InsightX: Data-Driven Consumer Behavior Analysis and Comparison Using Machine Learning

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***Abstract*—Retailers today have access to vast amounts of consumer data, yet many struggle to effectively analyze and use this data to optimize marketing strategies. Traditional methods are often too broad and fail to address individual consumer preferences. With big data, there is a significant opportunity to gain deeper insights into consumer behavior, but the challenge lies in transforming that data into actionable strategies that can personalize customer experiences, improve targeting, and ultimately drive sales. This project explores how big data can be used to better understand consumer behavior and improve retail marketing efforts, helping retailers make more informed decisions and achieve higher engagement and revenue.**

***Index Terms*—Consumer Behavior, Web Scraping, Machine Learning, Data Analytics, Predictive Modeling, Customer Segmentation, E-commerce**

I. Introduction

With the competitive retail market of the contemporary age, consumer behavior and deciphering its trends and patterns has gained a great amount of significance [6] [7]. With increasing access to big data, businesses can put it to use to gain more insights into customers' behaviour, likes, and buying decisions [1] [2]. Businesses are aware of the technology, but clueless about its application to their benefit. This data, if found, can be utilised to concoct more efficient and personalised marketing strategies to help sale the right products to the right consumer, thereby reaching out to consumers on a one-to-one level [21].

This study examines the ability of existing big data platforms to study the behaviour of existing customers and enhance retail marketing efforts as more accurate [4] [5] [7]. With the convergence of different types of platforms, such as Google Sheets, Python, multiple machine learning algorithms, and an easy-to-use website interface, the goal is to collect and analyse data from primary business sources and secondary online sources [20] [17]. The results that will be generated through the analysis will dictate practical marketing suggestions that are aligned with actual consumer trends [23].

We are looking to make inferences from varied sets of information- e.g., online buys, social networking activity, customer views, and marketplace trends- every factor that drives a consumer's browsing and buying journey- to better understand what drives consumer decision-making [9] [11]. This will help retailers target their advertising, price and stock control, and create more effective customer relationships [24].

Ultimately, our aim is to show how companies of all shapes and sizes can leverage big data to their benefit in clear and useful ways [14] [18]. Through the careful application of these tools, retailers can further optimise their targeting, improve the shopping experience, and boost engagement and sales [16]. By understanding customer preferences and purchasing patterns, retailers can create personalized shopping experiences, improve customer targeting, and ultimately boost engagement and sales [13] [23]. Through further implementation of this concept, we aim to give businesses more effective, data-driven marketing strategies, leading to enhanced customer satisfaction, increased sales, and a competitive edge in the retail industry. In doing so, we hope to give a clearly defined, data-based model for maximizing marketing spend in the continually evolving retail market [19] [25].

II. Literature Review

John, D., Smith, A., & Lee, J. (2021) did a review of the use of machine learning to predict customer preferences on e-commerce websites [1]. They focused on using decision trees and support vector machines (SVMs) in order to stratify user behaviour through factors like transaction records, browsing history, and demographic characteristics. It was shown that machine learning algorithms far surpass conventional statistical methods. This study highlighted the significance of real-time processing of data and algorithmic personalisation in increasing user interaction and conversion rates.

Smith, J., & Brown, M. (2020) looked into the wider context of consumer behaviour within online shopping environments, highlighting the importance of taking demographic and psychographic factors in consideration [2]. They used Python and Tableau, and recognized three key drivers of consumer decision-making: website usability, price transparency, and peer reviews. They suggested that good UX design and social proof are central in driving buying intent. This research is a valuable contribution to the topic of customer journey mapping and indicates the importance of comprehensive user experience design in digital retail initiatives.

Johnson, A., & Team (2022) proposed an architecture for real-time consumer feedback systems for improving responsiveness in customer care and product innovation [3]. Their

design employed real-time data streaming technology, including Apache Kafka, to immediately process customer feedback. Research showed that businesses implementing this method could lower complaint response times by 40% and enhance customer satisfaction through timely action. This research supports the importance of immediacy and automation in feedback loops and positions real-time analytics as a strategic advantage in competitive digital ecosystems.

Siddhant Sharma and Akhilesh A. Waoo (2023) organized a survey taking into observation different machine learning methods utilised in consumer behaviour analysis across e-commerce websites [4]. Their review included observing supervised, unsupervised, and reinforcement learning methods, judging their level of applicability to tasks such as churn prediction, purchase forecast, and recommender systems. They further discussed major datasets, evaluation criteria, and most frequent preprocessing. Its results suggest an increasing trend towards hybrid approaches that integrate behavior data and context information to improve prediction.

Leyla G. Muradkhanli and Zaman M. Karimov (2023) investigated the integration of big data analytics and machine learning to decode customer behavior patterns at scale [5]. Their research focused on the challenges and opportunities associated with processing large, heterogeneous data sources—from clickstream data to social media interactions. They put forward a unified analytics framework capable of supporting both descriptive and predictive insights. By showcasing case studies from various sectors, the paper presented how big data infrastructure, when paired with robust algorithms, can yield highly granular customer insights. This research tells of the technological foundations necessary for scalable and efficient consumer behaviour analysis in enterprise environments.

III. Objectives and Goals

A. Consumer preferences and trends identification.

Analysis of patterns, preferences and behavior while purchasing in order to understand why a consumer decides in a particular manner forms the main purpose here. Because of different trends in consumers' behavior, businesses make it easier to pick up where those products or services most effectively communicate to their target audience. Analysis helps organization remain competitive by bringing out changes in market demands and aligning offered products and services according to the expectations of consumers [6] [7].

B. Developing Focused Marketing Strategy

It becomes very well understood by the consumer behavior so as to allow businesses to design highly impactful marketing campaigns towards well-defined target groups. Businesses use customer data analysis for segmentation purposes based on various demographic, psychographic, and other behavioral factors so that customized marketing plans can be designed and proposed toward increased customer participation, loyalty, and conversion [2] [9].

C. Improving business choice and decision-making

Consumer behavior analysis is one of the sources of actionable information that informs decision-making in many business functions such as new product development, inventory management, pricing strategies, and customer service enhancement. The research helps to understand determinants and triggers of consumer satisfaction and loyalty, allowing the organization to intervene strategically with a view to enriching customers' experience and hence profitability. It also offers insights in the predictability of future market trends, preparing organizations on any forthcoming changes that might soon manifest in the market [4] [10].

D. Data Collection and Analysis

Initially, data was obtained from secondary sources, such as pre-existing datasets, and then, using various techniques, web scraping was used to extract information about consumer behavior from websites. Automated data collecting from customer review websites, e-commerce websites, and other valuable sources was made possible by web scraping techniques [21] [22]. Following collection, the data was processed and examined using a variety of techniques, including segmentation, pattern recognition, and predictive modeling [20].

E. Impact of Web Scraping on Analysis

By providing real-time and large-scale consumer data, web scraping increased the accuracy and scope of our analytical approach. This allowed better decision-making as businesses could tailor their marketing plans to fit consumer trends [14]. It improved consumer insights to provide more thorough knowledge of buying habits and preferences. Data processed automatically got rid of manual data entry tasks and improved efficiency. Including web scraping in this study improved the validity of consumer behavior forecasts and confirmed the data-driven decision-making process [13].

IV. Proposed Strategy

A. Data collection

The data gathering process was conducted via web scraping methods, which avoided the necessity of access to internal business databases [21]. Existing Amazon and Walmart were utilized at first [9] [11]. Dynamic data scraping was done to scrape product and customer-related data from Amazon, such as age, gender, frequency of browsing and purchase, level of satisfaction, payment method, use of promotional codes, and preferred product categories. Weekly sales data and dates were gathered for Walmart to examine time-based purchasing patterns [12]. This approach enabled real-time, mass data collection without the constraints usually placed by access restrictions or licensing that comes with proprietary business data. Consequently, the project was able to mimic real consumer behavior in e-commerce sites using publicly available data.

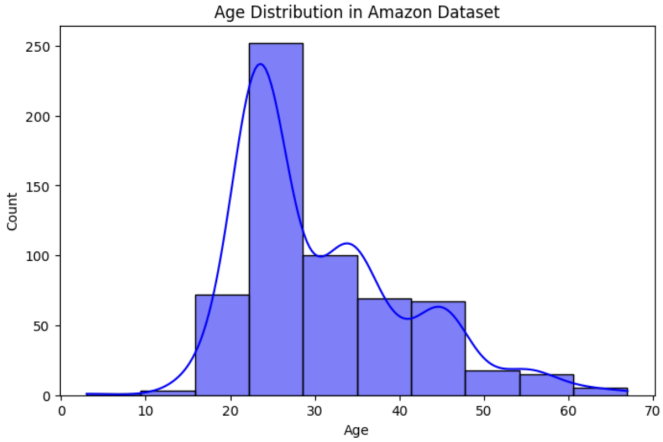

Fig. 1. Figure 1

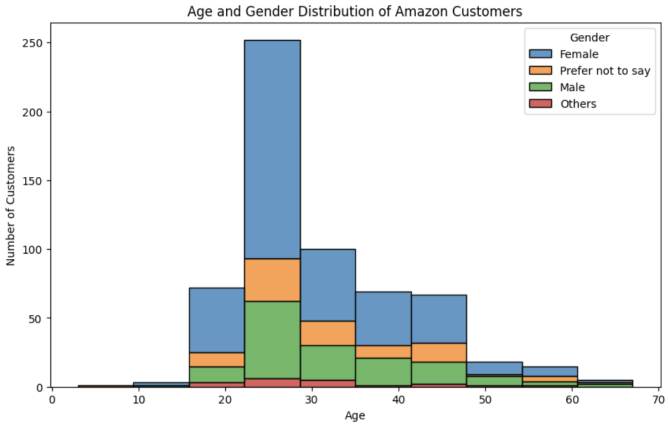

Fig. 2. Figure 2

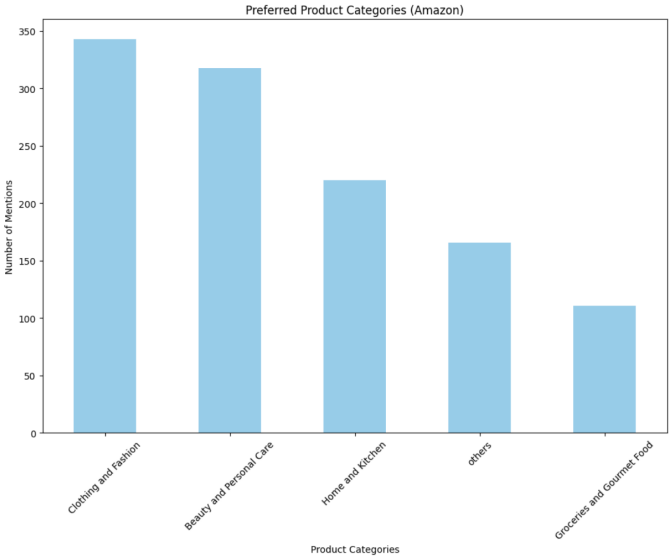

Fig. 3. Figure 3

B. Data cleaning and preparation

The scraped data, being unstructured and raw, needed massive cleaning and preparation prior to analysis [23]. First, duplicate columns from the Amazon dataset were eliminated for consistency. Missing values were dealt with by imputing them with the mode of each given column since the strategy is optimal with categorical data [17]. The 'Date' column of the Walmart dataset was changed to proper datetime format for temporal analysis. Other temporal features, like the season of the year, were derived from the month information in these dates. Categorical variables, such as gender, payment type, and use of promo codes, were label-encoded to convert them into forms acceptable by machine learning models. Each step in preprocessing made the dataset consistency-free and ready for exploratory and predictive analytics.

C. Exploratory Data Analysis

Exploratory Data Analysis (EDA) was conducted to investigate underlying patterns, demographic distributions, and behavioral trends in the Amazon and Walmart datasets [10] [14]. The analysis began with a histogram plotted on the Amazon data (see figure 1) to examine the distribution of customer ages. This visualization provided an initial insight into the age range most active on the platform, including which age brackets made the greatest contribution to online shopping activity. Next, a layered histogram (see figure 2) was created that stacked gender information over the age distribution. This allowed for the simultaneous observation of both age and gender trends, offering insight into how male and female consumers differed across various age brackets in terms of engagement and activity. Additionally, consumer behavior in Amazon was analyzed further through purchase preferences (see figure 3). The 'Purchase Categories' column, with various product interests listed separated by semicolons, was exploded into separate values for capturing every category alone. A bar graph was then created to display the frequency of mentions for every product category. This visualization showed what kinds of products were in demand among consumers, helping understand prevailing market demand. In the Walmart dataset, a time series line graph (See figure 4) was plotted using weekly sales data to find temporal sales trends. The sales were indexed by date, enabling a clear view of fluctuations over time. This revealed consistent patterns in consumer spending, along with identifiable peaks and troughs that suggested seasonal or event-driven variations in demand. To explore seasonality and its affect on consumer behaviour, a new 'Season' column was created from the 'Date' column by dividing months into quarters—Winter, Spring, Summer, and Fall. Sales for each season were summed up, and a bar graph (see figure 5) was charted to compare performance over these periods. The outcomes showed strong seasonality in consumer buying habits, with some seasons having considerably greater sales volumes than others. Finally, Amazon's subscription behavior was visualized through a pie chart (see figure 6) that showed the distribution of customers according to purchasing frequency. The pie chart divided the user segment into bins like one-time buyers,

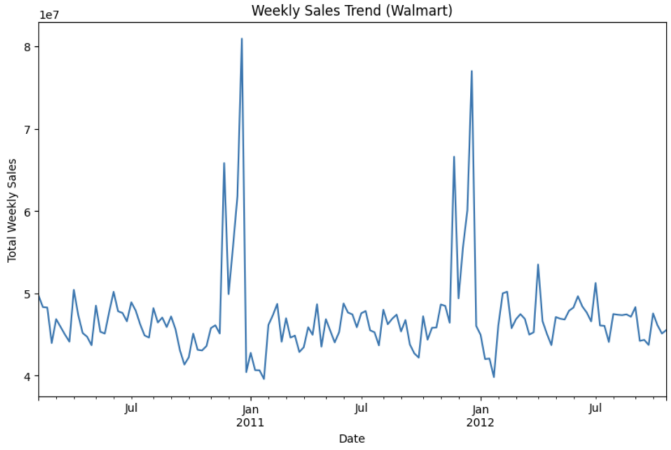

Fig. 4. Figure 4

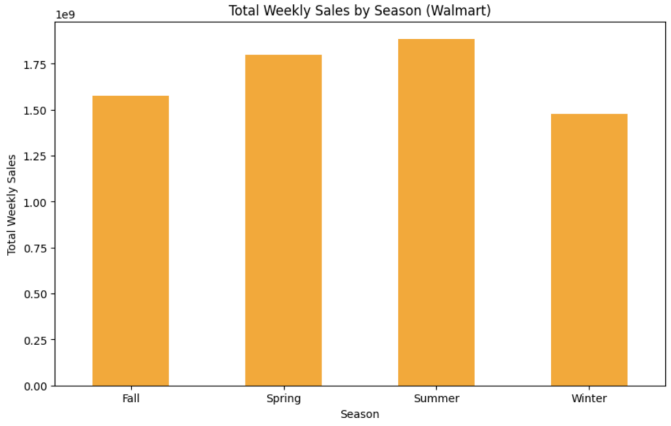

Fig. 5. Figure 5

occasional shoppers, and frequent customers. The visualization helped in bringing out consumer engagement levels and gave a clear view of customer retention and loyalty patterns. By means of this demographic, categorical, and temporal analysis, the EDA stage gave an initial overview of consumer behaviors and patterns. The findings from this stage informed the choice and training of machine learning models in later stages of the project.

D. Data Processing through Machine Learning

After data cleaning and exploratory data analysis, a variety of machine learning models were utilized to examine, segment, and forecast customer behavior based on the Amazon and Walmart datasets. Each model was chosen for a specific analytical objective, providing a diversified approach to interpreting and predicting customer interactions and sales performance [17] [16].

To start with, a Random Forest Classifier was utilized to forecast consumer purchase frequency on the Amazon website. This model was selected for its robustness and ability to handle high-dimensional data while effectively managing overfitting. The dataset was first split into training and testing

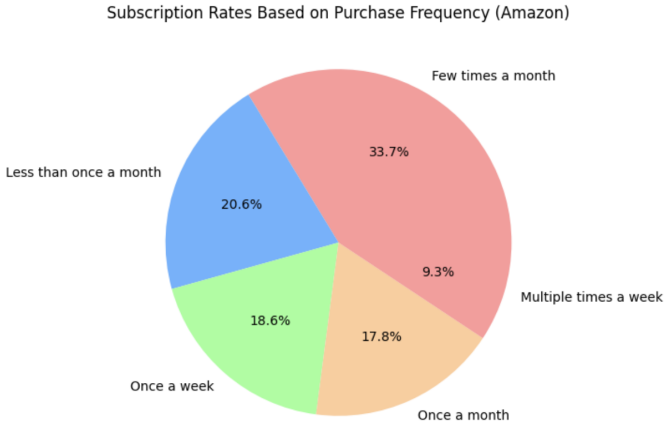

Fig. 6. Figure 6

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------ Model Evaluation ------
Classification Report:
              precision    recall  f1-score   support

           0       0.33      0.65      0.44        37
           1       0.54      0.61      0.57        23
           2       0.00      0.00      0.00        11
           3       0.38      0.14      0.21        21
           4       0.57      0.28      0.37        29

    accuracy                           0.40       121
   macro avg       0.36      0.34      0.32       121
weighted avg       0.41      0.40      0.37       121

Accuracy: 0.4049586776859504
```

Fig. 7. Figure 7

sets. Categorical variables were encoded, and missing values had been imputed during pre-processing. After training, the model estimated how often a customer will make a purchase, depending on characteristics like age, gender, browsing, satisfaction from shopping, payment method, and use of promotional codes. The performance of the model was tested (see figure 7) with accuracy metrics like F-1 score, precision, recall and support, and a confusion matrix (see figure 8), which graphically displayed the number of correct and incorrect predictions for all classes. This matrix assisted in determining where the model excelled and where it faltered, giving directions for future optimization. Then, KMeans clustering (see figure 9) was used to perform unsupervised segmentation of Amazon shoppers. This technique was used to find natural groupings in the data without labels. Attributes such as age, frequency of purchases, frequency of browsing,

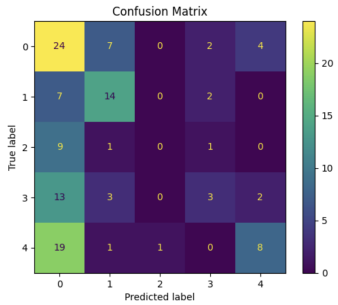

Fig. 8. Figure 8

Fig. 9. Figure 9

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Logistic Regression Accuracy: 0.512396694214876

Classification Report:
              precision    recall  f1-score   support

           1       0.56      0.53      0.54        19
           2       0.50      0.54      0.52        37
           3       0.54      0.69      0.61        45
           4       0.00      0.00      0.00        17
           5       0.33      0.33      0.33         3

    accuracy                           0.51       121
   macro avg       0.39      0.42      0.40       121
weighted avg       0.45      0.51      0.48       121
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Fig. 10. Figure 10

and shopping satisfaction were utilized to cluster consumers into four groups. Every cluster had a distinct consumer type, varying from infrequent consumers with low satisfaction to active and satisfied consumers. The outcome was presented graphically as a scatter plot plotting shopping satisfaction against age, and coloring every point by the assigned cluster. The clustering technique helped determine target segments for individual marketing actions and product recommendation. In order to simulate probable customer loss, Logistic Regression was used to forecast customer churn based on behavioral traits. Churn was implied through reduced frequency of purchase and satisfaction ratings. Logistic regression was chosen due to its ease of use, interpretability, and performance with binary classification problems. After having the model trained with a labeled set of data, predictions were generated on new unseen data to check the probability of a customer canceling his/her interaction with the platform. The outputs of the model were validated using standard metrics like accuracy, precision, recall, and F-1 score in the classification report (see figure 10). The business could proactively detect and retain the vulnerable customers by taking action prior to churn through this method. Lastly, for time series prediction, ARIMA (AutoRegressive Integrated Moving Average) model was applied to the Walmart weekly sales data. Following the conversion of

```
Sales Forecast (Next 10 Weeks):
 6435    752505.631160
6436    746684.569803
6437    740035.513446
6438    752786.655634
6439    743905.616137
6440    745981.225402
6441    744646.452798
6442    748945.607872
6443    744385.721145
6444    746855.488422
Name: predicted_mean, dtype: float64
```

Fig. 11. Figure 11

the 'Date' column into a datetime data type and assignment as the index, a univariate time series model was trained using past sales data. The model parameters (p=5, d=1, q=0) were selected after initial analysis and autocorrelation plots. After being trained, ARIMA was employed to predict sales for the following 10 weeks (see figure 11). This provided for the anticipation of future revenue trends, providing critical insights for financial forecasting, inventory planning, and promotion campaigns. Collectively, these machine learning methods offered a comprehensive analytical framework: classification to predict customer behavior, clustering for segmentation, logistic regression for churn prediction, and ARIMA for sales forecasting. This end-to-end solution not only facilitated greater consumer insights but also facilitated data-driven decision-making in customer relationship management and strategic sales planning.

V. Comparitive Analysis

Our research introduces an end-to-end consumer behaviour analysis pipeline that uniquely integrates web scraping, exploratory data analysis (EDA), machine learning (ML) classification, random forest classification, K-means clustering, logistic regression, ARIMA [24] [18]. Compared to existing studies, the work provides both methodological enhancements and practical applicability by removing the dependency on proprietary business data sources [1] [25].

A. Comparison with John, D., Smith, A., & Lee, J. (2021

John, D., Smith, A., & Lee, J. (2021) used machine learning algorithms such as decision trees and SVMs to predict consumer preferences using structured datasets.

Our study differs by using Random Forest and Logistic Regression models for higher generalization and accuracy, yielding robust performance for both categorical and ordinal outcomes. K-Means clustering is used to discover hidden segments in consumer demographics and behaviour. Label encoding, missing value imputation, and pie/bar charts are integrated to build a fully automated preprocessing pipeline before modelling, increasing efficiency and reliability.

B. Comparison with Smith, J., & Brown, M. (2020)

While Smith, J., & Brown, M. (2020) examined factors like UX and social proof using Python and Tableau for analysis, our research conducts web scraping to gather real-time consumer data directly from e-commerce platforms (e.g., Amazon, Walmart), bypassing the need for static, pre-provided datasets. We include seasonality analysis (e.g., sales trends across Winter to Fall) using timestamp engineering and visualization. We also utilize rich EDA with Seaborn and Matplotlib, including visualizations of gender-age distributions, payment method preferences, and category breakdowns for actionable marketing insights.

6. Comparison with Muradkhanli & Karimov (2023)

Their work emphasized big data platforms for consumer behavior analysis. In contrast, our study:

- Takes a lightweight, Pythonic approach using pandas, seaborn, and scikit-learn — suitable for academic research and SME implementation.

- Avoids dependency on enterprise-level big data infrastructure, yet delivers granular insights by combining multiple ML methods.

- Adds a time series forecasting component using ARIMA to predict future sales — a valuable addition for strategic planning.

C. Comparison with Johnson, A., & Team (2022)

Johnson's real-time feedback system is reliant on internal company infrastructure and streaming data like Kafka. In contrast, our system leverages publicly accessible online data via web scraping, eliminating the need for business-provided APIs or event streams. We achieve near real-time insights without unnecessary complexity by using scraping and lightweight preprocessing, while implementing visual reporting and clustering without requiring the integration of complex real-time systems, making it more feasible for startups and researchers.

D. Comparison with Sharma & Waoo (2023)

The study done by Sharma & Waoo (2023) discussed a wide range of ML techniques for customer behavior prediction. Our research contributes practically by implementing a working pipeline that combines classification, clustering, and forecasting in a unified codebase, not just reviewing methods.It demonstrates the effectiveness of web-scraped data for customer segmentation and modeling, which aligns with but at the same time also advances their theoretical review. We have validated our performane with use of real-world datasets like Amazon and Walmart, enabling replication and reproducibility, also confirming ability to adapt to different datasets.

E. Comparison with Muradkhanli & Karimov (2023)

Their work emphasized big data platforms for consumer behavior analysis. In contrast, our study takes a lightweight, Pythonic approach using pandas, seaborn, and scikit-learn, which are suitable for academic research and SME implementation. We have worked to avoid dependency on enterprise-level big data infrastructure, yet deliver granular insights by combining multiple ML methods, also adding a time series forecasting component using ARIMA to predict future sales — a valuable addition for strategic planning.

F. Key Differentiators of Our Study

- No Dependency on Business Data: Through web scraping, we built our dataset without direct business input, addressing the challenge of data inaccessibility for many researchers.
- Multi-Technique Pipeline: Our approach integrates demographic analysis, frequency segmentation, satisfaction prediction, clustering, and forecasting — a broader spectrum than most prior studies.
- Visualization-Driven EDA: Extensive use of visualizations improves interpretability, aiding marketers and decision-makers.
- Comparative Utility: The research showcases how different techniques complement each other — e.g., Random Forest for frequency prediction and KMeans for behavioral clustering.

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