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ON LEVERAGING GENERATIVE ARTIFICIAL INTELLIGENCE (GENAI) FOR BEHAVIOR LEARNING AND PERSONALIZED MARKETING OPTIMIZATION

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SUMMARY

Generative AI (GenAI), especially GPT-3.5-turbo, has transformed the e-commerce marketing process because it offers personalized learning experiences and improves the customer experience. In this paper, we discuss the use of GenAI in consumer behavior analysis and the development of customized marketing strategies. It has been observed that behavioral characteristics, such as purchase frequency and expenditure, are essential for customizing marketing activities, and that there is a strong correlation between these variables and customer satisfaction. The prediction of customer satisfaction was used as a Random Forest classification model and the results have shown that the model can predict customer satisfaction with an accuracy of 97% with the influence of purchase frequency and total spend being the most influential predictors. GenAI is an excellent way to automate content creation, engage more customers, and retain them. Importantly, personalized marketing messages generated by GenAI were more likely to engage consumers, mainly when used to address satisfied customers with upsell suggestions and to incentivize neutral and dissatisfied customers. Nevertheless, challenges remain regarding the authenticity of the content and the privacy of the data. The paper highlights the potential of GenAI to transform the nature of personalized e-commerce marketing by integrating data and real-time content development to increase customer satisfaction and business results.

Key words: *generative ai, personalized marketing, consumer behavior analysis, e-commerce, gpt-3.5-turbo, predictive analytics, customer engagement.*

INTRODUCTION

GenAI has developed considerably since its introduction in the middle of the 20th century, with its design evolving to incorporate more advanced machine learning algorithms capable of mimicking human thought. GenAI is an indication of a paradigm shift in the area of artificial intelligence. GenAI is a relatively new branch of artificial intelligence (AI) that has gained significant popularity among the general public since the launch of models such as ChatGPT and DALL-E [1]. With the help of GenAI [3], machines can now produce entirely original, meaningful content, such as text, images or music based on training data. GenAI, in contrast to traditional AI, which is more concerned with pattern recognition and decision-making, creates highly realistic, contextually appropriate outputs through deep learning models such as Transformer-based models and Generative Adversarial Networks (GANs) [1].

GenAI is changing various industries, especially marketing, and is undergoing one of the most radical changes. This feature of GenAI, being able to analyze user behavior and customize interfaces accordingly is a very vital factor in GenAI in marketing since it enhances pattern identification in user-related interaction, like how people browse and the level of engagement with the platform (through clicks and engagements). It is transforming the nature of advertising, consumer creation, and engagement by enabling businesses to automate, optimize, and customize marketing strategies at a scale never seen before [5]. It has been observed that AI-generated marketing images have a higher success rate than those generated by humans, as they are more realistic, creative, and efficient. It is worth noting that the use of AI in advertisements has been observed to increase engagement rates by up to 50 percent compared with conventional marketing strategies, reinforcing the growing influence of these technologies in the digital market [6]. Through GenAI, companies can reduce marketing expenses, accelerate content creation, and improve brand-to-consumer interactions, thereby gaining a competitive edge in the digital economy [11] [14].

The Kingdom of Saudi Arabia has realised the power of AI and how it will be applied in helping the country realise its Vision 2030. It is trying hard to execute its AI strategy in all industries. As part of technical development and economic diversification, it has been embracing AI and digital transformation as two major aspects of Vision 2030, investing in e-commerce, AI-based marketing, and new business solutions [2][4]. The Kingdom can be improved through GenAI to boost digital marketing, personalizing customers, and economic growth, turning it into an AI-oriented and globally competitive economy [9][10]. That corresponds to the ambitions of the Vision 2030 to make industries more productive, more digital, and simpler. GenAI will reshape the marketing industry and business innovations in Saudi Arabia because more people will use AI, which will widen the business prospects and lead to AI becoming a pioneer in terms of digital transformation [12][13].

GenAI and personalized marketing consists of studying customer behavior and delivering experiences and material that are specific to each customer. ChatGPT and other GenAI tools can analyze large volumes of information to provide dynamic, personalized content, messages, and product recommendations to customers, boosting customer engagement and buying rates. Recent studies show that GenAI will help the marketer in market analysis, lead creation, and reporting, leading to successful advertising. GenAI personalized marketing is not restricted, however. Among such problems are potential bias in AI-generated content, risk of data breach, and excessive reliance on automation that will result in a scenario where AI-generated content is the only way to communicate with customers. Additionally, the input of data into the system is also a major determinant of the quality of AI output; low data quality will reduce the capability of AI. Better said, this is an artificial manipulation of customer preferences and openness of AI-driven marketing strategies, which is ethically questionable. The use of GenAI in personalized marketing should be done in a responsible and effective way that has several limitations.

The paper has made significant contributions, which include,

- Combines GenAI and predictive analytics to generate individualized marketing content based on detailed analysis of consumer behavior.

- Uses GPT-3.5-turbo to automate content creation, adding a human-like personal touch and increasing e-commerce consumer engagement.
- Applying high-order machine learning to provide customer satisfaction and preference segmentation with actionable recommendations on enhancing customer retention and satisfaction.
- Demonstrates the application of GenAI models in the real-world e-commerce setting and offers a viable approach to solving personalized, scalable marketing tasks.
- Brings aid to the AI-powered marketing solutions, increasing the ability to develop personalized marketing communications and expand customer interactions.

The paper will be divided into five primary parts to provide the comprehensive analysis of the role that GenAI plays in e-commerce marketing. Section Two provides a thorough literature review of past studies on GenAI, customer behavior analysis, and customized marketing strategies. Section Three describes the research methodology, the procedures undertaken to gather and analyze the data, and the findings, which also present key insights into the impact of GenAI on user engagement and conversion rates. Section Four presents a conclusion and recommendations, summarizes the research's implications, and provides potential directions for future research.

LITERATURE REVIEW

In recent years, Generative AI (GenAI) together with digital marketing transformed how companies interpret and respond to user behavior, and to a significant degree, how they embrace business personalization methods [16][17]. GenAI that focuses on original content creation (text, image, audio, and video) is relevant in content-based and creatively-driven industry [18][19]. It is also capable of generating new outputs, which would be out of reach with the traditional AI models, making it invaluable in digital marketing, personalized content generation, customer interaction, and market research [20][21].

The history of AI started in the mid 20th century when it was decided to develop a machine that would have the ability to replicate the human intelligence [22][23]. However, the breakthrough truly occurred in the 21 st century wherein machine learning, in particular, deep learning and neural networks were developed [24]. GenAI systems can generate content that is in line with human creativity, because they are trained on large datasets [25]. GenAI is created to produce unique, original content based on the needs of the individual consumer compared to other AI systems, which enables businesses to produce what people need [26][27].

One of the most prominent advantages of GenAI is the availability of marketing tailored to the specific needs that have to be mentioned [28]. It has also become instrumental in the delivery of customized services and products based on the preferences of the users also referred to as customized marketing [29][30]. GenAI is strong due to the fact that it is a data-driven learner, which means that it is able to see the complex patterns in large volumes of data and produce the content that is very relevant. It may be streamlined to suit any media, such as text, pictures and even 3D models, to enhance content-making easier and consumer engagement better [31][32].

Certain tools and models play a vital role in the success of GenAI in marketing [33][34]. As an example, Transformer and GPT models are used in the natural language processing domain and could be used to produce convincing text. GANs and VAEs, in their turn, are used in generating content, including images and videos. These models are integrated into the work of different AI systems, such as IBM Watson and Adobe Sensei, to promote decision-making and contact with customers.

GenAI has its own issues, despite its potential, in particular, in the sphere of ethics, such as the tendency to biases in the content generated, the danger of privacy invasion, and the loss of human jobs [36]. One way to reduce these is by making sure that the content is produced openly and the businesses are responsible when it comes to AI. In addition, even though GenAI is capable of making a substantial degree of efficiency and personalization, it is crucial to balance its usage with human intervention to guarantee creativity and compliance with ethical norms in the business [35].

Overall, GenAI is changing the digital marketing environment by assisting companies in producing more individualized and interest-based content, developing better customer satisfaction, and functioning more efficiently. However, it needs to be approached with accuracy to reduce the possible barriers and provide the ethical and beneficial implementation of this process.

Table 1. Related Work Summary

Ref	Methodology	Key Findings	Gaps and Limitations
[32]	Combined the personality models (MBTI, Big Five) with RAG framework to improve personalized travel recommendations.	78% user satisfaction, 82% system accuracy.	Real-world testing is limited, can't capturing detailed user preferences
[33]	Conducted online interviews with 10 senior executives in customer-oriented roles using a snowball sampling approach. Data we r e analyzed through familiarization, coding, and theme development.	Identified six GenAI paradoxes in customer service and offered response techniques to address them, including balancing AI with human service, enhancing AI training and ensuring ethical AI deployment.	Small sample size and scope. Did not investigate the long-term effects of GenAI customer service.
[15]	A systematic review conducted of 31 studies on different GenAI models for consumer behavior prediction.	The study finds that GenAI models like transformers, GANs, and VAEs significantly enhance consumer behavior prediction by enabling personalized marketing, customer retention, and inventory management.	Data privacy concerns, limited real-world applications, ethical considerations.
[30]	ResNet-50, GRU, and transfer learning applied to consumer data.	Deep learning enhances marketing strategies by improving the prediction of consumer behavior.	Computational complexity requires large datasets for effective implementation.
[37]	Systematic review of 28 studies about GenAI models in (OCBA) online consumer behavior analysis.	GANs are the most used, most efficient and most cost- effective in OCBA	Data bias. Data privacy challenges.
[40]	The study adopts a conceptual approach by leveraging existing literature and practices to explore the impact of GenAI on consumer behavior and its implications for research, practice, and policy.	GenAI transforms consumer engagement, purchase decision-making, and brand interactions by enabling personalized recommendations, interactive experiences, and reshaping consumer behavior dynamics.	Lack of empirical validation, need for deeper policy analysis.
[39]	Analyzing Instagram posts and conducting a between-subjects experiment.	GenAI content has lower engagement and visit intentions when disclosed.	Lack of longitudinal analysis, need for more diverse social media platforms.
[38]	The study uses a controlled, multi- experimental laboratory design to investigate consumer attitudes toward GenAI ads, using statistical analysis, social identity theory, and the IKEA effect across two experiments.	The study shows that how much consumers engage with GenAI ads affects their opinions, with more involvement leading to a stronger connection to the brand. Perceived authenticity, in-group bias, and AI authorship awareness shape consumer attitudes.	Limited industry scope, more diverse ad formats needed.
[37]	Application of Elaboration Likelihood Model (ELM) and Expectancy-Value Theory (EVT).	User trust is crucial for AI-driven sustainability recommendations, influenced by Cognitive and heuristic factors.	Lack of real-world testing, complexity in balancing information depth.
[38]	Survey-based study using the UTAUT3 model on 510 university students.	Performance expectations, social influence, and hedonic motivation drive GenAI adoption.	Limited sample diversity; need for industry-wide validation.

[35]	GPT-4 applied to analyze pricing models and consumer reviews of 13,008 EV charging stations.	GenAI enhances pricing transparency and identifies user frustrations with cost and speed.	Potential biases in AI-generated insights, need for policy recommendations.
[28]	Experimental study analyzing AI-generated product recommendations and consumer choices.	AI-driven recommendations influence purchasing behavior and increase conversion rates.	Limited analysis of long-term consumer trust in AI recommendations.
[8]	For large-scale product reviews, the use of transformer models improves sentiment classification.	Enhanced precision in sentiment prediction provides clearer business insight.	Difficulties of managing subtle language and sarcasm in reviews.
[13]	Analysis of case studies of AI-based advertising campaigns in a range of industries.	Enhanced consumer engagement with marketing ideas generated by AI.	Cultural differences in sentiment expression render multilingual translation challenging, introducing biases and errors which hinder the development.
[7]	Summarizing of literature review in existing research on the impact of AI on consumer analytics.	The importance of anticipating customer patterns and behaviors is emphasized in the creation of personalized, creative, and responsive marketing strategies.	AI provides innovative insights but demands accurate execution and regulatory frameworks to address ethical concerns in AI-driven consumer research.

The studies explored above have revealed that GenAI models such as GANs, VAEs, and transformers assist in the marketing decision-making process, inventory management, and the analysis of customer emotions in customer recommendations [39]. Deep learning models, such as ResNet-50 and GRU have enhanced predictions in consumer behavior, leading to more successful targeted advertising, nevertheless, there are still several shortcomings, including ethical concerns of data privacy, bias in AI-generated content and complexity of computation [8][40]. Several researchers also highlight the significance of practical assessment and legislations that increase integrity and trust in AI enabled marketing activities. In addition, long-term consumer trust, the mismatch in engagement across platforms, and the scalability of AI-based personalization are research topics yet to be investigated [37].

Nevertheless, even as interest in GenAI and its use in marketing is increasing, existing research gaps remain, especially regarding personalized marketing approaches in the e-commerce industry. Interestingly, the special nature of GenAI in generating content based on customer interactions is also not widely discussed, nor are studies that fully assess the immediate effect of using GenAI on customer satisfaction. This study is expected to address this gap by investigating consumer purchasing behavior, as influenced by levels of satisfaction; the creation of personalized text messages to thank consumers for their experiences with product purchases; and the referral of consumers to purchase similar products based on their interes.ts.

IMPLEMENTATION, RESULTS, AND DISCUSSION

The section describes the study's implementation, the research design, the use of GenAI to study consumer behavior and create personalized marketing messages based on unique consumer factors, and the outcomes of each phase. It uses Python to process the data and the GPT-3.5-turbo model of the OpenAI to generate personalized marketing content. The study is based on the publicly available E-Commerce Customer Behavior dataset at Kaggle.

The Experiment Setup

Python is used in this research because it is easy to use and has a robust ecosystem, particularly for data analysis and API integration. Pandas are the two major libraries utilized to operate data manipulation operations and OpenAI API to communicate with artificial intelligence requires. The Pandas library allows performing effective data loading and filtering works, whereas the OpenAI library allows accessing GPT-3.5 Turbo and other AI models safely and efficiently. Using transformer-based architecture, a GPT-3.5 Turbo can generate the text in a practical way that closely resembles that of a human text and it is strongly applicable in situations of conversational application. Being able to cause response in a short time, the user experience becomes improved in the interactive environment. Also, it is an affordable choice to the larger models such as the GPT-4. The model comes up with quality responses that are contextually relevant. It is a perfect tool to use in many applications because of its features of handling complex questions effectively and thus it can achieve speed and accuracy in the majority of cases. Therefore, we decided to work with GPT-3.5 Turbo in the given research to make AI-based interactions as good and effective as possible. Such techniques like instant engineering, conditional logic, etc. introduce the personal touch to the automation of messages with a concentration on consumer satisfaction. The system is focused explicitly on API key management and error control, as well as on the increased stability and scalability, which is achieved via the automated programming. Python, Open AI, and Pandas are some of the necessary requirements that make the study of consumer interactions beneficial.

Research Design

This study involves a data-driven study approach, utilizing the dataset to investigate how GenAI can improve user behavior analysis and help the generation of personalized marketing strategies in the e-commerce area. The study is carried out in three main phases as follows:

1. *Phase I* - Data collection and preprocessing: In this phase, the dataset is cleaned, encoded, and normalized to become ready for analysis
2. *Phase II* - Classification-based user behavior analysis: This phase leads to learn the deeper patterns that could be used to guide personalizing by applying different classification algorithms to predict the user's 'Satisfaction Level', and then, the results of the best performing classifier will be utilized to drive the process of creating personalized content.
3. *Phase III* - GenAI-based personalized content creation: During this phase, the study will use OpenAI's GPT3.5-turbo to generate tailcoated marketing content based on each consumer behavior.

Figure 1 demonstrates the proposed design of using Generative AI (GenAI) in electronic commerce marketing. The model is additionally subdivided into two major phases that are Phases I, which is the data collection and preprocess that comprises cleaning, encoding and normalizing consumer behavior data. Phase II deals with examining the behavior of the users through classification tools that have predictive modelling approaches like the Random Forest and uses it to divide the users basing on the key predictors including purchase frequency, total spend and days since the last purchase. The step above will include GPT-3.5-turbo to generate personalized marketing material to both loyal and unhappy customers to optimize customer attraction and retention. The technology stack processes and communicates with each other using Python, Pandas, and OpenAI API.

The code of the implementation process of Generative AI (GenAI) to personalize marketing in e-commerce is presented in the sequential way in Algorithm 1. It starts with data preprocessing in which information on customer behavior is cleansed, coded, and normalised. The algorithm then goes to classification and machine learning models are estimated to predict the level of customer satisfaction by employing key behavioral determinants. Finally, we have content generation, i.e. the creation of customized marketing messages through the assistance of GPT-3.5-turbo based on the degree of satisfaction that is expected of a given customer. It will be employed in order to have a focused communication to enable the engagement and retention of customers.

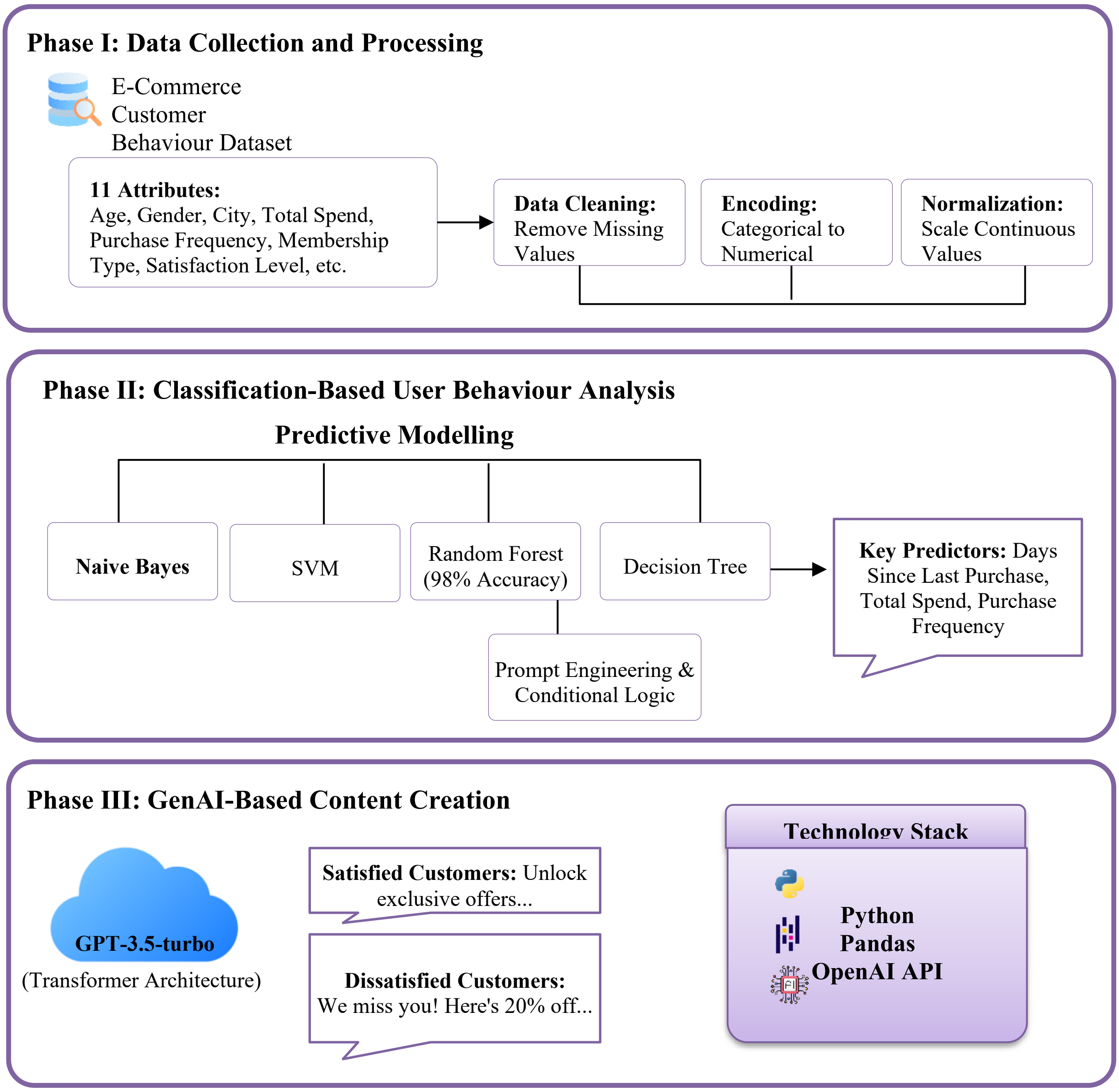

Figure 1. Architecture for Personalized Marketing Optimization Using Generative AI

Algorithm 1: Generative AI for Personalized Marketing Optimization

Input:

E-Commerce Customer Behavior Dataset (from Kaggle) with attributes such as Age, Gender, Total Spend, Purchase Frequency, Membership Type, Satisfaction Level, etc.

Step 1: Data Preprocessing

Load Dataset: Import the e-commerce customer behavior data.

Clean Data: Remove missing values and handle any inconsistencies in the dataset.

Encode Categorical Data: Convert non-numeric data (e.g., Gender, Membership Type) into numeric values.

Normalize Data: Scale continuous variables (e.g., Total Spend, Purchase Frequency) to ensure they are on the same scale.

Step 2: Behavior Analysis and Prediction

Select Key Features: Choose the most important features that affect customer satisfaction (e.g., Days Since Last Purchase, Total Spend).

Train Model: Use a machine learning model (e.g., Random Forest) to predict customer satisfaction levels (Satisfied, Neutral, Dissatisfied).

Evaluate Model: Check the model's performance using accuracy, precision, and recall metrics.

Step 3: Content Generation

Classify Customers: Based on the trained model, classify customers into three satisfaction categories:

Satisfied: Happy customers.

Neutral: Customers neither happy nor unhappy.

Dissatisfied: Unhappy customers.

Generate Personalized Messages:

For Satisfied Customers: Generate a message with a thank-you note and exclusive offers.

For Neutral Customers: Generate a message asking for feedback and offering a discount.

For Dissatisfied Customers: Generate a message with an apology and an incentive to regain trust.

Step 4: Output

Send Personalized Content: Use the generated messages to engage each customer, tailored to their satisfaction level.

Mathematical Description

Data Normalization

Each feature f_j is normalized using equation 1:

$$f_j' = \frac{f_j - \mu_j}{\sigma_j} \quad (1)$$

where μ_j is the mean and σ_j is the feature's standard deviation.

Classification Model

Equation 2 represents the classifier $f(x_i)$ expects the satisfaction level $\hat{y}_i$ for each client based on their features x_i:

$$\hat{y}_i = f(x_i) \quad (2)$$

Loss Function (Cross-Entropy)

Equation 3 shows the cross-entropy loss function used to train the model,

$$L(f) = -\sum_{i=1}^{m} \sum_{c=0}^{2} y_{i,c} \log\left(p(\hat{y}_i = c \mid x_i)\right) \quad (3)$$

where $y_{i,c}$ is the actual label and $p(\hat{y}_i = c \mid x_i)$ is the predicted probability for class c.

Content Generation

Personalized content is generated using the GPT-3.5 model based on customer features $x_i$and predicted satisfaction $\hat{y}_i$ are represented by equation 4,

$$C_{\text{gen}}(x_i, \hat{y}_i) = \text{GPT-3.5}(x_i, \hat{y}_i) \qquad (4)$$

Phase I: Data Collection and Preprocessing

Dataset Used in the Data Analysis: E-Commerce Data Set Used in the Data Analysis: e-commerce customer behavior dataset with 351 records and 11 attributes per single user on e-commerce websites.in the preparation of the data, the steps are: cleaning the data to get a format that can be read and analyzed by the machine learning model; first step involves removing the missing values of the dataset and second step consists in converting the categorical variables to numerical values (e.g, gender, city and type of membership).third step is to put the continuous variables to normal (e.g, total amount spent, purchase frequency) to ensure that each feature has a similar scale. this facilitates both more stability and effectiveness of every subsequent machine learning model.

Dataset Description

Kaggle, which is one of the biggest online data science competitions, offers the E-Commerce Customer Behaviour Dataset. It consists of 351 records incorporating 11 various attributes that characterize multiple bits of the consumer on an e-commerce site. The 11 attributes comprise demographic data, buying behaviours and level of customer satisfaction. This is why it would be an ideal place to learn personalised marketing in an e-commerce context. Also, the dataset will aim at giving an understanding of the relationship between the preferences, purchase behaviours, and the engagement metrics of consumers and level of satisfaction. It helps in making decisions to optimize consumer experience and create effective e-commerce marketing strategies.

- **Name of dataset:** E-Commerce Customer Behavior Dataset
- **Source:** Kaggle
- **Size of dataset:** A total of 351 records dispersed over 11 columns, every entry reflects a unique client with comprehensive information on their platform engagement.
- **Attributes of the dataset:** The dataset includes the following columns, as shown in Table 2.

Table 2. Dataset Attributes and Description

#	Attributes	Description
1	**Consumer ID**	A special number that is used to identify key information for every consumer.
2	**Gender**	Gender-based analytics are made possible by the consumer's gender (male or female).
3	**Age**	The customer's age, which helps with age-based consumer segmentation.
4	**City**	This provides geographic insights into the consumer's native city.
5	**Membership Type**	The consumer's loyalty level is indicated by their membership type (Gold, Silver, Bronze).
6	**Total Spend**	The amount of money spent on the platform, which is a measure of consumer spending patterns.
7	**Items Purchased**	The number of products the consumer has bought.
8	**Average Rating**	An assessment of consumer satisfaction that reflects the rating given to the objects that were bought.
9	**Discount Applied**	How much of the consumer's purchases were discounted.
10	**Days Since Last Purchase**	This measure, which helps determine repeat buying patterns, counts the days since the consumer's most recent purchase.
11	**Consumer satisfaction level**	A qualitative indicator of the consumer's experience that can be classified as either satisfied, neutral, or unsatisfied.

Dataset Significance

This database was selected based on its design that alignment the study objective through characteristics which help in segmenting consumers based on their behaviors, buying patterns to predict buying behavior and its causes such as discounts and analyzing the level of satisfaction, classifying customers based on their satisfaction to improving e-marketing strategies.

Dataset Processing

Step 1: Downloading the data and setting up the environment

Importing the customer behavior data from the Kaggle platform and examining it to get an initial impression of what its contents are like and its structure. Sets up the framework by importing required libraries and utilities into memory and placing them at our disposal for us to utilize the rest of the code. The pandas library is used to load the data from the file and subsequently print out the first five rows of data to understand the nature of each variable and the type of data (numeric/textual/logical) that it ought to be in order to prepare it for processing, as shown in Figure 2.

```
First 5 rows of the dataset:
   Customer ID  Gender  Age           City Membership Type  Total Spend  \
0          101  Female   29       New York            Gold      1120.20
1          102    Male   34    Los Angeles          Silver       780.50
2          103  Female   43        Chicago          Bronze       510.75
3          104    Male   30  San Francisco            Gold      1480.30
4          105    Male   27          Miami          Silver       720.40

   Items Purchased  Average Rating  Discount Applied  \
0               14             4.6              True
1               11             4.1             False
2                9             3.4              True
3               19             4.7             False
4               13             4.0              True

   Days Since Last Purchase Satisfaction Level
0                        25          Satisfied
1                        18            Neutral
2                        42        Unsatisfied
3                        12          Satisfied
4                        55        Unsatisfied
```

Figure 2. Dataset Overview

Step 2: Data Visualization

To improve the user experience and buying behavior, a better interpretation of the consumer behavior and drawing insights into the dataset should be reached through visualization of the important variables of distribution by age, types of memberships, purchase frequency, and total expenditure. It facilitates the decision-making process in the formulation of e-commerce marketing strategies that are well-crafted with the help of data. See Figure 3, a vertical chart depicting the number of customers who are aged by the age category. The median age group that comes out is 30 and then 32, then somewhere in the middle is the age group of 27 to 36. Customers aged below 28 and above 40 make the lowest percentages. This will enable us to reach the target population in the age bracket that is in the peak of their activities and place advertisements in the sites they frequent most including Instagram and Tiktok.

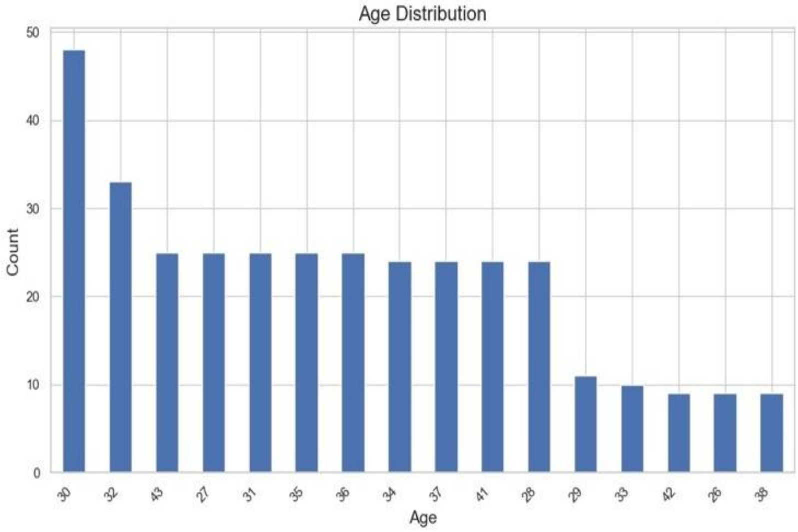

Figure 3. Age Distribution

Figure 4 represents the pie chart of the customers based on gender. The sample of data is equal in that a balance between males and females is ideal. Statistically, balance is good because it enables the comparison of the gender purchasing behavior without necessarily having to adjust or narrow the sample which will help in making more precise machine learning models in predicting consumer behavior free of bias.

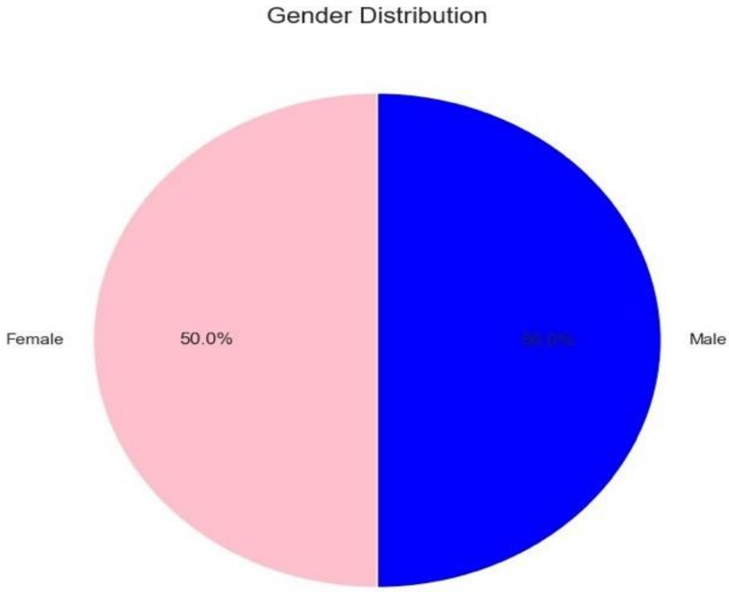

Figure 4. Gender Distribution

Figure 5 of Violin Plot depicts the distribution of the item of purchased by the city type, and the three types of memberships; Gold, Silver and Bronze. The city of San Francisco has the highest purchase rate average of more than 20 items and other cities such as Chicago and Houston have a lower purchase rate. Gold membership comes with increased purchase rates and this is why we need to market it. We are researching the cultural and economic dynamics affecting it and adjusting the promotional campaigns to enhance their interest in cities with poor performance.

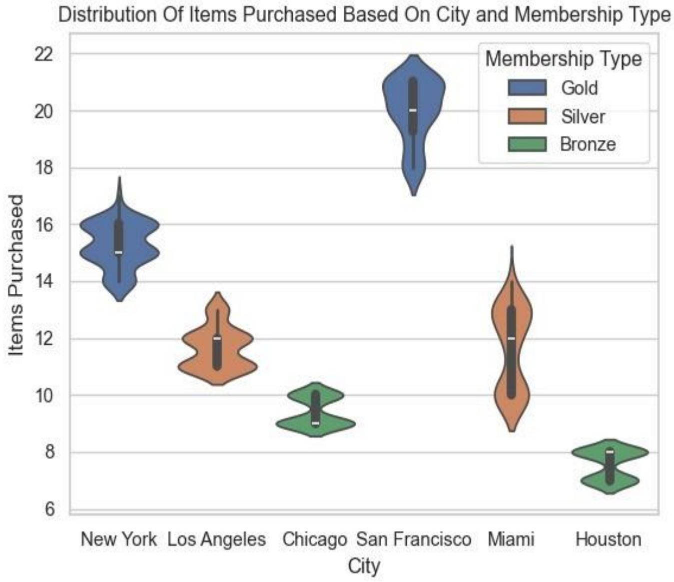

Figure 5. The Distribution of the Number of Items Purchased by City and Membership Type

Figure 6 demonstrates the distribution of total spending in the form of a histogram using a probability density curve (KDE). It is not normal and is asymmetrical but it has numerous peaks that indicate variations in spending patterns. Customers have different groups, some of which are high spenders, some average spenders and some very low spenders. This results into customer segmentation in terms of the behavioral patterns to tailor offers depending on the segment, e.g. loyalty programs, or special offers.

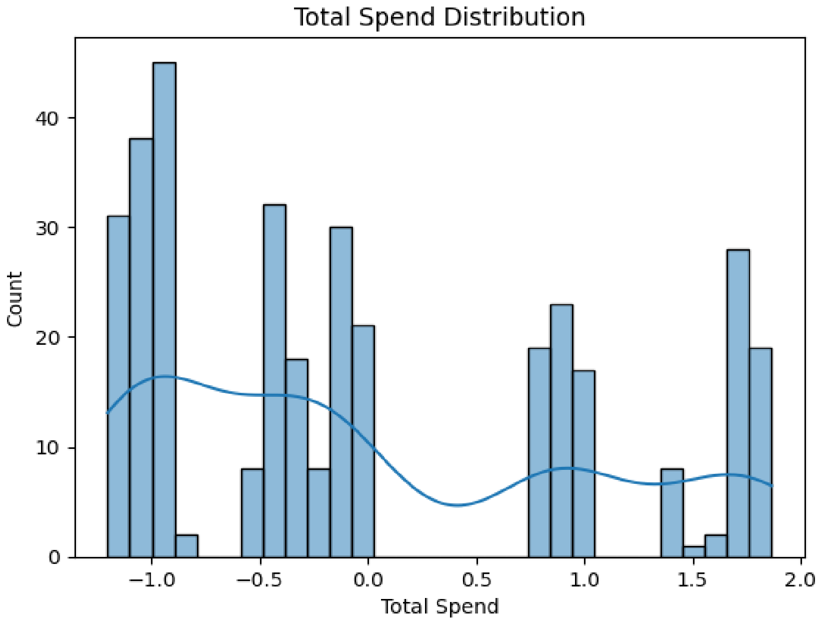

Figure 6. Total Spend Distribution

Step 3: Data cleaning and processing

Beginning to handle missing values by deletion or imputation. The outcome was that all the values are available, and no missing ones as shown in Figure 7.

	0
Customer ID	0
Gender	0
Age	0
City	0
Membership Type	0
Total Spend	0
Items Purchased	0
Average Rating	0
Discount Applied	0
Days Since Last Purchase	0
Satisfaction Level	0

dtype: int64

Figure 7. Null Values

Also, converting text data such as gender, city, membership, and satisfaction to numerical values and Boolean fields, e.g., discount applied to binary values as shown in Figure 8 and 9. Standardization was also carried out to ensure all features have the same range, so the data becomes ready for statistical analysis and machine modeling without contradiction or prejudice among value types.

```
Summary of the dataset:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 350 entries, 0 to 349          Before
Data columns (total 11 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Customer ID               350 non-null    int64
 1   Gender                    350 non-null    object
 2   Age                       350 non-null    int64
 3   City                      350 non-null    object
 4   Membership Type           350 non-null    object
 5   Total Spend               350 non-null    float64
 6   Items Purchased           350 non-null    int64
 7   Average Rating            350 non-null    float64
 8   Discount Applied          350 non-null    bool
 9   Days Since Last Purchase  350 non-null    int64
 10  Satisfaction Level        348 non-null    object
dtypes: bool(1), float64(2), int64(4), object(4)
memory usage: 27.8+ KB
None
```

Figure 8. Encoding Data Part I

```
Summary of the dataset:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 350 entries, 0 to 349        After
Data columns (total 11 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Customer ID              350 non-null    float64
 1   Gender                   350 non-null    int64
 2   Age                      350 non-null    float64
 3   City                     350 non-null    int64
 4   Membership Type          350 non-null    int64
 5   Total Spend              350 non-null    float64
 6   Items Purchased          350 non-null    float64
 7   Average Rating           350 non-null    float64
 8   Discount Applied         350 non-null    int64
 9   Days Since Last Purchase 350 non-null    float64
 10  Satisfaction Level       350 non-null    int64
dtypes: float64(6), int64(5)
memory usage: 30.2 KB
None
```

Figure 9. Encoding Data Part II

Step 4: Descriptive statistics

In analyzing the distribution characteristic of each variable, there were descriptive statistics that showed the mean as the general prevailing value, the standard deviation as the variability of each data and the minimum/maximum limits being used to detect anomalies. This analysis demonstrates the level of variance between the variables as demonstrated in Figure 10 especially the variable "Days Since Last Purchase" which has a high level of variation and the values vary between -1.31 to 2.71. This means that there are customers who have just long time delayed to make purchases and others who just made purchases recently.

	Customer ID	Gender	Age	City	Membership Type	Average Rating	Discount Applied	Days Since Last Purchase	Satisfaction Level	Engagement Score	Cluster	Average_Spending_per_Item	Age_x_Membership_Type
count	350.000000	350.000000	3.500000e+02	350.000000	350.000000	3.500000e+02	350.000000	3.500000e+02	350.000000	350.000000	350.000000	350.000000	350.000000
mean	0.000000	0.500000	2.023778e-16	2.502857	1.002857	-7.765217e-16	0.500000	1.015061e-16	1.025714	-6.168275	0.931429	0.693391	-0.533137
std	1.001432	0.500716	1.001432e+00	1.707473	0.817076	1.001432e+00	0.500716	1.001432e+00	0.798940	26.428445	0.964045	1.379893	0.880859
min	-1.727109	0.000000	-1.561939e+00	0.000000	0.000000	-1.758026e+00	0.000000	-1.310468e+00	0.000000	-162.698687	0.000000	-4.447494	-3.123877
25%	-0.863555	0.000000	-7.395565e-01	1.000000	0.000000	-8.955237e-01	0.000000	-8.634271e-01	0.000000	-2.107703	0.000000	0.769561	-0.739557
50%	0.000000	0.500000	-2.255677e-01	2.500000	1.000000	1.394789e-01	0.500000	-2.673729e-01	1.000000	-0.446483	0.500000	0.954161	-0.286953
75%	0.863555	1.000000	6.996122e-01	4.000000	2.000000	8.294807e-01	1.000000	8.502287e-01	2.000000	0.032476	2.000000	1.164239	0.000000
max	1.727109	1.000000	1.933185e+00	5.000000	2.000000	1.519482e+00	1.000000	2.712898e+00	2.000000	28.729257	2.000000	3.343795	0.576842

Figure 10. Descriptive Statistics

Exploratory Data Analysis (EDA)

Correlation Analysis

The correlation matrix analyzes the correlations between variables using Pearson's coefficient. It shows the relationships between variables, where 1 indicates a perfect positive correlation, -1 indicates a perfect negative correlation, and 0 indicates no correlation, as shown in Figure 11.

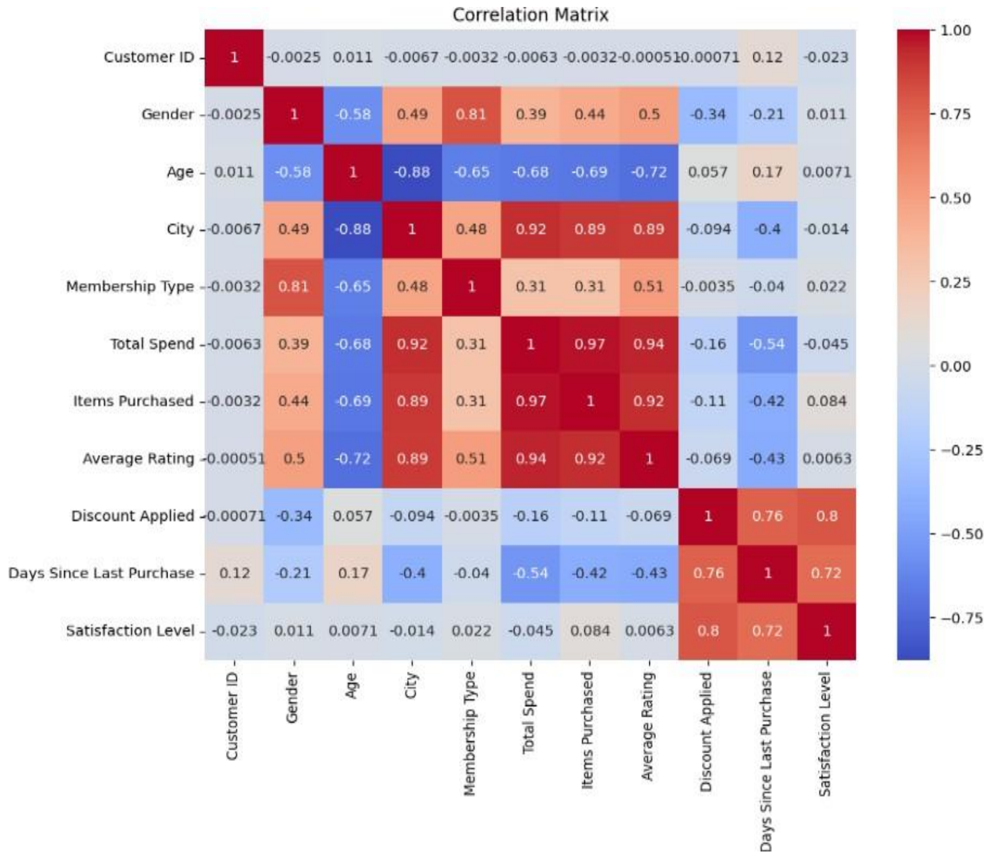

Figure 11. Correlation Analysis

The correlation between the two variables is strong as there is a positive relationship between "Total Spend" and Items Purchased (approximately 0.97) meaning that the more purchases, the higher the total spending. There is a positive correlation between the "Average Rating" and the "Total Spend" (= 0.94) where the customers with higher Spend provide their higher ratings. Moreover, the correlation between the "Discount Applied" and the contentment level is very positive (~ 0.80), which implies that customers receiving discount are more contented. The satisfaction level 0.72 is positively correlated with the number of days since the last purchase meaning that satisfied customers make repeat purchases in the nearest future. Finally, these variables can be considered excellent candidates to be included in the statistical or predictive models because they have a high correlation with customer behavior and customer satisfaction rates.

Features' Importance

The significance of the variables was put to test in order to identify the most conclusive variables in customer behaviour. According to the classification model as shown in Figure 12, used in predicting customer segments, e.g., active or inactive, the most important variable alone was the variable of Days Since Last Purchase, meaning that the behavioral time is important in classifying the customers. Financial qualities like "Total Spend" and "Discounts Applied" also helped to improve the accuracy of the model significantly and the demographic characteristics like "Gender" and "Membership Type" had low and practically negligible impact, which may indicate the necessity to pay special attention to the behavioral patterns instead of its fixed features.

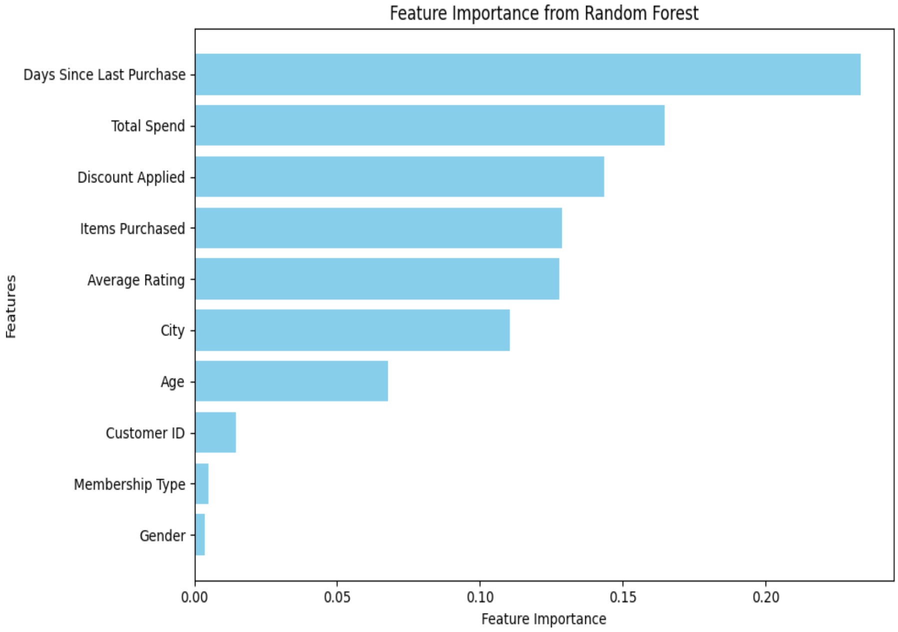

Figure 12. Feature Importance with the Classification Model

The features selected based on their importance and the strength of their association with the level of satisfaction based on the above are: "Days Since Last Purchase", "Total Spend", "Discount Applied", "Items Purchased", and "Average Rating."

This result confirms the view that purchase behavior and the temporal frequency of the customer are the strongest determinants of value comprehension and classification overall, with a call for the deployment of marketing initiatives focused more on temporal and behavioral engagement and less on stable demographic characteristics. For instance, focused campaigns may be created for long- time non-buying customers, with promotion offers or reminder personalization to re-activate them. Further, investment is required in monitoring purchase frequency and count of products purchased as ongoing interaction indicators and leveraging them in intelligent recommendation systems through personalization of messages based on real customer behavior. It is also advisable to execute regular predictive models to monitor the evolution of the importance of these variables over time, which helps in continuous adaptation to emerging buying patterns and customer interests.

Phase II: Classification-based User behavior Analysis Consumer behaviour is evaluated using supervised machine learning classifiers that are employed in prediction of customer satisfaction with three target classes of customer satisfaction, including satisfied, neutral and unsatisfied. The feature selection is the initial step in applying the supervised learning to identify the three most significant variables related to customer satisfaction; purchase frequency, total amounts spent and days since last purchase. After selecting the features, the second exercise is the training and testing of four popular supervised classifiers (Naive Bayes, Support Vector Machine (SVM), Random Forest and Decision Tree) that are applied on a pre-processed dataset. The evaluation of these classifiers is based on a number of evaluation metrics (accuracy, precision, recall, F1 score and confusion matrix) to compare the actual and predicted labels of each of the three classes of satisfaction. An evaluation of the trained and tested classifiers leads to Random Forest being superior to all the other classifier models hence Random Forest as the model that gives the best trade-off between the precision and recall hence it is the most effective model to use in the following stages of content generation and decision making.

The classification-based approach used for analyzing consumer behavior in the dataset, different supervised machine learning classifiers are employed to predict consumer 'Satisfaction Levels' using behavioral indicators, selected as predictors, based on their significance to consumer behavior and marketing achievement. Four well- known supervised classifiers, Naive Bayes, Support Vector Machine (SVM), Random Forest, and Decision Tree, will be trained and assessed using five standard evaluation metrics all over three target classes: Satisfied (Class 0), Neutral (Class 1), and Unsatisfied (Class 2). The evaluation metrics are: (1) accuracy, which is the overall percentage of correctly predicted labels out of all predictions; (2) precision, which indicates how many predicted positive instances were actually positive, so that higher precision implies lower false positives; (3) recall, which measures how many actual positive instances were correctly identified, so that higher recall implies lower false negatives; and (4) F1-Score, which is the average of precision and recall. It balances both measures, which is very important when handling imbalanced datasets, and finally (5) a confusion matrix that displays the actual and predicted labels for each class. It allows the visualization of TP, FP, TN, AND FN.

RESULTS DISCUSSION

The confusion matrices of the selected models are extracted and compared in Figure 13. It indicates that the Random Forest classifier outperforms the other three classifiers in terms of classification accuracy, giving the optimum balance of TP while minimizing both types of error (FP and FN). In view of this study, the Random Forest should be chosen as the model that will guide GenAI personalized content creation, to ensure that recommendations are built upon accurate satisfaction predictions. Figure 14 depicts the Random Forest confusion matrix. The large values of TP and TN indicate that Random Forest is highly efficient in detecting both positive and negative classes, while the small values of FP and FN indicate a few misclassifications.

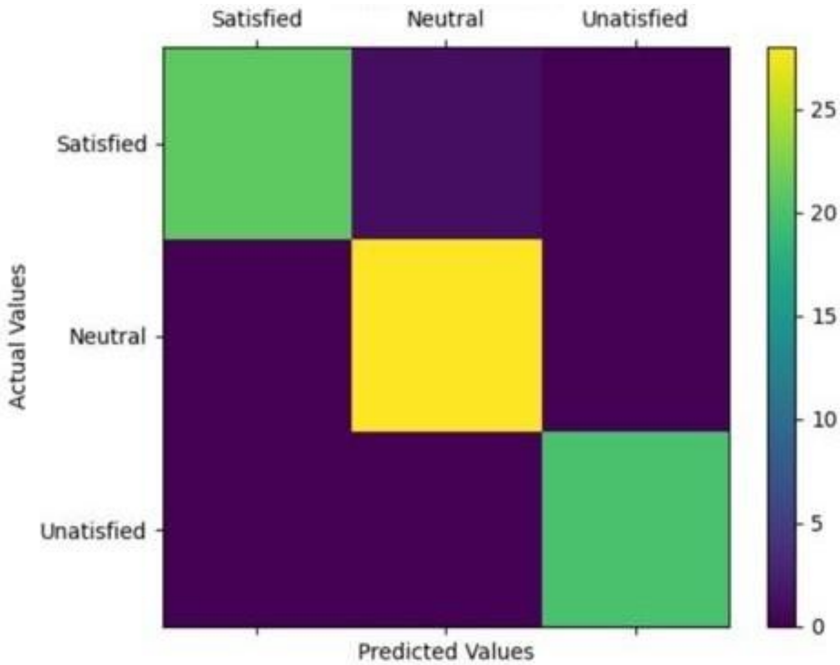

Figure 13. Random Forest Confusion Matrix

The evaluation results for the classifiers' accuracy, precision, recall, and F1-Score is recorded in Table 3. It showed that all models achieved high values of accuracy (>=97%), implying that the dataset was well-prepared and

rich in significant knowledge. Regarding the three satisfaction classes, the "Satisfied" class (Class 0) proved to be most challenging for some models, especially in terms of precision. Although Naive Bayes and SVM models were effective in identifying "Neutral" and "Unsatisfied" classes, they have less precision when predicting "Satisfied" class. This minor variation could be due to overlap between the "Satisfied" and "Neutral" classes' behavior indicators, leading to rare misclassification.

On the other hand, the Random Forest classifier outperforms all other classifiers in all metrics and classes, with ideal precision and recall for the "Unsatisfied" class. This proves also reliability in accurately identifying different consumer groups, which is valuable for scenarios where consumer behavior-based content is essential.

Table 3. Evaluation Results for All Classifiers

Classifier		**Precision**			**Recall**			**F1-Score**		**Accuracy**
	Class 0	**Class 1**	**Class2**	**Class 0**	**Class 1**	**Class2**	**Class 0**	**Class 1**	**Class2**	
Random Forest	1	0.97	1	0.95	1	1	0.98	0.98	1	0.98
Decision Tree	1	0.93	1	0.91	1	1	0.95	0.97	1	0.97
Naive Bayes	0.92	1	1	1	0.93	1	0.96	0.96	1	0.97
Support Vector Machine	0.92	1	1	1	0.93	1	0.96	0.96	1	0.97

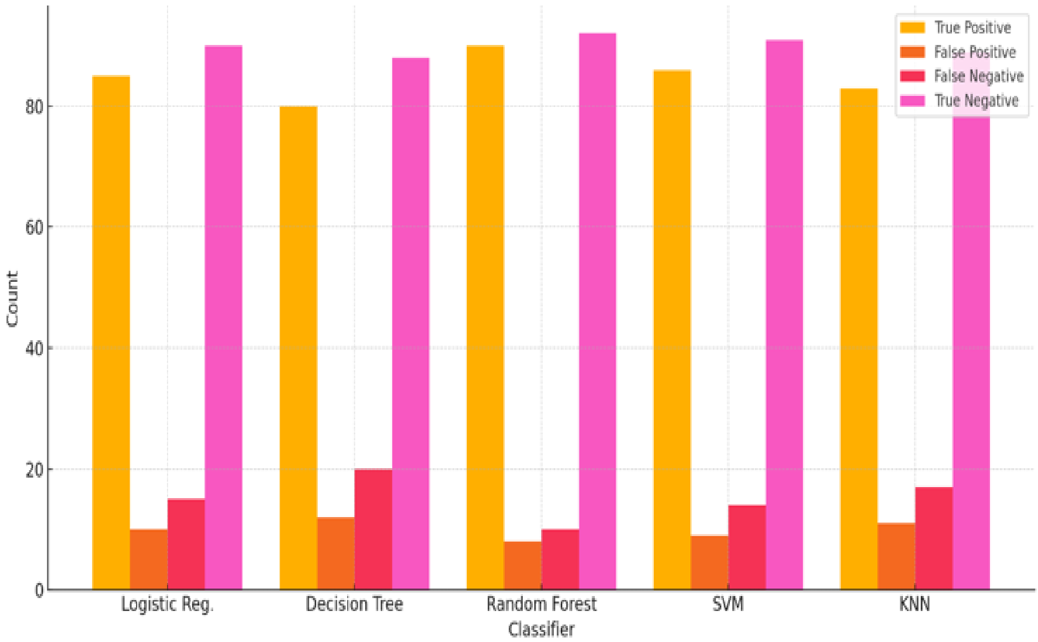

Figure 14. Confusion Matrix Comparison Among all Classifiers

Given the above classification results in Figure 14, Random Forest performs consistently well across all satisfaction levels, with particularly strong results for Neutral and Satisfied users. Also, the minimal confusion between classes ensures that users receive content that matches their actual experience, reducing the risk of irrelevant or inappropriate messaging. Therefore, the Random Forest model is obviously the best option for guiding the next phase of this study. The capacity to maintain high precision and recall across all satisfaction classes guarantees that each consumer receives content that meets their presumed perceptions. This capability to anticipate is vital for marketing since mismatched messaging can result in lower engagement or even unsatisfied consumers. Additionally, Random Forest is flexible, hence perfect for dynamic environments like e- commerce platforms. Eventually, coupling the strength of predictability in Random Forest with the originality and language-context comprehension of GenAI, this method enables the provision of personalized marketing interactions that are precise and effective.

Accuracy

Accuracy is a measure of the general rightness of the model, it measures how many things have been predicted correctly divided by the number of instances are represented in equation 5:

$$Accuracy = \frac{TP + TN}{TP+TN+FP+FN} \quad (5)$$

Where, TP = True Positives (the correctly predicted positive cases), TN = True Negatives (the correctly predicted negative cases), FP = False Positives (the incorrectly predicted positive cases), FN = False Negatives (the incorrectly predicted negative cases).

Precision

Equation 6 represents the precision which measures how many of the predicted positive instances are actually positive.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (6)$$

Recall

Recall (alternatively called sensitivity) is a measurement of the number of actual positive cases there were correctly recognized by the model are shown in equation 7:

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (7)$$

F1-Score

Precision and recall are harmonic thus yielding the F1-score. It gives a compromise between the two particularly in cases where the distribution of the classes are skewed represented in equation 8:

$$\text{F1-Score} = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision+Recall}} \quad (8)$$

Confusion Matrix

A confusion matrix is a table that is employed to define the performance of a classification model. In the case of three classifying problems (e.g., Satisfied, Neutral, Dissatisfied), the confusion matrix will take the form are shown in equation 9,

$$\begin{bmatrix} \text{TP}_0 & \text{FP}_{0,1} & \text{FP}_{0,2} \\ \text{FP}_{1,0} & \text{TP}_1 & \text{FP}_{1,2} \\ \text{FP}_{2,0} & \text{FP}_{2,1} & \text{TP}_2 \end{bmatrix} \quad (9)$$

Where, TP0, TP1, TP2: True positives of the classes 0,1, 2 (e.g. Satisfied, Neutral, Dissatisfied). FP: False alarms between real and forecasted classes.

Phase III: GenAI-Based Personalized Content Creation

The GPT-3.5-turbo software application used by the company to generate personalized marketing to the customers is based on the degree of expected customer satisfaction with the company products. To formulate the customer attributes that will be included in the different levels of satisfaction, the model will look into the customer behavior and spending patterns as well as the level of satisfaction that is associated with a given customer. With these variables, GPT-3.5 is used to generate real-time context-sensitive messages to any customer that is designed by the information regarding the above attributes. In one case, a satisfied customer would be contacted and presented with a message that would thank him and would offer a recommendation of other products whereas a neutral customer would be contacted and asked about his thoughts and incentives would be given to him to recommend increased engagement. Conversely, in sending messages where the customer is dissatisfied, the business will relay a message that is sympathetic and will include apology message with an offer or discount in a bid to regain customer confidence and subsequent satisfaction.

The paper demonstrates that generative AI is a valuable tool that can efficiently process consumer behavior data and produce valuable insights and personalized interactions to enhance customer satisfaction and relationship management to a great extent. The study work produces individualized insights and engagement messages based on the activity and the level of happiness of a specific client by processing the satisfaction level of the consumers with an e-commerce dataset through OpenAI GPT-3.5-turbo. The primary aims are enhancing the experience of the consumer by using narrow tactics of engagement, automating communication based on the satisfaction level and converting data on complex consumer behavior into insights that can be understood and expressed in a natural language. The results show that it is possible to use generative AI to achieve solutions, which can be implemented in practice, allowing the company to respond to changes in business more quickly due to the comprehensive understanding of the customers. The research places businesses in a place to improve consumer relationships, build loyalty, and generate revenue within the competitive market environment because the data is transformed into a customized comprehensible interaction..

Generating Customer Insights

As companies look to better understand customer experiences and develop strategies to improve satisfaction and retention, customer insights are critical. If organizations can identify what makes customers satisfied or unsatisfied, they can take action on the customer concerns and determine what can be improved. GenAI implementation is necessary because it examines customer demographics and activities, and clarifies customer behavior regarding satisfaction or dissatisfaction. For example, the GenAI retrieval system extracts customer profiles from an e-commerce data set and prompts the GPT-3.5 Turbo model to create human-readable customer satisfaction status explanations. If say, a Silver member has not purchased anything for an extended period, the member may feel abandoned, which could be problematic as the member could still be satisfied from prior experiences.

Such insights can help businesses know where to prioritize resources in efforts to drive loyalty through the highest impact customer satisfaction factors. Using those insights, organizations can improve service delivery and create a more agile, metrics-driven customer-centric service capacity in the company's focus on overall business performance and competition. Figure 15 shows customer satisfaction insights that predict outcomes for a satisfied customer: Often buys, Frequently gives the highest scores, and Got a discount on today's purchase.

Figure 16 provides an insight into a dissatisfied customer and it is highlighted that there is a long distance between last purchase although he spends well and gets discounts, and this could lead to dissatisfaction.

Generated Insight:

Based on the information provided, this customer, a 29-year-old female from New York, holds a gold membership and has made a total spend of $1120.2 across 14 purchased items. She has received an average rating of 4.6, and a discount was applied to her most recent purchase 25 days ago.

The customer might be satisfied because she has been an active shopper, making multiple purchases and receiving a high average rating for her purchases. Additionally, being a gold member likely means she enjoys certain perks and benefits that enhance her shopping experience. The discount applied to her recent purchase could have also contributed to her satisfaction, as it shows she is receiving value for her purchases. Overall, the combination of positive shopping experiences, membership benefits, and discounts received may have led to her feeling satisfied with her overall experience.

Figure 15. Generated Insight for Satisfied Customer

Generated Insight:

It seems like the customer in question, a 27-year-old male from Miami, has made quite a few purchases (13 items) and spent a decent amount ($720.4). However, despite receiving an average rating of 4.0 on his purchases and benefiting from a discount, he has not made a purchase in the last 55 days. This gap in activity could indicate that he was not completely satisfied with his overall experience, leading to the 'Unsatisfied' satisfaction level.

Figure 16. Generated Insight for Unsatisfied Customer

Personalized Engagement Messaging

The personalized engagement messages are a major element of the effective customer relationship management. GPT-3.5 can be used to automatically create tailored messages to each client based on their satisfaction level, which will increase customer engagement and experience in general. Customized messages will be aimed at capturing the customers based on their personal needs, views, and experiences. This personalized approach is an indication of deep insight into unique consumer experiences, creating the potential of meaningful customer encounters, retention, and upselling opportunities.

The Engagement Process Considers Three Key Satisfaction Categories

Loyal Customers

Receive warm, personalized thank-you notices rewarding them for loyalty and good experience, along with well- targeted product upsell suggestions. This type of interaction rewards good behavior and creates new revenue, as shown in the upsell suggestions. This type of interaction rewards good behavior and creates new revenue, as shown in Figure 17.

Figure 17. Loyal Customers

Neutral Customers

Receive welcoming requests for feedback accompanied by courteous invitations to provide their experience or feedback. Besides feedback requests, messages come accompanied by enticing discount offers intended to make customers keep going and remain satisfied, as shown in Figure 18.

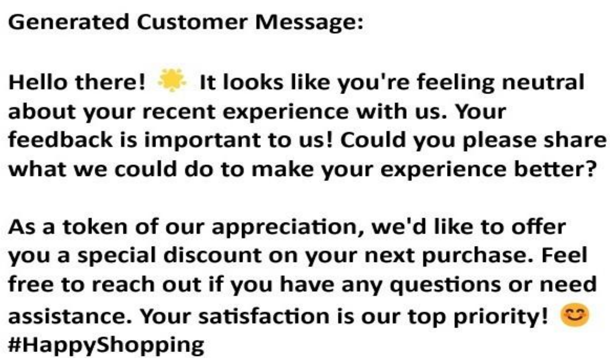

Figure 18. Natural Customers

Dissatisfied Customers

Receive empathetic, thoughtful messages that are designed to identify and apologize for any failures or negative experiences. These messages give retention advantages such as free products, discounts, or customized assistance consultations to apologize and regain loyalty and trust, as shown in Figure 19.

Generated Customer Message:

Hi there! I'm sorry to hear that you are unsatisfied with your recent purchase experience. We always strive to provide the best service to our valued customers like you. To make it right, we would like to offer you a special retention incentive. Would you prefer a free item from our selection or a support call to address any concerns you may have? Your feedback is important to us, and we want to ensure your satisfaction. Thank you for being a part of our community in Miami!

Figure 19. Dissatisfied Customers

The AI has elaborate explanations on the levels of satisfaction of customers which can be easily used to respond to business. It also enhances customer experience and customer retention by offering messages of customization during engagement. The research confirms the capability of AI-based personalization efforts to improve customer relationships, customer loyalty, customer satisfaction, and customer revenue growth putting companies at competitive marketplaces.

CONCLUSION AND FUTURE WORK

This paper discussed the opportunities of GenAI, in this case, GPT-3.5-turbo, in interpreting user behavior and increasing customized marketing plans in the e-commerce industry. With a combination of machine learning classification models and tools of creating generative content, the study showed how GenAI could assist e-commerce in comprehending customer satisfaction and creating customized marketing messages. The experiment findings indicated that the Random Forest classifier was the most accurate in predicting the level of customer satisfaction. Such predictions were then practically applied to create individual marketing content using GenAI. The paper, also, mentioned the importance of such indicators of behavior as the frequency of purchases, the sum of money spent, and the use of discounts as the tools to create the right customer profiles and the targeting strategy. Additionally, natural and contextually relevant messages were generated using GPT-3.5-turbo and were in line with the experiences of individual consumers. This contributed to the quality of communication as well as assisting in the enhancement of customer engagement and satisfaction. The results prove that using GenAI as an effective tool to automate content production and still achieve a personalized touch are possible. Nonetheless, the study acknowledges the issue of GenAI application as well such as data privacy, content authenticity, and ethical issues. These problems should be tackled in order to be able to responsibly introduce AI to the marketing industry.

Overall, the study shows that GenAI predictive analytics can be used to enhance marketing performance greatly. The research is recommended to be extended in future studies, which should involve the application of the GenAI models to larger data volumes and investigate how it will affect customer loyalty and brand performance in the long run.

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