Business intelligence through data visualization: a case study using marketing campaign dataset

Aditi Bansal, Ankit Gupta
Department of Computer Science and Engineering, Chandigarh College of Engineering and Technology, Chandigarh, India

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ABSTRACT

In today's competitive business environment, data-driven marketing strategies are essential for successful campaign outcomes. This study presents a comprehensive analysis of marketing campaign data, emphasizing its role in enhancing customer engagement, improving decision-making, and increasing conversion rates. It explores the complexity of campaign dynamics and consumer behavior, demonstrating how business intelligence and data visualization techniques support informed marketing decisions and actionable insights. Advanced data science methods such as data cleaning, feature engineering, and cross-validation enhance predictive accuracy and campaign optimization. Visualization plays a central role in transforming raw data into interpretable insights, enabling businesses to identify trends in customer preferences and purchasing behavior. Key findings reveal that customers aged 51–70, particularly those with higher education and income levels, show the greatest purchasing power, especially for wine and meat products. These insights help align marketing strategies with data-driven understanding to design personalized campaigns that resonate with target audiences. By combining analytical methods with effective visualization, businesses can develop impactful campaigns that drive engagement, boost conversions, and foster revenue growth. The study concludes with directions for future research, including real-time data processing and automated decision-making systems to ensure continuous improvement in digital marketing strategies.

Corresponding Author:

Aditi Bansal
Department of Computer Science and Engineering, Chandigarh College of Engineering and Technology
Chandigarh, India
Email: aditi.bansal0703@gmail.com

1. INTRODUCTION

In today's digital economy, businesses are increasingly accepting data-based strategies to gain a competitive advantage and make informed decisions that increase customer experience and optimize marketing performance [1]. Business intelligence has proven to be a critical tool that allows organizations to use large volumes of marketing data to identify customer preferences, audience segment, and monitoring of real-time campaign efficiency. Marketing campaigns generate rich data involving demographic data, behavioral data and response patterns that can reveal action knowledge when correctly analyzed and help to maximize return on investment (ROI) [2]. Integration of data science into marketing has revolutionized how companies approach consumers, and shifts a focus from strategies based on intuition based on evidence-based decision-making [3].

Despite the availability of large-scale data, traditional marketing approaches often do not affect limited analytical abilities, fragmented data systems and insufficient understanding of consumers' behavior

[4]. These restrictions result in missed opportunities, ineffective targeting and suboptimal assignment of resources. In addition, marketing analysts face challenges in solving data quality problems [5], obtaining relevant functions and interpreting complex data sets. Without the right tools and methods, valuable information can remain hidden within the raw data, leading to inaccurate forecasts and weak campaign [6] results. There is an urgent need for advanced analytical and visualization approaches that can process complex information and provide intuitive and decision-making information for marketing teams.

To solve these challenges, this document proposes a comprehensive analysis based on data [7] that combines efficient data processing, functional engineering and visualization of data to support strategic marketing decisions. The methodology includes cleaning and transformation [8] of raw data, deriving meaningful attributes and using interactive visual dashboards for communication of key findings. The aim is to demonstrate how visualization [9] techniques can extract special knowledge from marketing data, especially when identifying customers segments with high value and optimizing campaign strategies [10]. Through a case study using a data file for a real-world marketing campaign, we will investigate how visualization tools such as column charts, thermal maps and KPI can detect patterns in buying behavior, customer demography [11] and campaign sensitivity. The findings not only verify the potential of visualization in marketing analysis, but also provide specific recommendations for strengthening the future design of the campaign.

The remaining part is arranged as follows: Section 2 discusses the literature review, section 3 outlines the methodology, section 4 represents experimental results and analysis and section 5 closes future research directions.

2. LITERATURE REVIEW

Several studies have explored effective strategies for analyzing marketing campaign data using advanced data techniques, with a growing emphasis on data visualization as a critical component for extracting and communicating insights. A comprehensive study also evaluated the effectiveness of marketing campaigns using both traditional and online data analysis. The research highlighted challenges businesses face when evaluating traditional marketing due to limited metrics, especially compared to digital marketing. Visualization techniques such as comparative bar charts and performance dashboards were used to represent campaign performance across channels, helping stakeholders understand the impact of key factors. The integration of traditional analysis with modern tools was shown to enhance decision-making and improve campaign evaluation by visualizing trends and outcomes across multiple data sources [12].

Another study employed the theoretical context-content-methodology (TCCM) framework to analyze 64 research papers, identifying dominant theories, key variables, and methodologies in marketing analytics. Visualization played a pivotal role in mapping the distribution of methodologies and theoretical frameworks over time using timeline graphs and bubble plots. These visual tools effectively illustrated the divergence between traditional and data-driven marketing approaches and helped in identifying research gaps and emerging trends [13].

The development of data-driven marketing was explored by Rosario and Dias [14], who presented frameworks to guide managers and marketers in applying data-based strategies. Their study used flow diagrams and concept maps to visualize decision-making pathways and the interaction between data collection, analysis, and strategy implementation. These visual aids clarified complex processes and enhanced comprehension of the data-driven marketing cycle [14].

Another study examined how big data analytics has transformed marketing strategies through improved decision-making, customer segmentation, and efficiency. The researchers employed various visual techniques such as heat maps, cluster diagrams, and decision trees to illustrate consumer behavior patterns derived from transaction logs, social media interactions, and browsing behavior. These visualizations made it easier to interpret large and complex datasets, ultimately supporting data-driven marketing improvements [15]. Marketing mix analysis through the lens of business intelligence was discussed in a study by Fan *et al.* [16], which focused on how big data can optimize the 4Ps: product, price, place, and promotion. They utilized multi-dimensional charts and dashboards to visualize the interplay among marketing mix elements. These tools enabled better strategic alignment by presenting performance metrics and optimization results in a clear, interactive format [16].

A study explored consumer repurchase behavior prediction using long short-term memory (LSTM) neural networks. Visualization techniques such as line graphs of prediction accuracy over time and heatmaps of consumer engagement metrics were employed to demonstrate the model's effectiveness. These visuals helped in communicating the power of deep learning in capturing sequential purchase patterns, ultimately supporting strategies for customer retention [17].

These studies highlight the evolving landscape of marketing analytics, emphasizing the integration of big data technologies, machine learning models, social media insights, and balanced marketing strategies to improve campaign success rates. This case study deals with a gap in available frames of marketing analysis based on visualization that supports decision-making without complicating modeling, thereby increasing the tools for business news for experts.

3. METHOD

A structured approach was adopted to analyze the marketing campaign data [18]. This methodology leverages modern data science tools and techniques to process, explore, and visualize the dataset. Python was used as the primary programming language due to its robust ecosystem of data analytics libraries. Specifically, the Pandas library facilitated data manipulation and preprocessing, while Seaborn and Matplotlib were employed for creating statistical visualizations. These tools offer flexibility, ease of use, and scalability, making them ideal for exploratory data analysis (EDA) and business intelligence tasks.

The analysis process consists of several essential phases: data cleaning, feature engineering, exploratory data analysis, and dashboard-based visualization for key performance indicator (KPI) extraction. Each phase was designed to ensure that insights drawn from the data are accurate, actionable, and easy to interpret. Figure 1 illustrates the complete data analysis process through flowchart.

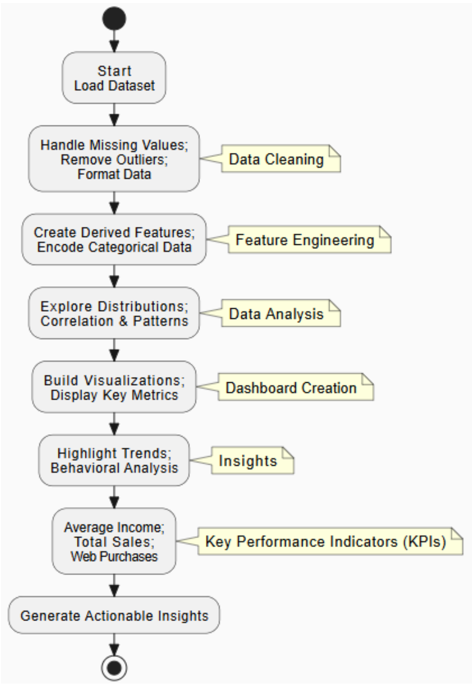

Figure 1. Flowchart of data processing and visualization pipeline

3.1. Dataset description

The dataset used in this study was obtained from a publicly available marketing campaign dataset on Kaggle [19]. It contains anonymized customer data from multiple campaigns, including demographic details, purchasing behavior, and campaign responses. The main attributes are described:

- ID: unique identifier for each customer.
- Year birth: year in which the customer was born (used to calculate age).
- Education: categorical variable describing the education level (e.g., basic, graduation, master’s, PhD).
- Marital status: relationship status (e.g., single, married, together, divorced).
- Income: customer’s annual income in dollars (cleaned by removing currency symbols for numerical analysis).
- Kidhome: number of children in the household.
- Teenhome: number of teenagers in the household.
- Recency: number of days since the customer’s last purchase.
- MntWines, MntFruits, MntMeatProducts, MntFishProducts, MntSweetProducts, MntGoldProducts:

expenditure on various product categories.
- NumDealsPurchases: number of purchases made with discounts.
- NumWebPurchases, NumCatalogPurchases, NumStorePurchases: purchases by respective channels.
- numwebvisitsmonth: number of website visits in the past month.
- AcceptedCmp1–5: binary indicators of campaign responses.
- Response: overall campaign response (1 = Positive, 0 = Otherwise).
- Complain: binary flag indicating customer complaints.
- Country: country of residence (e.g., SP, CA, US, AUS, GER, IND).

3.2. Data cleaning

Data cleaning was performed to enhance accuracy, consistency, and usability [20]. The following steps were implemented:
- Loading data: the dataset was loaded using Pandas for inspection and preliminary analysis of missing or inconsistent values.
- Income column cleaning: the income field, which included currency symbols and textual anomalies, was cleaned and converted to a numeric format for precise computation.
- Outlier handling: boxplots were used to detect outliers in income and age. Values above $200,000 for income and over 100 years for age were removed.
- Missing values: null entries in Income were replaced with the mean income to preserve dataset integrity and prevent model bias.

3.3. Feature engineering

New features were engineered to improve analysis and model performance:
- Age calculation: the age field was calculated as 2024 − year birth, yielding a more intuitive age attribute.
- Categorical encoding: categorical variables such as education were encoded ordinally (e.g., basic=1, graduation=2, master’s=3, PhD=4) to facilitate meaningful numerical analysis.

3.4. Data analysis

EDA was conducted using statistical visualizations to uncover hidden patterns and relationships:
- Boxplots: used to identify the distribution and central tendency of income and age, along with detection of outliers [21].
- Heatmaps: illustrated correlations between key numerical variables (e.g., product spending and income) to understand purchasing behaviors [22].
- Histograms: provided frequency distribution of customer segments based on income groups and age ranges [23].

Each visualization has been selected to address a specific analytical question: Which customers’ segments spend the most? What demography do most respond to campaigns? How do shopping channels with review correlate?

3.5. Dashboard visualization

To support business decision-making, an interactive dashboard was built using data visualization tools to present key insights in an accessible format:
- Bar graphs: displayed customer purchases segmented by education level, income, and age groups.
- Pie charts: represented the demographic distribution of customers across marital status and age categories.
- KPI metrics: included average income, total sales, web engagement rates, and customer satisfaction indicators to support strategic planning [24].

Dashboard serves as a practical tool for marketing analysts to interpret performance campaigns and segmentation of customers visually and interactively. The integration of the structured EDA, the meaningful design of the function [25] and intuitive visualization makes this methodology robust for marketing applications in the real world.

4. RESULTS AND DISCUSSION

This section presents the key results derived from the exploratory and visual analysis of the marketing campaign dataset. Insights are also compared with findings from previous research to validate the analytical outcomes.

4.1. Income distribution

Income was a crucial attribute analyzed to identify purchasing capacity and its relation to demographic factors. As shown in Figure 2, customers with a Basic education level exhibited significantly lower and less variable income distributions, whereas those with higher education levels graduation, master's, and PhD had broader income ranges and higher median values.

- The cleaned income column showed reduced noise and fewer outliers, offering a more accurate depiction of customer earnings.
- Outliers above $150,000 were present in each education category, suggesting some high-income individuals across all groups.

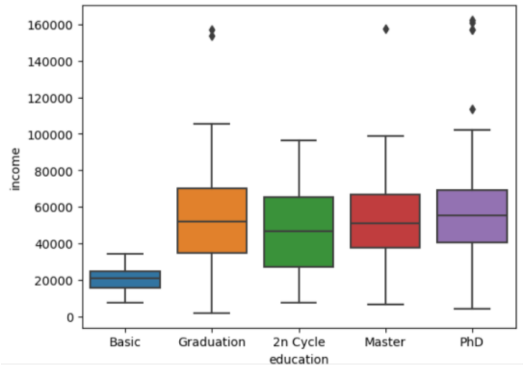

Figure 2. Income distribution by education level

4.2. Age insights

Figure 3 highlights customer purchases segmented by age groups. Customers aged 51 to 70 made the most purchases across all product categories, especially in wines and meat products, followed by the 36 to 50 age group.

- These two segments demonstrated the highest purchasing capacity, establishing them as ideal targets for future campaigns.
- Customers aged 18 to 35 and those 71 and older showed minimal purchases, indicating that campaign content and product offerings may need adjustment for better engagement.

4.3. Correlation analysis

The heatmap in Figure 4 reveals key relationships between numerical variables.

- Strong correlations between MntWines, MntMeatProducts, and MntGoldProducts imply that customers who spend on premium goods are likely to spend across multiple categories.
- Income showed mild positive correlations with spending variables, while variables like marital Status and kidhome showed little to no correlation with income.
- The negative correlation between recency and NumWebPurchases indicates that recent customers are highly active online a useful insight for digital retargeting strategies.

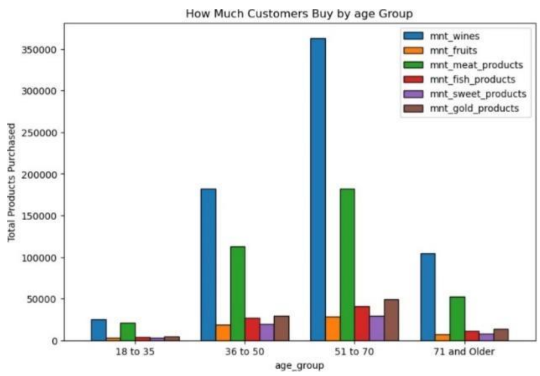

Figure 3. Total products purchased by age group

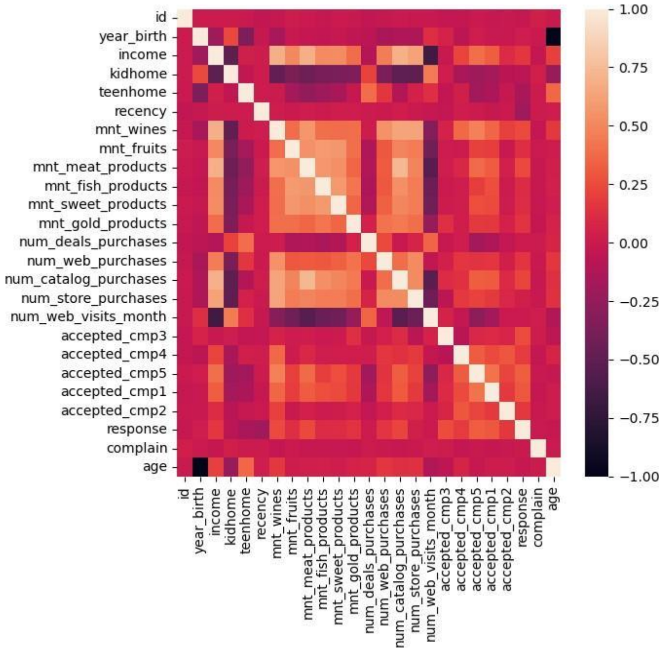

Figure 4. Heatmap for key variables

4.4. Key performance indicators

This section summarizes high-level metrics extracted from the dashboard (Figure 5).

- Average income: $51,958.81, reflecting a moderately affluent customer base.
- Total web purchases: 11,771 transactions indicating high online interaction.
- Total sales: $1,343,277 in revenue, validating campaign effectiveness.
- Customer complaints: only 20 logged complaints suggest positive customer experience and satisfaction.

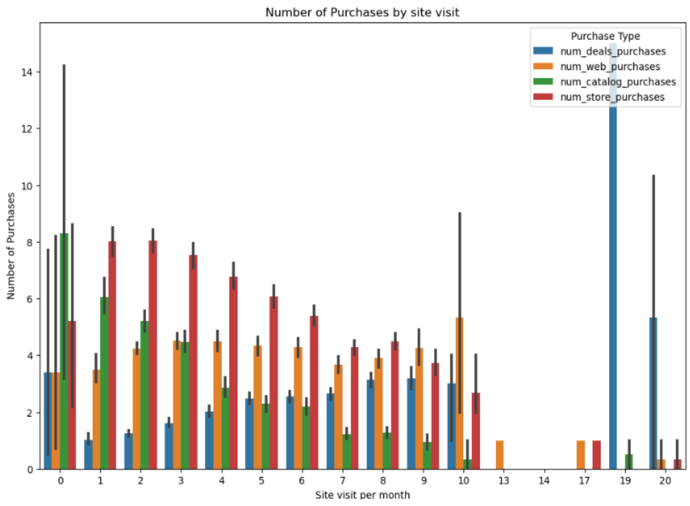

Figure 5. Number of purchases by site visit

4.5. Distribution analysis

The analysis identified dominant demographics and regional performance patterns.

- Age group: over 52.3% of customers fall in the 51–70 age range.
- Education level: those with Graduation or PhD qualifications demonstrated the highest expenditures.
- Country-wise: Figure 6 shows that customers from the United States and Spain made the most purchases, highlighting strong regional engagement.

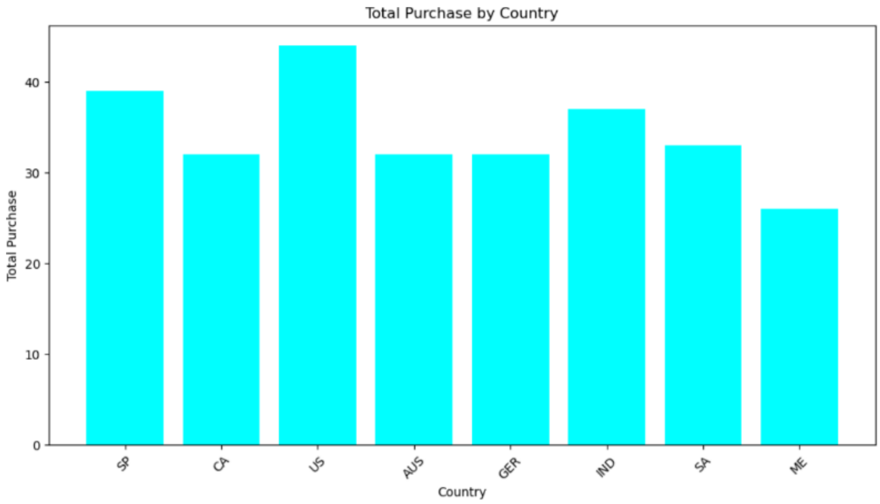

Figure 6. Purchases by country

4.6. Purchase behavior analysis

Income remains a key factor in purchasing behavior as shown in Figure 7. Customers earning over $100,000 contribute disproportionately to total revenue.

- Income vs purchases: affluent customers show higher spending across all categories.
- Product preferences: Figure 8 confirms that wine is the top-selling category ($675.3K), followed by meat products ($369.5K), suggesting these should be focal points in future promotional strategies [26].

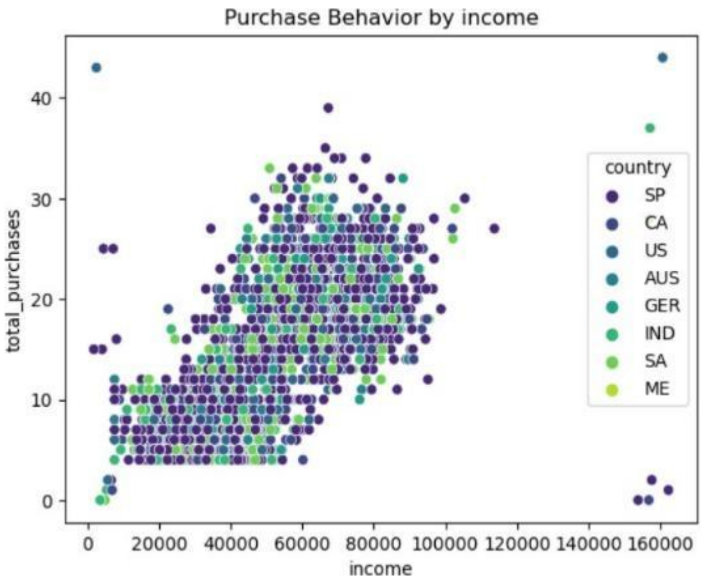

Figure 7. Purchases by income and country

4.7. Summary table

Table 1 presents a summary of the key insights obtained from the visual and exploratory data analysis conducted in this study. In conclusion, the results not only validate known marketing hypotheses—such as education and income influencing purchasing behavior but also reveal new opportunities for segmentation and targeting through visual and KPI-based analysis. These findings support data-driven decision-making in business intelligence applications and align with the visual intelligence discussed in prior literature.

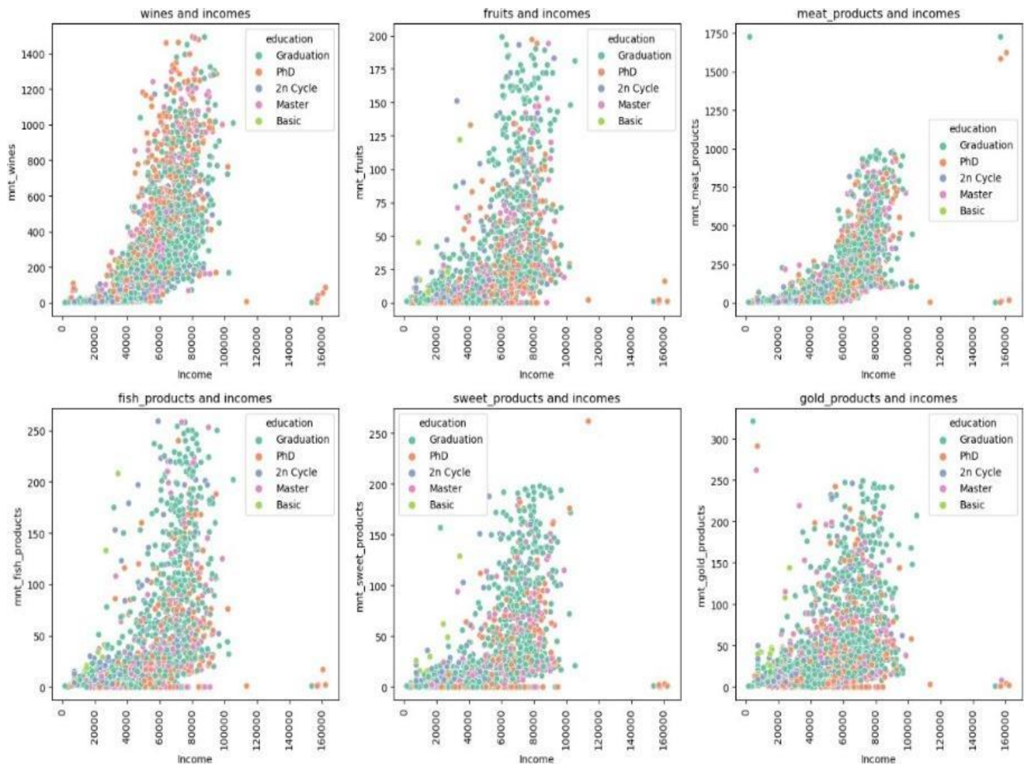

Figure 8. Sales of different products by education and income

Table 1. Summary of key insights from visual analysis

Insight area	Key findings
Income distribution	Higher education correlates with higher income; some high income individuals exist across all education levels
Age-based behavior	Customers aged 36–70 account for most purchases, especially in wines and meat products
Product affinity	Strong co-purchasing trend among premium products (wine, meat, gold)
Web engagement	High web purchases from recent customers; strong digital inter action
Geographic trends	US and Spain are top markets in terms of purchase volume

5. CONCLUSION

This study presents a comprehensive analysis of marketing campaign data using business intelligence and data visualization techniques. By applying meticulous data cleaning methods and effective feature engineering, the analysis improved data integrity and enabled refined customer segmentation. Visualization tools, including heatmaps, bar charts, and KPI dashboards, played a crucial role in translating complex data into actionable insights. The results revealed that customers aged 51–70, particularly those with higher education levels such as graduation or PhD, demonstrated the highest purchasing power. Products such as wine and meat were identified as top-selling categories, while income levels above \$100,000 were associated with significantly higher purchase volumes. Regionally, the United States and Spain emerged as key markets with the most substantial customer engagement and spending.

Despite these contributions, the study has a few limitations. The analysis was conducted on a single dataset, which may limit the generalizability of the findings. Additionally, the study focused primarily on exploratory data analysis and did not include predictive modeling or classification of campaign responders. Future work can address these limitations by incorporating machine learning techniques to predict campaign outcomes and customer behavior more accurately. Real-time data processing and the development of dynamic dashboards could further enhance responsiveness and strategic planning. These advancements would supportmore adaptive marketing approaches and foster improved customer interaction in an increasingly data-centric business environment.

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AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Aditi Bansal	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			
Ankit Gupta		✓		✓	✓	✓		✓		✓		✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

We the undersigned authors, hereby declare that there is no conflict of interest of any kind related to the content, authorship, or submission of this manuscript. We affirm that the manuscript is original, has not been published previously, and is not under consideration for publication elsewhere. All authors have made significant contributions to the research and preparation of the manuscript. Furthermore, all authors have reviewed the final version and have approved its submission. No financial, personal, or professional interests exist that could have influenced the work reported in this manuscript. Authors state no conflict of interest.

INFORMED CONSENT

Not applicable. This study utilized a publicly available, anonymized dataset and did not involve human participants requiring informed consent.

ETHICAL APPROVAL

Not applicable. This study did not involve any human or animal subjects requiring ethical approval.

DATA AVAILABILITY

The dataset used in this study is openly available on Kaggle at https://www.kaggle.com/datasets/rodsaldanha/arketing-campaign. It contains anonymized information related to a marketing campaign, including customer demographics, campaign responses, and transactional attributes. All data used were publicly accessible and used in accordance with Kaggle's terms of use. No personally identifiable information was included in the dataset.

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BIOGRAPHIES OF AUTHORS

Aditi Bansal is currently pursuing a B.E. in Computer Science and Engineering as a third-year student at Chandigarh College of Engineering and Technology, Chandigarh, India. She can be contacted at email: aditi.bansal0703@gmail.com.

Ankit Gupta received the B.E. (CSE), M.Tech. (CSE), and Ph.D. degrees. He is currently an assistant professor in the Department of Computer Science and Engineering at Chandigarh College of Engineering and Technology, Chandigarh, India. His research interests include artificial intelligence, web intelligence, web analytics, multi-criteria decision making, and information retrieval. He can be contacted at email: theankit@yahoo.com.