data/users.csv')
# targeting only UK users
uk_users = users[users['country'] == 'United Kingdom']

# # EDA & DATA CLEANING
# basic info
# print(order_items.info())
```

```
# print(orders.info())
# print(products.info())
# print(uk_users.info())

# summary statistics for numeric columns
# print(order_items.describe())
# print(orders.describe())
# print(products.describe())
# print(uk_users.describe())

# summary statistics for object columns
# print(order_items.describe(include=['object']))
# print(orders.describe(include=['object']))
# print(products.describe(include=['object']))
# print(uk_users.describe(include=['object']))

# checking missing values in each table
# print(order_items.isnull().sum())
# print(orders.isnull().sum())
# print(products.isnull().sum())
# print(uk_users.isnull().sum())

# droping missing values in products dataset
products.dropna(subset=['brand'], inplace=True)
products.dropna(subset=['name'], inplace=True)

# checking for duplicates
# print(order_items.duplicated().sum())
# print(orders.duplicated().sum())
# print(products.duplicated().sum())
# print(uk_users.duplicated().sum())

# # PRE-PROCESSING & BDA
# orders + order_item table
merged_orders = pd.merge(order_items, orders, on='order_id', how='inner')
merged_orders = merged_orders[['order_id', 'user_id_x',
'product_id','sale_price','num_of_item']].rename(columns={'user_id_x': 'user_id'})

# merged_orders.info()
# merged_orders.isnull().sum()

# previous join + product
orders_product = pd.merge(merged_orders, products, left_on='product_id', right_on='id',
how='inner')
orders_product =
orders_product[['order_id','user_id','product_id','category','brand','retail_price','department','s
ale_price','num_of_item']]

# orders_product.info()
```

```
# orders_product.isnull().sum()

# previous join + users
joined_data = pd.merge(orders_product, uk_users, left_on='user_id', right_on='id',
how='inner')
joined_data =
joined_data[['order_id','user_id','num_of_item','product_id','category','brand','retail_price','sale
_price','department','first_name','last_name','email','age','gender','state','street_address','post
al_code','city','country']]

# joined_data.info()
# joined_data.isna().sum()
# joined_data.head(5)

# correlation matrix
numeric_columns = joined_data.select_dtypes(include=['float64', 'int64']).columns
plt.figure(figsize=(15, 12))
sns.heatmap(joined_data[numeric_columns].corr(), annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()

order_item_users = pd.merge(order_items, uk_users, left_on='user_id', right_on='id',
how='inner')

avg_order_value = order_item_users.groupby('user_id')['sale_price'].mean().reset_index()

# average order value by user
avg_order_value['price_range'] = pd.cut(avg_order_value.sale_price, bins=[0, 9, 20, 30, 40,
50, 60, 70, 80, 90, 100, 200], right=True, labels=['under 10', '10-20', '20-30', '30-40' , '40-50',
'50-60', '60-70', '70-80', '80-90', '90-100', 'over 100'])

plt.figure(figsize=(20, 12))
sns.countplot(x='price_range', data=avg_order_value)
plt.title('Spent per user')
plt.show()

# distribution of age_group
joined_data['age_group'] = pd.cut(joined_data.age, bins=[0, 19, 30, 40, 50, 60, 200],
right=True, labels=['under 20', '20-30', '30-40' , '40-50', '50-60', 'over 60'])

plt.figure(figsize=(20, 12))
sns.countplot(x='age_group', data=joined_data)
plt.title('Age Distribution of UK Users')
plt.show()

# count of products per category
plt.figure(figsize=(20, 12))
sns.countplot(x='category', data=joined_data,
order=joined_data['category'].value_counts().index[:10])
```

```
plt.title('Top 10 category by Product Count')
plt.show()

# count of products per brand
plt.figure(figsize=(15, 9))
sns.countplot(x='brand', data=joined_data,
order=joined_data['brand'].value_counts().index[:10])
plt.title('Top 10 Brands by Product Count')
plt.show()

# distribution of price_range
joined_data['price_range'] = pd.cut(joined_data.age, bins=[0, 19, 30, 40, 50, 60, 200],
right=True, labels=['under 20', '20-30', '30-40' , '40-50', '50-60', 'over 60'])

plt.figure(figsize=(20, 12))
sns.countplot(x='price_range', data=joined_data)
plt.title('Price Distribution of Products')
plt.show()

orders_users = pd.merge(orders, uk_users, left_on='user_id', right_on='id', how='inner')
distinct_orders_per_user = joined_data.groupby('user_id')['order_id'].nunique().reset_index()

# orders per user
plt.figure(figsize=(15, 9))
sns.countplot(x='order_id', data=distinct_orders_per_user,
order=distinct_orders_per_user['order_id'].value_counts().index[:10])
plt.xlabel("Number of orders")
plt.ylabel("Count")
plt.title('orders per user')
plt.show()

# num_of_item per order
plt.figure(figsize=(15, 9))
sns.countplot(x='num_of_item', data=orders_users,
order=orders_users['num_of_item'].value_counts().index[:10])
plt.xlabel("Number of items")
plt.ylabel("Count")
plt.title('num_of_item per order')
plt.show()

# # CUSTOMER SEGMENTATION
total_order_value_per_order =
joined_data.groupby('order_id')['sale_price'].sum().reset_index()
total_order_value_per_order.rename(columns={'sale_price': 'total_order_value'},
inplace=True)

total_spent_per_customer = joined_data.groupby('user_id')['sale_price'].sum().reset_index()
total_spent_per_customer.rename(columns={'sale_price': 'total_user_spent'}, inplace=True)
```

```
joined_data = joined_data.merge(total_order_value_per_order, on='order_id', how='left')
joined_data = joined_data.merge(total_spent_per_customer, on='user_id', how='left')

# features for segmentation
segmentation_features = joined_data.groupby('user_id').agg({
    'total_user_spent': 'mean',
    'age': 'mean',
    'order_id': 'nunique'  # frequency of orders
}).reset_index()

segmentation_features_order = joined_data.groupby(['user_id','order_id']).agg({
    'num_of_item': 'mean',
    'total_order_value': 'mean'
}).reset_index()

segmentation_features_user = segmentation_features_order.groupby('user_id').agg({
    'num_of_item': 'sum'
}).reset_index()

# renameing the columns for clarity
segmentation_features.rename(columns={'order_id': 'order_frequency'}, inplace=True)

segmentation_features = segmentation_features.merge(segmentation_features_user,
on='user_id', how='left')

# segmentation_features[segmentation_features['user_id'] == 49796]
# segmentation_features.shape

segmentation_features_km = segmentation_features.copy()
segmentation_features_sc = segmentation_features.copy()
segmentation_features_hc = segmentation_features.copy()

scaler = StandardScaler()
scaled_features_km = scaler.fit_transform(segmentation_features_km[['total_user_spent',
'age', 'order_frequency', 'num_of_item']])
scaled_features_sc = scaler.fit_transform(segmentation_features_sc[['total_user_spent',
'age', 'order_frequency', 'num_of_item']])
scaled_features_hc = scaler.fit_transform(segmentation_features_hc[['total_user_spent',
'age', 'order_frequency', 'num_of_item']])

# ## KMeans Clustering
# determining the optimal number of clusters using the Elbow Method
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, random_state=42)
    kmeans.fit(scaled_features_km)
    wcss.append(kmeans.inertia_)

# plotting the Elbow Method
```

```
import matplotlib.pyplot as plt
plt.plot(range(1, 11), wcss)
plt.title('Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()

for k in range(2, 6):  # testing k values from 2 to 5
    kmeans = KMeans(n_clusters=k, random_state=42)
    labels = kmeans.fit_predict(scaled_features_km)
    silhouette = silhouette_score(scaled_features_km, labels)
    print(f"Silhouette Score for k={k}: {silhouette}")

kmeans = KMeans(n_clusters=2, random_state=42)
kmeans_labels = kmeans.fit_predict(scaled_features_km)
segmentation_features_km['Cluster'] = kmeans_labels

cluster_analysis = segmentation_features_km.groupby('Cluster').mean()
print("Cluster Analysis")
print(cluster_analysis)

cluster_sizes = segmentation_features_km['Cluster'].value_counts()
print("Cluster Sizes:")
print(cluster_sizes)

# ## Spectral Clustering
for k in range(2, 6):  # testing k values from 2 to 5
    spectral = SpectralClustering(n_clusters=k, affinity='nearest_neighbors',
random_state=42)
    labels = spectral.fit_predict(scaled_features_sc)
    silhouette = silhouette_score(scaled_features_sc, labels)
    print(f"Silhouette Score for k={k}: {silhouette}")

spectral = SpectralClustering(n_clusters=2, affinity='nearest_neighbors', random_state=42)
spectral_labels = spectral.fit_predict(scaled_features_sc)
segmentation_features_sc['Cluster_Spectral'] = spectral_labels

cluster_analysis = segmentation_features_sc.groupby('Cluster_Spectral').mean()
print("Cluster Analysis:\n")
print(cluster_analysis)

cluster_sizes = segmentation_features_sc['Cluster_Spectral'].value_counts()
print("Cluster Sizes:")
print(cluster_sizes)

# ## Hierarchical Clustering
for k in range(2, 6):  # testing k values from 2 to 5
    linkage_matrix = linkage(scaled_features_hc, method='ward')
    hierarchical_labels = fcluster(linkage_matrix, t=k, criterion='maxclust')
```

```
    silhouette = silhouette_score(scaled_features_hc, hierarchical_labels)
    print(f"Silhouette Score for k={k}: {silhouette}")

linkage_matrix = linkage(scaled_features_hc, method='ward')
hierarchical_labels = fcluster(linkage_matrix, t=2, criterion='maxclust')
segmentation_features_hc['Cluster_Hierarchical'] = hierarchical_labels

cluster_analysis = segmentation_features_hc.groupby('Cluster_Hierarchical').mean()
print("Cluster Analysis:")
print(cluster_analysis)

cluster_sizes = segmentation_features_hc['Cluster_Hierarchical'].value_counts()
print("Cluster Sizes:")
print(cluster_sizes)

clustered_data = pd.merge(joined_data, segmentation_features_hc, on='user_id',
how='inner')
clustered_data =
clustered_data[['order_id','user_id','num_of_item_x','product_id','category','brand','retail_price
','sale_price','department','first_name','last_name','email','age_x','gender','state','street_addre
ss','postal_code','city','country','total_order_value','total_user_spent_x','order_frequency','Clu
ster_Hierarchical']].rename(columns={'num_of_item_x':
'num_of_item','age_x':'age','total_user_spent_x':'total_user_spent','Cluster_Hierarchical':'clus
ter'})

# visualizing Product Category Distribution per Cluster
category_distribution = clustered_data.groupby(['cluster',
'category']).size().reset_index(name='count')

plt.figure(figsize=(20, 10))
sns.barplot(data=category_distribution, x='category', y='count', hue='cluster', dodge=True)
plt.title('Product Category Distribution by Cluster')
plt.xticks(rotation=90)
plt.show()

# analyzing Brands per Cluster
brand_distribution = clustered_data.groupby(['cluster',
'brand']).size().reset_index(name='count')
top_brands = brand_distribution.groupby('brand')['count'].sum().nlargest(10).index  # Top 10
brands

brand_distribution = brand_distribution[brand_distribution['brand'].isin(top_brands)]

plt.figure(figsize=(12, 6))
sns.barplot(data=brand_distribution, x='brand', y='count', hue='cluster', dodge=True)
plt.title('Top Brand Distribution by Cluster')
plt.xticks(rotation=45)
plt.show()
```

```
# # RECOMMENDATION ENGINE
def create_train_test_data(clustered_data, test_size=0.2):
    train_data, test_data = train_test_split(clustered_data, test_size=test_size,
random_state=42)

    test_data = test_data[['user_id', 'product_id']].drop_duplicates()

    train_data = train_data.reset_index(drop=True)

    return train_data, test_data

clustered_data['gender_encoded'] = LabelEncoder().fit_transform(clustered_data['gender'])

# extracting user data
user_data = clustered_data.groupby('user_id').agg({
        'gender_encoded':'first',
        'total_user_spent':'mean',
        'order_frequency':'mean',
        'product_id':lambda x: list(x), # List of purchased products
        'cluster':'mean'
    }).reset_index()
user_data.rename(columns={'product_id':'purchased_products'}, inplace=True)

user_data['price_range'] = user_data['total_user_spent'] / user_data['order_frequency']

# extracting product data
product_data =
clustered_data[['product_id','gender_encoded','sale_price']].drop_duplicates()
product_data.rename(columns={'sale_price':'price_range'}, inplace=True)

def get_recommendations(user_data, product_data, n=3):
    # standardising numerical features
    scaler = StandardScaler()
    user_features = scaler.fit_transform(user_data[['gender_encoded', 'price_range']])
    product_features = scaler.fit_transform(product_data[['gender_encoded', 'price_range']])

    recommendations_list = []
    user_data = user_data.reset_index(drop=True)

    for user_id in user_data['user_id'].unique():
        user_index = user_data[user_data['user_id'] == user_id].index[0]
        user_vector = user_features[user_index].reshape(1, -1)

        similarity_scores = cosine_similarity(user_vector, product_features).flatten()
        product_data['similarity_score'] = similarity_scores

        # including all products (no exclusion)
```

```
        product_data_sorted = product_data.sort_values(by='similarity_score',
ascending=False)
        top_recommendations = product_data_sorted.head(n)

        for _, row in top_recommendations.iterrows():
            recommendations_list.append({
                'user_id': user_id,
                'product_id': row['product_id'],
                'similarity_score': row['similarity_score']
            })

    return pd.DataFrame(recommendations_list)

# top 5 recommendations
recommendations_df = get_recommendations(user_data,product_data,5)

def evaluate_recommendations(recommendations_df, test_data, k=10):
    recommendations_df = recommendations_df.groupby('user_id').apply(lambda x:
x.nlargest(k, 'similarity_score'))

    actual_purchases = test_data.groupby('user_id')['product_id'].apply(set).to_dict()

    precisions, recalls, accuracies = [], [], []

    for user_id in recommendations_df['user_id'].unique():
        recommended_products = set(recommendations_df[recommendations_df['user_id'] ==
user_id]['product_id'].tolist())

        actual_products = actual_purchases.get(user_id, set())

        true_positives = len(recommended_products & actual_products)
        precision = true_positives / k if k > 0 else 0
        recall = true_positives / len(actual_products) if len(actual_products) > 0 else 0
        accuracy = true_positives / len(recommended_products) if len(recommended_products)
> 0 else 0

        precisions.append(precision)
        recalls.append(recall)
        accuracies.append(accuracy)

    precisions = np.array(precisions)
    recalls = np.array(recalls)
    accuracies = np.array(accuracies)

    avg_precision = precisions.mean()
    avg_recall = recalls.mean()
    avg_accuracy = accuracies.mean()
    avg_f1 = (2 * avg_precision * avg_recall) / (avg_precision + avg_recall) if (avg_precision +
avg_recall) > 0 else 0
```

```
    return avg_precision, avg_recall, avg_f1, avg_accuracy

# spliting the data into training and testing sets
train_data, test_data = create_train_test_data(clustered_data)

for k in [3, 5, 7, 10]:
    precision_k, recall_k, f1_k, accuracy_k =
evaluate_recommendations(recommendations_df, test_data, k=k)
    print(f"K={k}: Precision={precision_k:.4f}, Recall={recall_k:.4f}, F1={f1_k:.4f},
Accuracy={accuracy_k:.4f}")

num_users = recommendations_df['user_id'].nunique()
num_products_recommended = recommendations_df['product_id'].nunique()
print(f"Users with recommendations: {num_users}")
print(f"Unique products recommended: {num_products_recommended}")

recommended_in_test = recommendations_df['product_id'].isin(test_data['product_id']).sum()
total_recommended = recommendations_df['product_id'].nunique()
print(f"Overlap with test data: {recommended_in_test}/{total_recommended} products")

joined_data[joined_data['user_id'] == 49796]

recommendations_df[recommendations_df['user_id'] == 49796]

# # GEN AI
# merging product and user details with recommendations

product_recommendations = pd.merge(recommendations_df, products, left_on='product_id',
right_on='id', how='inner')

product_recommendations =
product_recommendations[['user_id','product_id','similarity_score','category','name','brand','r
etail_price','department']]

user_recommendations = pd.merge(product_recommendations, uk_users, left_on='user_id',
right_on='id', how='inner')

user_recommendations =
user_recommendations[['user_id','product_id','similarity_score','category','name','brand','retai
l_price','department','first_name']]
user_recommendations[user_recommendations['user_id'] == 49796]

# grouping recommendations by user_id
grouped_recommendations = user_recommendations.groupby('user_id').apply(
    lambda x: x[['name', 'category']].to_dict(orient='records')
).to_dict()

# Set up OpenAI API Key
```

```
openai.api_key =
"

                                "


def generate_campaign_message(user_id, recommendations):

    product_list = ", ".join([f"{rec['name']} ({rec['category']})" for rec in recommendations])
    prompt = f"""
    Create a personalized marketing email for User {user_id}.
    The email should recommend the following products: {product_list}.
    Make it engaging, friendly, and persuasive, focusing on why the user should buy these
products.
    """

    response = openai.ChatCompletion.create(
        model="gpt-3.5-turbo",
        messages=[
            {"role": "system", "content": "You are a marketing assistant who specializes in
creating campaigns."},
            {"role": "user", "content": prompt}
        ],
        max_tokens=150,
        temperature=0.7,
    )

    return response['choices'][0]['message']['content'].strip()

# generating campaigns for each user
campaign_messages = {}
for user_id, recommendations in grouped_recommendations.items():
    campaign_messages[user_id] = generate_campaign_message(user_id,
recommendations)

# printing campaign messages
for user_id, message in campaign_messages.items():
    print(f"Campaign for User {user_id}:\n{message}\n")
```

APPENDIX E - OTHER SUPPORTING MATERIALS

ID	Task Name	Start	End	Duration
1	Dissertation Process	2024-11-18	2025-01-08	38 days
2	Literature Review	2024-11-18	2024-11-22	5 days
3	Data Cleaning, Pre-Processing and BDA	2024-11-25	2024-11-29	5 days
4	Customer Segmentation and Recommendation Engine using ML	2024-12-02	2024-12-13	10 days
5	Gen AI Implementation	2024-12-16	2024-12-20	5 days
6	Final Analysis, Synthesis of Findings and Report Writing	2024-12-23	2025-01-08	13 days

figure 7 - Process Timeline

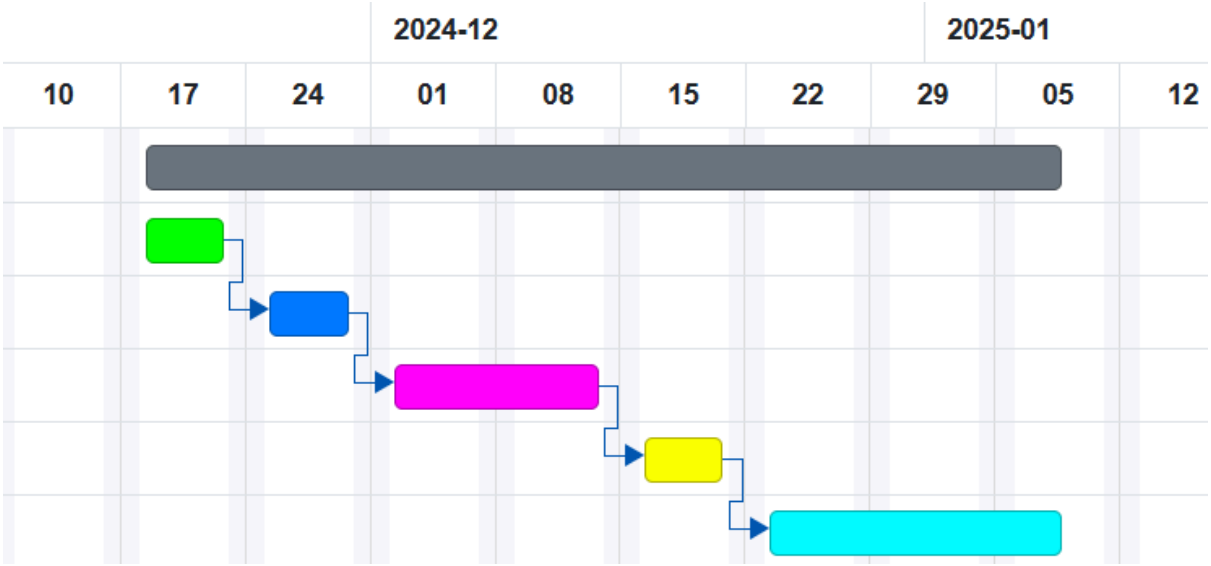

figure 8 - Gantt Chart

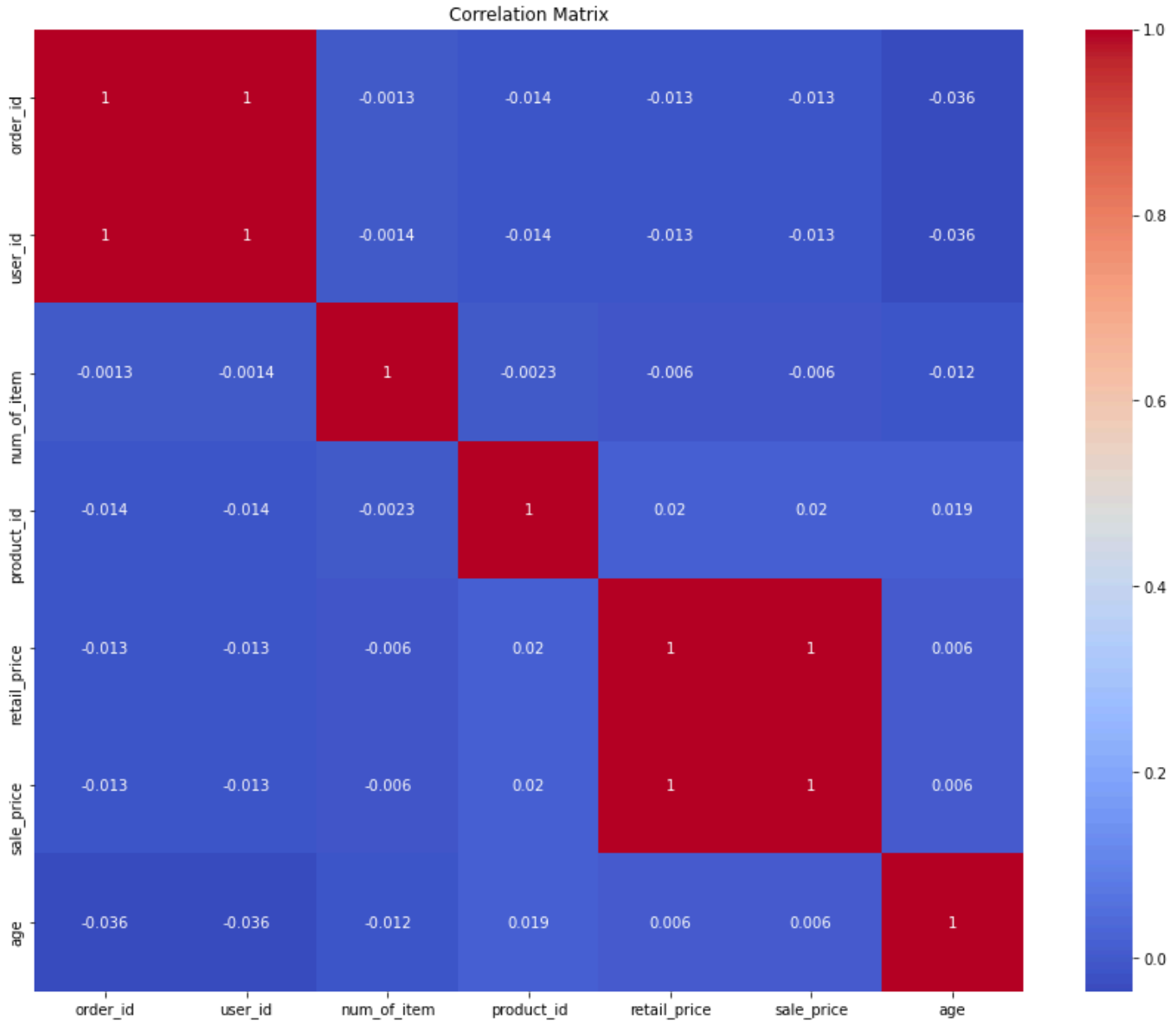

figure 9 - Correlation Matrix

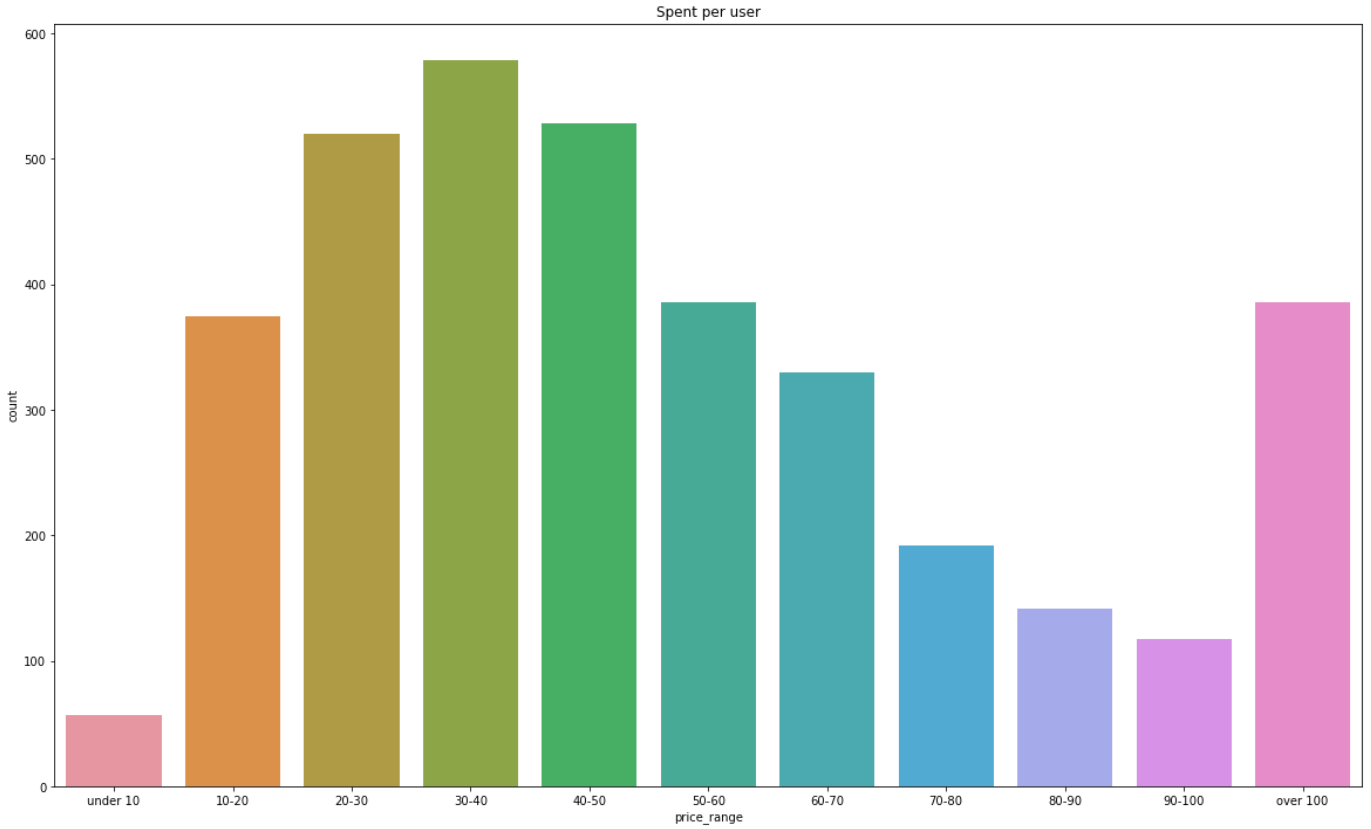

figure 10 - Bar Chart: User Spent

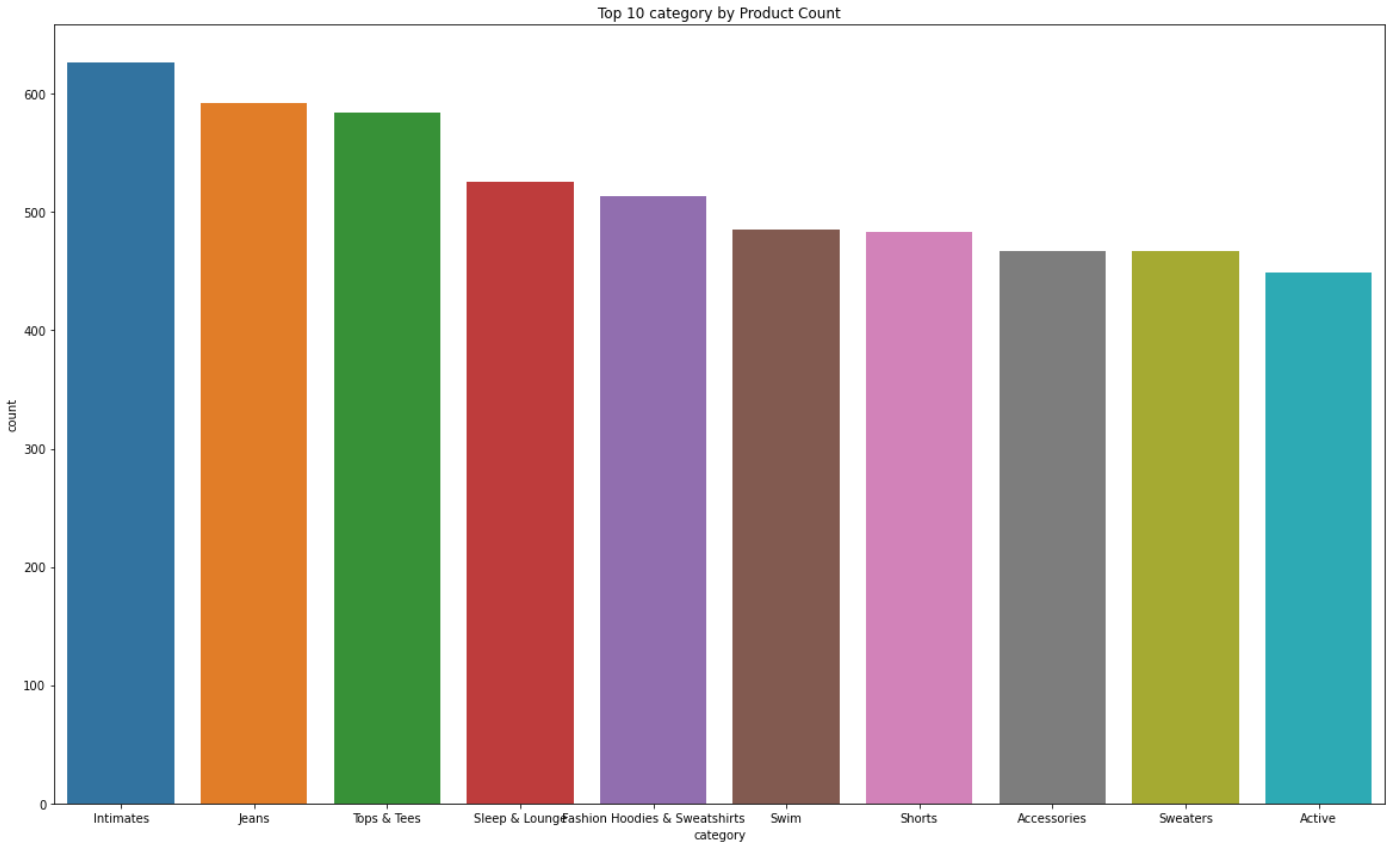

figure 11 - Bar Chart: Top Categories

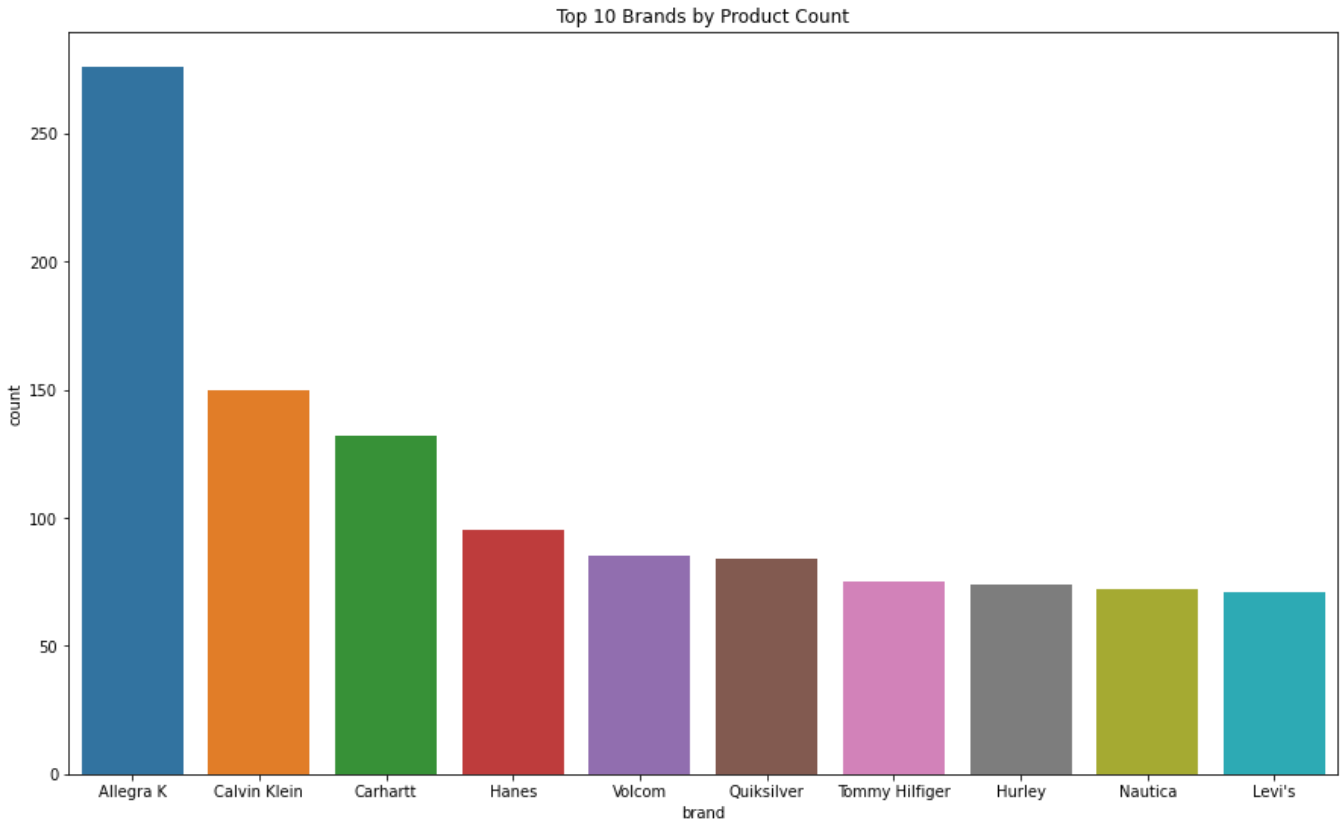

figure 12 - Bar Chart: Top Brands

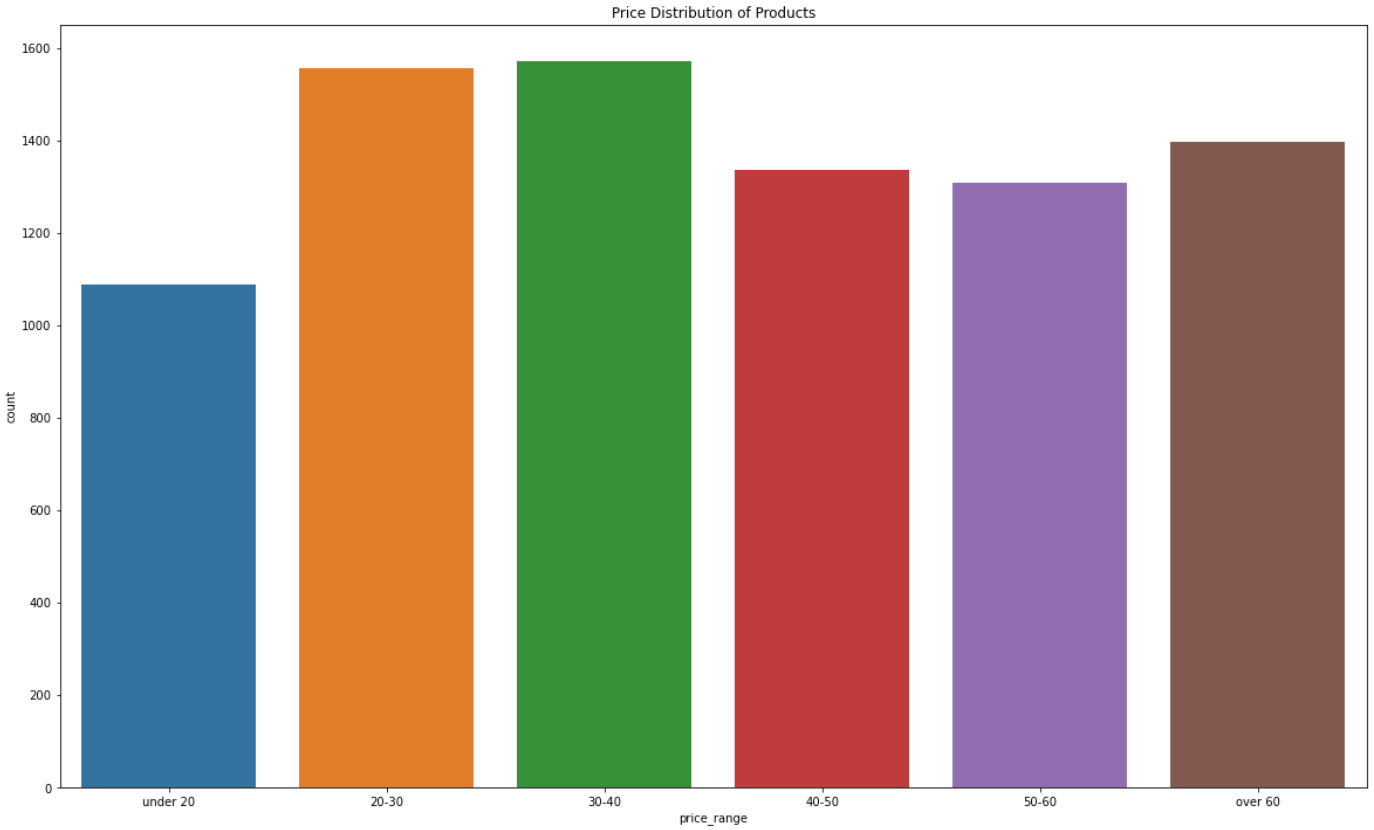

figure 13 - Bar Chart: Price Distribution of Products

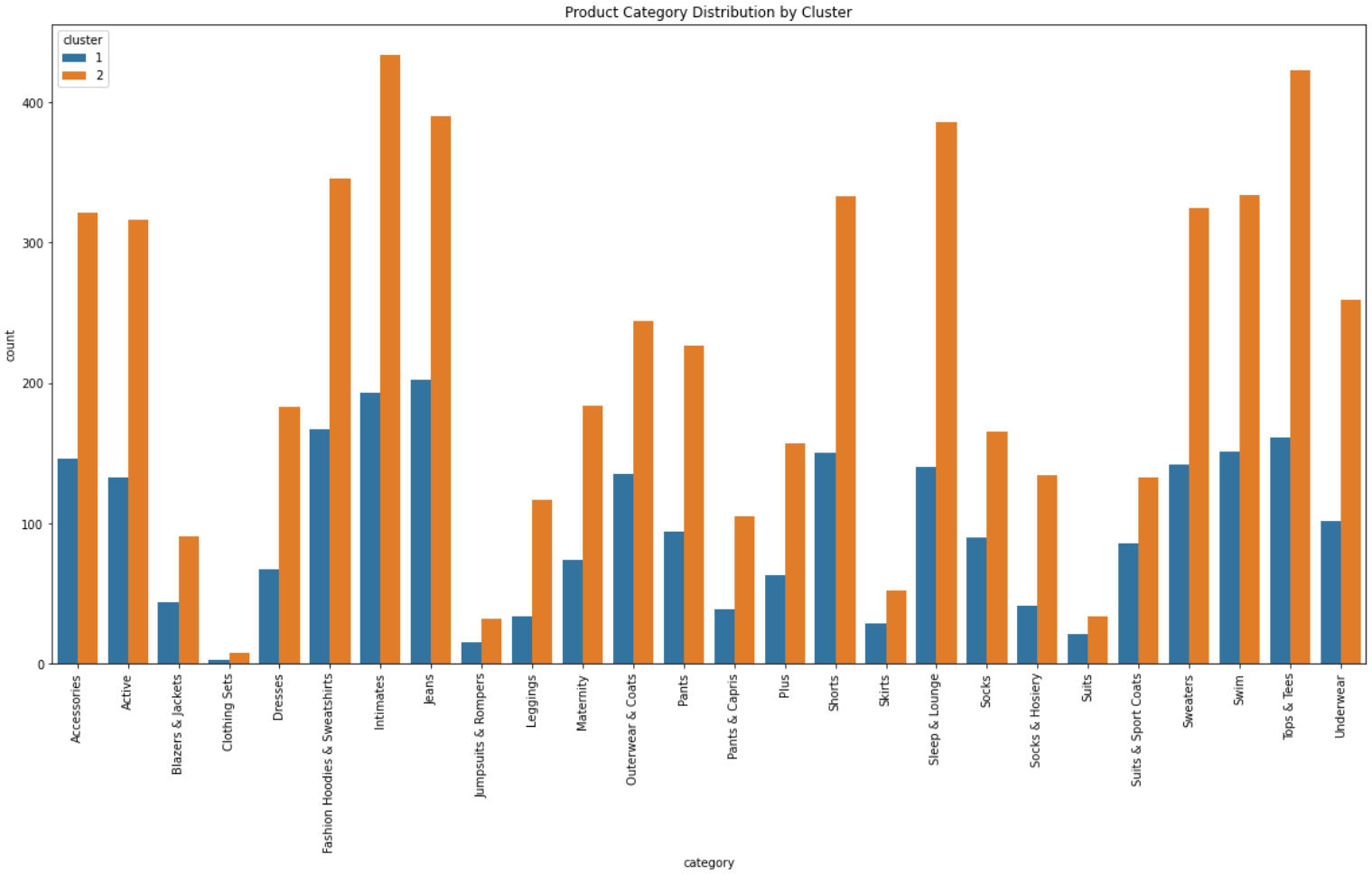

figure 14 - Bar Chart: Product Category Distribution by Cluster

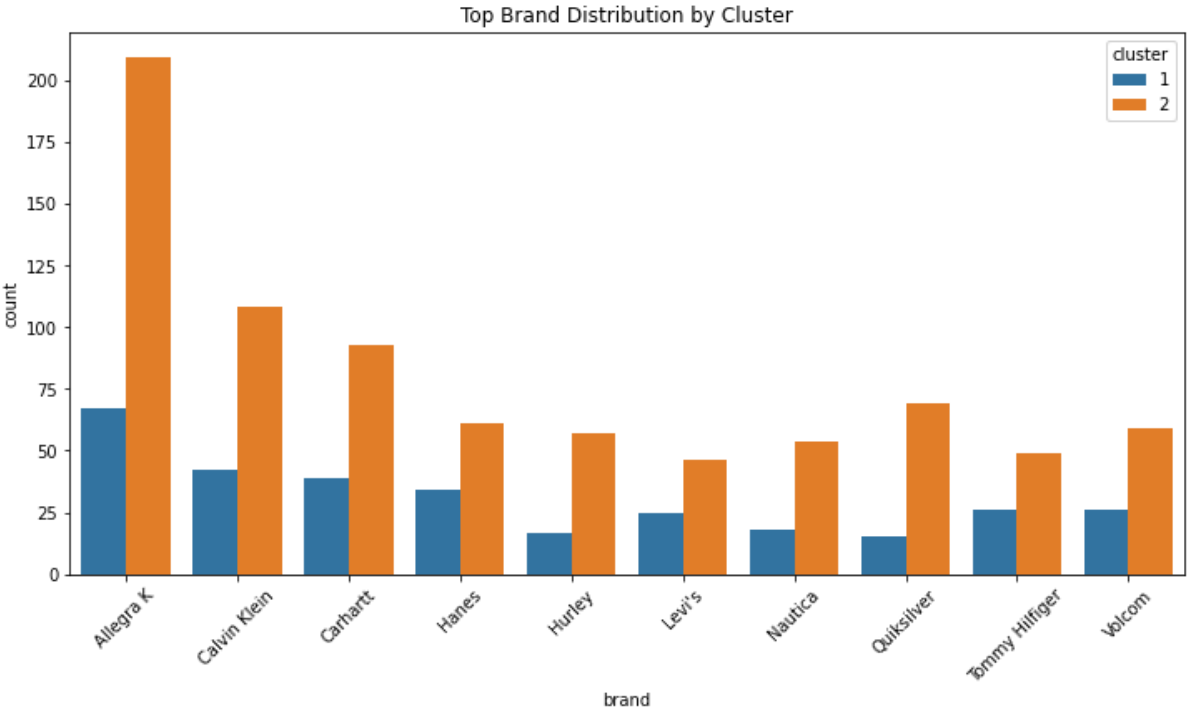

figure 15 - Bar Chart: Top Brand Distribution by Cluster