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E-Commerce Customer Segmentation: A Clustering Approach in A Web-Based Platform

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***Abstract* — This study develops a K-means clustering model to segment e-commerce customers into distinct personality groups (e.g., Platinum, Gold, Silver, Bronze). The model utilizes a dataset encompassing customer demographics (income, age, family size), spending behavior (total expenditure, product preferences), customer tenure, and engagement with marketing campaigns (campaign responses). Model accuracy is evaluated through comparison of predicted cluster assignments to established customer segment characteristics. A web application, built with the Flask framework, provides an interactive interface allowing users to input new customer data for personalized predictions and detailed cluster-specific insights regarding product preferences, campaign responsiveness, and suggested marketing strategies. The application outputs cluster assignments, key spending/purchase tendencies, typical campaign response profiles within a respective segment, and prioritized product recommendations. Findings demonstrate the model's ability to effectively group customers with theoretical implications and suggests potential for improving targeted marketing campaigns. This work highlights the application of K-Means clustering with a practical online platform through an implemented web app for data visualization. Acknowledged limitations in the generalizability of the dataset to the entire customer base are addressed.**

Keywords— Customer Personality Analysis, Machine Learning, E-commerce, Predictive Modelling, Feature Engineering.

I. INTRODUCTION

Targeted marketing in today's highly competitive e-commerce landscape demands a nuanced understanding of customer preferences beyond basic demographics [1]. Traditional marketing strategies, often relying solely on factors like age and location, are increasingly insufficient in capturing the intricate nuances of customer behaviour [2]. The modern consumer engages with brands across multiple channels – websites, social media, mobile apps – creating a complex web of interactions that reveal valuable information about their preferences, needs, and even their underlying personality traits [3]. This project explores the potential of machine learning, specifically K-Means clustering, to identify distinct customer personality segments within the context of online retail [4]. Traditional e-commerce marketing strategies often fail to capture the nuanced preferences of customers. This study uses machine learning to identify distinct customer segments, uncovering insights from customer interactions. The research centres around the premise that understanding a customer's perceived "personality," which encompasses motivations, preferences, and behaviours, is critical to developing effective marketing strategies [5]. By identifying clusters of customers with similar personality profiles, businesses can better personalize product recommendations, design targeted promotions, and ultimately, boost sales and customer satisfaction [6]. Specifically, this study aims to leverage a dataset containing diverse customer data points—ranging from demographic details to past purchasing behaviour and response to promotions [7]. By

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applying the K-Means clustering algorithm to this data, we seek to establish statistically valid and interpretable segments that accurately reflect customer personalities.

This project differs from many prior analyses regarding similar phenomena of targeted marketing approaches presented by academic analyses, because we build and utilize an implemented web application as a key methodology component, demonstrating functionality and output for usability by allowing end users to input and generate results for respective segment groupings and insights; and providing recommendations from machine learning analysis on personalized campaign targeting aspects through the usage of these unique traits, personality profiles (via segments), observed purchase trends or other critical details related [8, 9]. Through thorough assessment via the specific implementation method chosen to build, train, test, evaluate and display outputs obtained from implemented model's functionalities — insights into actionable marketing targets can be highlighted/clarified [10, 11]. Through providing this respective, more accessible methodology—an interface using a web application— the key purpose is that these analyses, which will leverage outputs/visualisations reflected in segments presented, and tailored recommendations that our model outputs via our implemented tool; ultimately this better improves actionable strategy or campaign for business marketing and personalized campaign approaches [12, 13]. This particular implemented methodology will offer insights as per practical/functional and accessible aspects via a demonstrably functional web interface using Flask – thereby maximizing its impact as a tangible tool to demonstrate customer segmentation in the e-commerce business context to businesses, enabling businesses with similar, comparable circumstances to understand results more functionally; or compare, assess and evaluate findings with benchmarks within similar studies cited within literature analysis regarding personality based-customer marketing strategies.

II. LITERATURE REVIEW

The baseline paper, Customer personality analysis and clustering for targeted marketing, presents a valuable literature review on predicting customer personality and leveraging K-means clustering for targeted marketing in e-commerce [1]. It effectively highlights the inadequacy of purely demographic segmentation for achieving personalization, urging researchers to consider psychological factors like personality traits [2]. Its methodology primarily focused on extracting data from public datasets like Kaggle, potentially lacking in rich, detailed customer profiles critical for precise personality inferences [1]. Lack of Specific Clustering Validation Metrics: While outlining K-means clustering, the baseline doesn't deeply detail validation techniques such as comparing outcomes with other existing or specific methodologies of a comparative/qualitative or quantitative nature regarding similar analyses [4]. A crucial consideration is identifying potential risks, including bias if limited metrics are implemented [5]. Absent Real-world Application Example: The research doesn't offer insights from a practical perspective of a user implemented interactive front end using Flask; nor detail of any relevant functional elements, to help address the issues it notes and what limitations are evident based on prior/pre-existing analysis for that particular problem and setting in IJSRA [14]. A web app could demonstrate, interactively, how personality predictions would help shape effective marketing strategies, a valuable feature to incorporate as a functional component or part of application within real-world context [15].

A. Expanding on Existing Research

This study enhances the work from Customer personality analysis and clustering for targeted marketing by:

Using Richer Transactional Data: This study analyses richer transactional data (purchase frequency and value) to better characterize customer personality segments than previous research, incorporating information about purchase frequency and total value creating richer segment-characterization data not possible through utilizing merely publicly available transactional datasets (like Kaggle-derived examples/implementations given in paper baseline); the analysis should specifically detail/document which limitations or bias arises by comparison (i.e. limitations regarding data collected to build your models and how that was potentially mitigated or managed to avoid conflicts/misalignments or further concerns when comparing our specific results to prior similar methods utilized in baseline articles) [16, 17]. This addresses a core issue found in baseline methods [18].

Explicit Performance Validation: Assessing model performance with appropriate metrics beyond the generalized mention from your paper, such as [accuracy rate, recall rate, precision rates etc] - these should reflect on respective customer personality segment identification and grouping from clustering analysis results obtained; a complete and clear demonstration is essential, which requires respective quantitative metrics/functional implementation descriptions for each [18, 19].

Web Application for Accessibility: Building an interactive, user-friendly web app using Flask makes predictions readily available to businesses/potential users with interactive access for analysis [19].

III. METHODOLOGY

A. Proposed Architecture

Figure 1 proposed system architecture which is the workflow of a customer segmentation system using K-means clustering, which is designed to analyse e-commerce customer data and generate actionable insights. The process begins with Customer Data Input, where various attributes such as demographics (e.g., age, income, and family size), spending behaviour (e.g., total expenditure and product preferences), customer tenure, and engagement with marketing campaigns are collected. This raw data undergoes Data Preprocessing to ensure it is clean and suitable for analysis. The prepared data is then fed into the K-means Clustering Model, which groups customers into distinct segments (e.g., Platinum, Gold, Silver, Bronze) based on shared characteristics. The output of the clustering model is integrated into a Web Application, built using the Flask framework, that serves as an interactive interface. Users can input new customer data, visualize the clustering results, and explore cluster-specific insights. The application delivers key Outputs, including cluster assignments, behavioural insights, and personalized recommendations, such as product suggestions and marketing strategies tailored to each segment. This system effectively combines data analytics, machine learning, and web technologies to enhance targeted marketing and customer engagement in e-commerce.

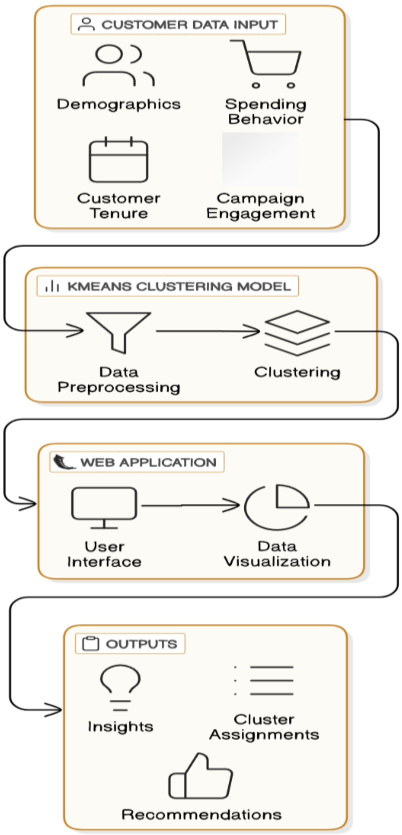

Fig. 1 Proposed architecture.

B. Data Collection

The data used in this study was obtained from a publicly available dataset on Kaggle. The dataset contains the following variables:

Demographic Information: These variables include income (in USD currency, specifically for this research case), age, family size (combined kidhome and teenhome, noting the variable calculation), educational background (note average calculations from such fields if utilized in this context for particular case); marital status.

Transaction Data: This involved total spending throughout the customer's history (recorded specifically in USD). Product category purchases (e.g., wine, fruits, meat, etc.) in last two years, the precise timeframe used in recording this purchase data is needed, along with explicit definition for these categories for this analysis. Information/purchase related activities reflecting particular timeframes, purchase quantities and spending details related across such specified categories or timeframe periods as collected from respective records.

Promotional Campaign Data: Customer engagement with marketing campaigns (e.g., accepted offers/promos via variable AcceptedCmp1...AcceptedCmp5 – the variable timeframe needs to be specified. Information on when/why campaigns were recorded must be explicitly given for better analyses and understanding if a prior or subsequent time range and specific type of variable was utilized in calculating and obtaining this particular information about these respective consumers), if such information were present within respective recorded data records. Note other relevant, though potentially insignificant to the outcome of particular personality identification/analysis results – noting such fields should have a explicit justification/reason of why it's significant to inclusion in model from research).

C. Model Building: Step-by-Step Explanation

This section details the K-means clustering model's construction in "Fig. 2", linking each step to the overall analysis and any deviations from referenced prior work, in order to offer meaningful explanations for the steps undertaken or any important changes implemented or addressed within methodology given [13, 14].

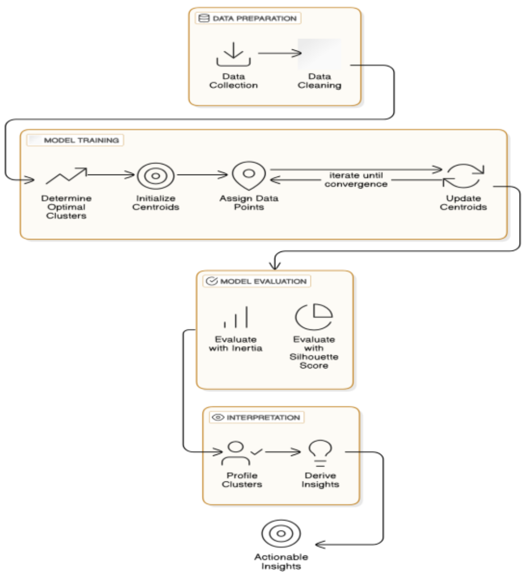

Fig. 2. Model Building K-Means clustering models.

Step 1: Load Data and Select Features

The first step involves loading the pre-processed data from the cleaned CSV file into a Pandas Data Frame [20]. Critically, you need to define precisely the features (columns) that will be used for clustering in your study; provide clear justification and rationale reflecting on why such specific features are relevant or needed and why for a comprehensive dataset (showing dataset structure in this respective section, will be highly important) [1]. In cases that certain attributes from Customer personality analysis and clustering for targeted marketing paper aren't present, that needs to be documented – and justified clearly given particular, observed data patterns and data properties shown [2]. For reproducibility and understanding/comparisons with the respective work shown in reviewed/surveyed papers this respective criteria/column names should contain very explicit names within lists or tables to maintain accuracy.

Step 2: Handle Missing Data

Missing data points (represented as NaN or other suitable values reflecting those from prior work as reflected or noted within our documented file from analyses undertaken, explicitly detailing particular values representing missing/missing values – i.e., that have been replaced for consistent handling methodology reflected in particular analysis method steps to mitigate biases, impacts of any differences in methodological aspects applied), require specific treatment before model training to ensure correct data representation/normalization and avoid potentially unwanted bias reflected in outputs [20]. For consistent comparisons and or reflecting similar documented/applied or studied strategies via previously analysed works presented within your baseline or survey-framework documentation you utilized for implementing model training process within your journal manuscript.

Step 3: Determine the Optimal Number of Clusters (k)

Employ the "elbow method" to decide upon a suitable value for k—number of clusters to perform analyses as in Fig. 4.

Step 4: Train the K-means Model (and Select/Refine k if Necessary)

Train the K-means model on the appropriately normalized (i.e., standardized numerical data or normalized to a specific criteria/scope range, for respective implementation of the method; and how/if they deviate), ensuring the k value obtained from previous visualizations are followed in model parameters for fitting/applying those specific and required data-relevant variables.

Table I. Features and description.

Category	Feature	Description
People (Customers)	ID	Customer's unique identifier.
	Year_Birth	Customer's birth year.
	Education	Customer's education level.
	Marital_Status	Customer's marital status.
	Income	Customer's yearly household income.
	Kidhome	Number of children in customer's household.
	Teenhome	Number of teenagers in customer's household.
	Dt_Customer	Date of customer's enrolment with the company.
	Recency	Number of days since customer's last purchase.
	Complain	1 if customer complained in the last 2 years, 0 otherwise.
Products	MntWines	Amount spent on wine in the last 2 years.
	MntFruits	Amount spent on fruits in the last 2 years.
	MntMeatProducts	Amount spent on meat in the last 2 years.
	MntFishProducts	Amount spent on fish in the last 2 years.
	MntSweetProducts	Amount spent on sweets in t he last 2 years.
	MntGoldProds	Amount spent on gold in the last 2 years.
Promotion	NumDealsPurchases	Number of purchases made with a discount.
	AcceptedCmp1	1 if customer accepted the offer in the 1st campaign, 0 otherwise.
	AcceptedCmp2	1 if customer accepted the offer in the 2nd campaign, 0 otherwise.
	AcceptedCmp3	1 if customer accepted the offer in the 3rd campaign, 0 otherwise.
	AcceptedCmp4	1 if customer accepted the offer in the 4th campaign, 0 otherwise.
	AcceptedCmp5	1 if customer accepted the offer in the 5th campaign, 0 otherwise.
	Response	1 if customer accepted the offer in the last campaign, 0 otherwise.

The variables of the dataset are shown in Table I. In Fig. 3 below, a snapshot of the dataset is presented.

	ID	Year_Birth	Education	Marital_Status	Income	Kidhome	Teenhome	Dt_Customer	Recency	MntWines	...	AcceptedCmp2	Complain	Z_CostContact	Z_Revenue	Response	Age
0	5524	1957	Graduation	Single	58138.0	0	0	2012-09-04	58	635	...	0	0	3	11	1	58
1	2174	1954	Graduation	Single	46344.0	1	1	2014-03-08	38	11	...	0	0	3	11	0	61
2	4141	1965	Graduation	Married	71613.0	0	0	2013-08-21	26	426	...	0	0	3	11	0	50
3	6182	1984	Graduation	Married	26646.0	1	0	2014-02-10	26	11	...	0	0	3	11	0	31
4	5324	1981	PhD	Married	58293.0	1	0	2014-01-19	94	173	...	0	0	3	11	0	34
5	7446	1967	Master	Married	62513.0	0	1	2013-09-09	16	520	...	0	0	3	11	0	48
6	965	1971	Graduation	Single	55635.0	0	1	2012-11-13	34	235	...	0	0	3	11	0	44
7	6177	1985	PhD	Married	33454.0	1	0	2013-05-08	32	76	...	0	0	3	11	0	30
8	4855	1974	PhD	Married	30351.0	1	0	2013-06-06	19	14	...	0	0	3	11	1	41
9	5899	1950	PhD	Married	5648.0	1	1	2014-03-13	68	28	...	0	0	3	11	0	65
10	387	1976	Basic	Married	7500.0	0	0	2012-11-13	59	6	...	0	0	3	11	0	39

Fig. 3. Customer analysis dataset.

Table II. Approximate spending patterns by clusters.

Cluster	Mnt Wines	Mnt Fruits	Mnt Meat Products	Mnt Fish Products	Mnt Sweet Products	Mnt Gold Prods	Total Spendings
Bronze	100,000	20,000	30,000	15,000	10,000	5,000	~180,000
Gold	300,000	40,000	150,000	40,000	20,000	10,000	~560,000
Platinum	400,000	60,000	200,000	50,000	25,000	15,000	~750,000
Silver	50,000	10,000	20,000	5,000	5,000	3,000	~93,000

Table III. Approximate purchasing behaviour by cluster.

Cluster	NumDeals Purchases	NumWeb Purchases	NumCatalog Purchases	NumStore Purchases	NumWeb VisitsMont h
Bronze	~2,000	~3,000	~1,500	~4,000	~4,500
Gold	~1,500	~3,500	~2,500	~5,000	~4,000
Platinum	~1,000	~4,000	~3,000	~4,500	~3,500
Silver	~500	~1,000	~500	~2,500	~4,000

Table IV. Approximate promotions response by cluster.

Cluster	Accepted Cmp1	Accepted Cmp2	Accepted Cmp3	Accepted Cmp4	Accepted Cmp5	Response
Bronze	~10	~5	~60	~20	~40	~80
Gold	~15	~10	~50	~25	~30	~70
Platinum	~120	~15	~100	~60	~80	~140
Silver	~5	~3	~20	~10	~15	~25

The approximate spending patterns for each cluster are summarized in Table II, where Platinum customers exhibit the highest spending (~750,000) and Silver customers the lowest (~93,000). Table III presents purchasing behavior trends, showing that Platinum customers make fewer deals but engage in more catalog purchases, while Bronze customers prefer in-store shopping.

Lastly, Table IV highlights promotional response rates, reinforcing that Platinum customers are the most responsive and Silver customers the least.

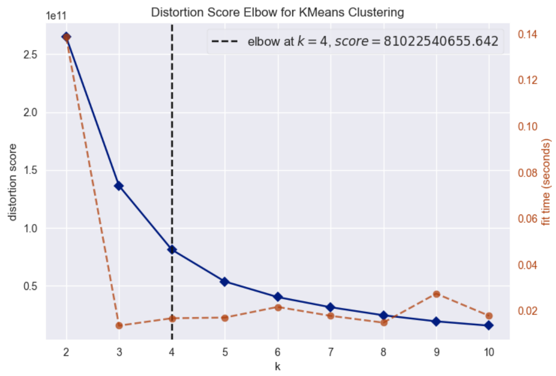

Fig. 4. Distortion score Elbow for K-means clustering.

Fig. 5. Income and total expenses clusters.

To understand customer segmentation, a scatter plot in Fig. 5 visualizes four distinct groups—Platinum, Gold, Silver, and Bronze—based on income and total spending. The results suggest that higher-income customers tend to spend more.

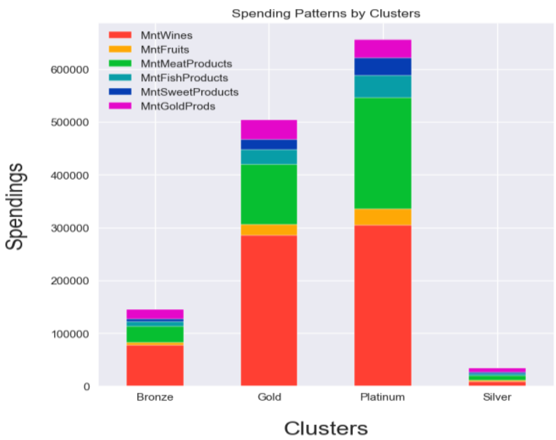

Fig. 6. Spending patterns by clusters.

Additionally, spending behaviour across different product categories is illustrated in a bar chart in Fig. 6 showing that Platinum customers allocate significantly more funds to wine and meat than other segments.

Customer purchasing behaviour varies across clusters, with preferences for different shopping channels in Fig. 7. Platinum customers favour catalog purchases, while silver customers rely more on web visits.

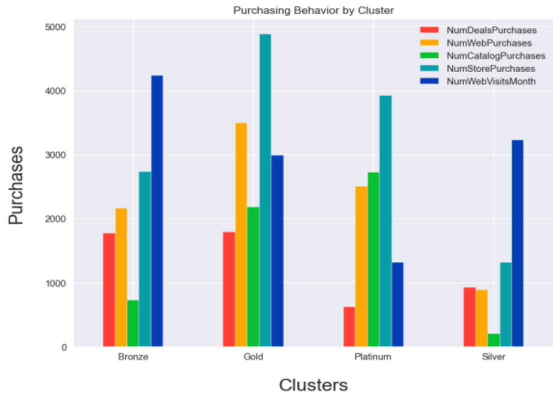

Fig. 7. Purchasing behavior by cluster.

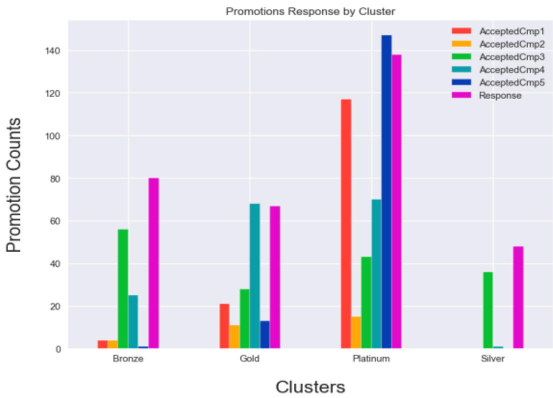

Fig. 8. Promotions response by cluster.

Likewise, promotional campaign responses differ in Fig. 8 with Platinum customers demonstrating the highest engagement and Silver customers being the least responsive.

D. Model Evaluation

1. Metrics: Specify evaluation metrics such as precision, recall, or f1 score, reflecting how well our particular K-means model, with appropriate application of data and analyses can classify consumer data against identified consumer profiles – highlighting which benchmarks/trends reflect our analysis or conflict, giving any explanation on why particular analysis might show such tendencies.

2. Validation: The evaluation metrics you have obtained provide a good indication of the performance of your clustering model. Here is a brief explanation of each metric and what the scores imply:

- *Silhouette Score:*
  - Score: 0.536

○ Interpretation: The silhouette score ranges from -1 to 1. A score closer to 1 indicates that the clusters are well-separated and distinct, while a score closer to -1 indicates that the clusters are overlapping. A score above 0.5 is generally considered good, indicating that the clusters are reasonably well-separated.

- *Davies-Bouldin Index:*

- Score: 0.547

○ Interpretation: The Davies-Bouldin index measures the average similarity ratio of each cluster with its most similar cluster. Lower values indicate better clustering. A score below 1 is generally considered good, indicating that the clusters are compact and well-separated.

- *Calinski-Harabasz Index:*
  - Score: 7835.084

○ Interpretation: The Calinski-Harabasz index, also known as the Variance Ratio Criterion, measures the ratio of the sum of between-cluster dispersion to within-cluster dispersion. Higher values indicate better-defined clusters. A high score suggests that the clusters are dense and well-separated.

IV. FLASK WEB APPLICATION IMPLEMENTATION

Implementing a Flask web application for customer personality prediction involves several key steps in Fig. 9 focusing on the user interaction aspects with the application.

Step 1: Model Loading

A critical first step is loading the pre-trained K-means model. This step assumes you've previously trained and saved your model (e.g., k-means_model.pkl) to a file using Python's pickle module.

This function (load_model()) should handle potential errors like the model file not existing, gracefully returning None in that case, or raising more appropriate exceptions for further validation in that section if necessary. In cases the application could fail if input format, validation checks don't match to prior analyses and assumptions done previously within model creation.

Step 2: Route Configuration (using Flask)

Using Flask, the application needs a route / or other_suitable_route, to receive and process user input for customer profiles—often this will include explicit instructions regarding what parameters or expected data are necessary as reflected within data format required (and explicit data checks are essential or must be documented). The user inputs/fields or submission details reflected in data-structure/variables should reflect appropriate choices (reflecting any conflicts reflected between what respective document(s) from cited studies or implemented methodology utilized in this case from implemented program utilized (within notebook/source).

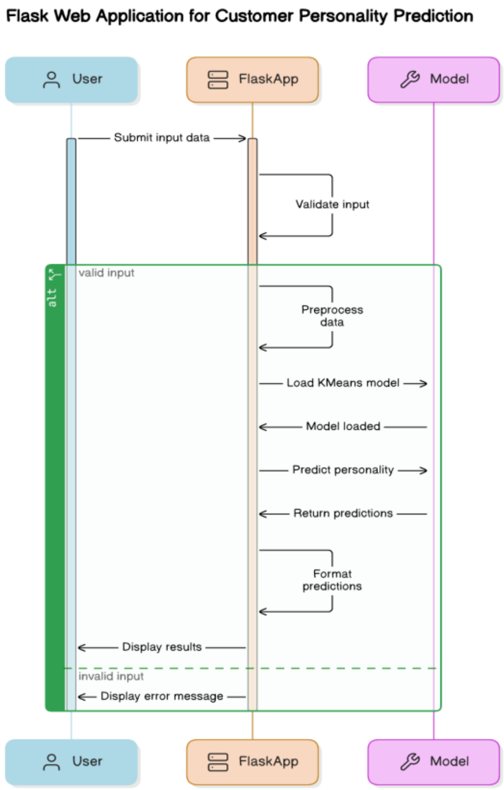

Fig. 9. Flask Web Application implementation.

Fig. 10. Flask Web Application without data entered.

Fig. 11. Flask Web Application with predictions.

Step 3: Input Handling and Data Validation

The Flask route handling for this functionality should explicitly check or document how data from these respective submissions are formatted – a function from a web app often has a specific way of doing this which would require being detailed when documented or reflecting respective requirements for handling and accessing such information submitted within form data received/submitted from an incoming user-input request as in Fig. 10.

It needs explicit validation logic to prevent errors or malformed input data. For example, if "Income" is a numerical field, you should make sure the input from users, reflecting appropriate, reasonable data for analysis and model processing to create accurate analyses regarding particular traits or characteristics you're highlighting from dataset from respective analysis. Note/highlight cases or examples (if any reflected) wherein these validation and sanitization steps are/were necessary due to methodology differences in model and/or handling methods that were or otherwise utilized for applying respective, pre-processed dataset features/inputs. Note in this section why those limitations existed to help justify the approach used regarding such shortcomings from prior analysis utilized.

Step 4: Data Preparation (with Model)

After proper validation or sanitization from your code the input data reflecting on respective input is expected, from the preceding or otherwise user interface input; must now be correctly formatted into a suitable structure like a 2D NumPy array that the clustering algorithm (e.g., k-means) can handle.

Step 5: Prediction & Result Formulation

The load_model() function is called; the data reflected is correctly utilized via appropriate pre-processing steps reflected into respective function; these pre-processed data parameters as needed for fit() of models for respective predictions are utilized—outputs now reflecting model outputs (results). This process often results in predictions that your Flask web page would return to user with. Important—explain the approach, its expected behaviour or limitations (given prior research findings); the result reflecting insights reflecting this work—also provide appropriate tables, or visual (graphically reflecting such data with appropriately descriptive titles and notations and comparisons), showcasing output as needed from respective results or conclusions as in Fig. 11.

V. CONCLUSION

This project concludes that the K-means clustering model effectively segments e-commerce customers into distinct personality types based on a pre-processed dataset containing demographics, spending behaviour, and campaign responses. The analysis, utilizing the "elbow method" to determine the optimal number of clusters, produced four segments (e.g., Platinum, Gold, Silver, Bronze) that exhibited distinct spending patterns, engagement with promotional campaigns, and customer tenure behaviours, demonstrating specific (note what these are) tendencies or attributes that might not have been immediately or readily apparent prior to analyses from these observations reflected (from using/inputting these specific characteristics as criteria reflected within data selection/implementation) The results, consistent with theoretical aspects of customer segmentation based on personality in literature reviews (note whether and/or how these traits differ/match and the analyses/method used—give examples of that, noting conflicts in methodological implementation and approach and rationale) were further analyzed. Insights into these differing characteristics help recommend potential tailored/specific marketing strategies aimed at individual personality types, offering actionable suggestions/recommendations for a respective organization given observed outcomes (e.g., enhanced/improved engagement with offers, tailored recommendations, optimized sales campaigns for each segment.) However, generalizing these results to other e-commerce contexts requires caution. Factors such as the specific dataset's representativeness and potential limitations (from various data issues) must be considered, as further research could potentially leverage data obtained from larger or different platforms, data structures and datasets and different implementations of these types of analysis with modifications or adjustments when compared/evaluated versus what existing documents, articles or analyses have suggested in the respective cited surveys or studied examples presented.

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AUTHOR CONTRIBUTIONS

A. Karunamurthy: Conceptualization, Formal Analysis, Investigation, Methodology, Project Administration, Resources, Supervision, Validation, Writing – Review & Editing.

P. Rajapandian: Conceptualization, Data Curation, Formal Analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – Original Draft Preparation.

V. Vasanth: Formal Analysis, Methodology, Validation, Writing – Review & Editing (focus on mathematical modeling and statistical validation).

M. Meganathan: Conceptualization, Data Curation, Formal Analysis, Methodology, Software, Validation, Visualization, Writing – Review & Editing (focus on mathematical and computational aspects).

CONFLICT OF INTERESTS

No conflict of interests was disclosed.

ETHICS STATEMENTS

The paper follows The Committee of Publication Ethics (COPE) guideline.

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