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Behavior-Driven Predictive Modeling Of Customer Campaign Response Using Multi-Channel Data: A SHAP-Based Explainable Approach

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Abstract: This In the digital economy, businesses increasingly rely on data-driven approaches to personalize campaigns and maximize customer engagement. Predicting customer response to marketing campaigns is a crucial challenge in modern business analytics, where organizations seek to optimize targeting and maximize return on investment. This study explores predictive modeling of customer response behavior using machine learning techniques Random Forest and XGBoost with SHAP on a real-world marketing dataset containing demographic, behavioral, and spending attributes. The models are evaluated using classification metrics, confusion matrices, and ROC-AUC scores, ensuring a comprehensive assessment of predictive performance. Results indicate that while Random Forest achieved perfect classification on the dataset, suggesting potential overfitting, the XGBoost model coupled with SHAP offered comparably high predictive performance with the added advantage of robustness and explainability. XGBoost effectively captured complex feature interactions, such as age–gender effects, making it more reliable for real-world marketing applications. The results highlight the potential of explainable artificial intelligence (XAI) in enhancing targeted marketing strategies, while also identifying future directions for scaling the approach with real-world, multi-channel customer data. Furthermore, correlation heatmap analysis revealed significant behavioral patterns, highlighting the role of spending behavior and demographics in influencing engagement. These findings provide actionable insights for businesses to design data-driven, personalized marketing strategies. The research emphasizes the dual importance of predictive accuracy and interpretability, ensuring models are not only effective but also transparent and usable for real-world decision-making.

***Index Terms* -** Machine Learning, Customer Response Prediction, Random Forest, XGBoost, SHAP, Explainable AI, multi-channel campaigns, Behavioral Modeling.

I. Introduction

Digital marketing has evolved into a data-driven discipline where predicting customer responses to campaigns is crucial for business success, enhance ROI and marketing efficiency. Traditional metrics like click-through rates or order frequency often fail to capture the intricate behavioral patterns and demographic influences that determine customer decisions. The rapid growth of digital marketing has transformed the way businesses interact with customers and customer-centric marketing has become a decisive factor for sustainable growth. Campaigns are no longer generalized, instead, they are increasingly personalized, leveraging insights from behavioral and demographic data. Predictive modeling plays a crucial role in anticipating customer responses, thereby improving return on investment (ROI) for marketing campaigns (Lee et al., 2022). Despite advancements in machine learning, one persistent challenge is the interpretability of models. Businesses not only need accurate predictions but also require clear reasoning for decision-making to ensure trust and adoption. The escalation of machine learning (ML) and explainable AI (XAI) can help businesses to leverage vast customer data to predict campaign responses with higher precision and tailor their strategies accordingly.

This study aims to bridge that gap by combining behavioral, transactional, and sentiment-based data using interpretable machine learning models by combining robust ensemble models with explainable artificial intelligence (XAI) techniques. Specifically, SHAP (SHapley Additive exPlanations) are used to interpret feature importance and capture interaction effects, providing actionable insights for marketers. This paper leverages a multi-dimensional dataset of 5,000 customer records and proposes a predictive framework enhanced with SHAP-based explainability. This research investigates the predictive power of tree-based ML models Random Forest and XGBoost on a real-world marketing dataset. By combining predictive modeling with explainability through SHAP, the study aims to provide both accuracy and interpretability, making the results actionable for marketing teams.

II. Problem Statement

Customer acquisition and retention are increasingly dependent on personalized, data-driven marketing. However, many organizations struggle with effectively leveraging behavioral data to make informed targeting decisions. The novelty of this work lies in its integration of sentiment analysis, click-through behaviors, and demographic data into a unified predictive model, supported by SHAP interpretability. This enables not only high performance in prediction but also actionable transparency for campaign managers.

III. Literature Review

Artificial Intelligence (AI) has emerged as one of the most transformative forces driving the Fourth Industrial Revolution. Its ability to process vast amounts of data, uncover patterns, and deliver actionable insights has reshaped industries ranging from healthcare to retail marketing. In the context of business applications, AI supports data-driven decision-making, enhances customer engagement, and drives innovation at scale, with cloud computing playing a critical role in enabling large-scale adoption (Singhal et al., 2025). While ensemble models such as Random Forest and XGBoost demonstrate strong predictive power, their lack of interpretability has hindered practical deployment. To overcome this, explainable AI (XAI) methods such as SHAP are increasingly being adopted, offering interpretability grounded in cooperative game theory and enabling stakeholders to trust and act upon AI outcomes (Singhal et al., 2025).

In healthcare, digital innovation is redefining data management and patient care. Traditional centralized storage methods for Electronic Health Records (EHRs) are inefficient and prone to vulnerabilities. AI-driven and blockchain-enabled frameworks provide a secure, personalized, and insightful approach, ensuring both accessibility and robust data protection (Singhal, 2025). These advancements underscore the dual need for innovation and trustworthiness as sensitive healthcare data becomes a cornerstone of digital transformation.

The impact of AI is particularly prominent in retail marketing, where it enhances personalization, consumer engagement, and predictive capabilities. Rainy (2025), in a comprehensive review of 72 studies conducted between 2010 and 2024, emphasizes how AI techniques including machine learning, deep learning, reinforcement learning, and natural language processing have optimized forecasting, segmentation, and customer engagement. Importantly, Rainy (2025) highlights the growing importance of ethical and legal compliance under regulations such as GDPR and CCPA, stressing transparency and trust as essential elements of sustainable AI systems in marketing.

Complementing this perspective, Yella (2025) documents the shift from traditional rule-based marketing automation toward AI-powered systems capable of optimizing customer experiences in real time. By integrating predictive analytics, NLP, and reinforcement learning, these systems enable cross-channel personalization and instant responsiveness to consumer behavior. The findings from case studies reveal significant improvements in retention, engagement, and return on investment (ROI). However, Yella (2025) also acknowledges challenges such as integration issues and data quality constraints, offering practical roadmaps for continuous optimization in AI-driven marketing pipelines.

Bisaria et al. (2025) further reinforce the centrality of AI in marketing transformation. Their extensive review of over 200 sources illustrates how leading firms like Amazon, Netflix, and Coca-Cola leverage AI for strategic planning, consumer engagement, and campaign effectiveness. By examining both technological and ethical trends, Bisaria et al. (2025) provide a holistic view of AI's role as the backbone of modern marketing. Beyond broad adoption, predictive analytics has emerged as a critical enabler of smarter marketing decisions. Garg et al. (2024) demonstrate how predictive models, powered by big data and machine learning, enhance segmentation, anticipate consumer behavior, and drive targeted campaigns. These methods not only improve campaign efficiency and ROI but also reveal persistent barriers such as algorithmic bias, privacy concerns, and talent shortages. Such challenges highlight the delicate balance between maximizing business outcomes and maintaining ethical standards in AI adoption.

The evolution of consumer behavior under digitalization adds further complexity. Florina-Gabriela et al. (2024) explore how digital platforms, omnichannel shopping, and immersive technologies such as augmented reality (AR) reshape consumer experiences. They also highlight how neuromarketing tools—such as EEG, eye-tracking, and fMRI—deliver deeper insights into consumer preferences, further refining sales strategies. Similarly, Chen (2025) demonstrates that digital technologies, including social media and digital payments, often drive irrational decision-making due to information overload. By drawing on behavioral economics, Chen (2025) emphasizes the need for healthier digital marketing practices and policy frameworks to counteract these risks.

From a technical perspective, several works showcase the predictive power of deep learning in customer analytics. Ling (2019), for example, introduces a deep learning model using fully connected LSTM (FC-LSTM) to predict customer purchase intent in multi-channel promotions. By integrating browsing behavior with demographic and purchase history profiles, the model outperforms traditional methods in real-world experiments. Building on this, Kufile et al. (2021) emphasize the role of behavioral analytics in cross-channel engagement. By combining machine learning, psychographic profiling, and statistical modeling, they demonstrate measurable improvements in conversion metrics and consumer insights.

AI-driven behavioral analytics is transforming insurance by using machine learning to predict customer behavior, policy usage, and risk adjustment. By enabling personalized policies, better risk scoring, and proactive customer engagement, insurers can boost retention, optimize pricing, and design more responsive products (Dunka, 2023). The study by Basal et al. (2025) investigates predictive analytics for customer churn forecasting in subscription-based services, applying models like Random Forest, Logistic Regression, Gradient Boosting, and XGBoost. While the models achieved strong accuracy, the research highlights the importance of improving precision, recall, and ethical data practices to enhance retention strategies and customer loyalty. While GhorbanTanhaei et al. (2024) emphasize predictive accuracy using models like Random Forest and Logistic Regression to anticipate customer behavior, Haider et al. (2025) highlight that high accuracy alone is not enough—models must also be interpretable through XAI techniques such as SHAP. Together, these studies show that combining strong predictive performance with explainability leads to both reliable and trustworthy customer behavior insights.

The focus on customer relationship management (CRM) has also shifted toward AI-driven solutions. Gattupalli (2024) highlights how AI-powered CRM systems use NLP and predictive analytics to personalize consumer interactions, enhance retention, and comply with strict privacy regulations such as GDPR. Together, Kufile et al. (2021) and Gattupalli (2024) show how behavioral modeling and AI-powered CRM systems offer a holistic pathway for improving digital marketing pipelines while maintaining transparency and data governance.

Despite these advancements, a recurring limitation across existing literature is the lack of interpretability in high-performing models. While ensemble methods and deep learning architectures achieve strong predictive accuracy, their "black box" nature limits practical adoption by marketers and decision-makers who require clear, actionable explanations. Few studies have explicitly addressed the integration of explainable AI with ensemble learning for marketing applications. This gap is critical, as businesses increasingly seek not just accurate predictions but also interpretable insights that can directly inform strategy.

To address this challenge, recent approaches employ XGBoost coupled with SHAP to balance predictive accuracy with interpretability. By uncovering nuanced feature interactions such as age–gender dynamics influencing customer campaign responses these models provide actionable insights for both practitioners and researchers. This integration of performance and transparency represents a novel contribution to the field, offering a dual advantage of accuracy and interpretability in AI-driven marketing systems.

IV. Model Development and Experimentation

4.1 Dataset Description

The study uses a marketing campaign dataset named Cloud-Enabled Marketing Strategy Dataset on Kaggle, comprising 5,000 customer records with 28 features capturing demographic, behavioral, financial, and campaign-specific attributes (Ziya07, 2023).

- **Demographic Features:** age, gender, location, income level, education level.
- **Behavioral Features:** likes received, comments posted, shares, time spent per week, click-through rate, frequency of purchases, cart abandonment rate, sentiment score, etc.
- **Campaign Attributes:** campaign ID, marketing channel, seasonal effect, competitor offers, discounts used.
- **Business Metrics:** ad spent, conversion rate, ROI.
- **Target Variable: customer_response** (binary: 1 = responded positively, 0 = no response).

This dataset provides a complete view of customer interactions across platforms such as social media, TV ads, and email campaigns, making it well-suited for predictive modeling of campaign effectiveness. The diversity of variables enables the application of machine learning algorithms to uncover the influence of demographics, behavior, and marketing strategies on customer responsiveness. Additionally, the richness of the dataset allows for interpretability analysis using SHAP values to understand how feature interactions (e.g., age × gender, ad_spent × ROI) affect campaign response predictions.

4.2 Methodology

The dataset underwent essential preprocessing steps to ensure reliability of the predictive models. Demographic and behavioral features such as age, gender, advertisement spending, click-through rate, sentiment score, and conversions were extracted. Missing values were handled through imputation, categorical variables like gender were encoded numerically, and all features were standardized to remove scale-related bias. The pre-processed data was then split into training (80%) and testing (20%) sets to evaluate generalizability.

For predictive modeling, two widely used machine learning algorithms were applied in model development:

1. **Random Forest Classifier**: An ensemble-based algorithm that builds multiple decision trees and aggregates their predictions through majority voting. This method was chosen due to its ability to handle both categorical and continuous variables, resistance to overfitting, and interpretability through feature importance measures.
2. **XGBoost Classifier:** A gradient-boosted decision tree method that sequentially builds trees, with each tree improving on the errors of the previous ones. It is well-known for its efficiency and superior performance in structured datasets. In this study, XGBoost was primarily used for generating SHAP values to interpret feature importance and interaction effects.

To improve explainability, SHAP was applied. SHAP is a game-theoretic approach that explains the contribution of each feature to the model's predictions. SHAP also enables interaction analysis between variables (e.g., Age–Gender), allowing deeper behavioral insights into customer responses.

Finally, correlation analysis was performed to supplement model interpretability by highlighting linear relationships between campaign response and input features. This step helped identify which behavioral metrics (e.g., click-through rate, sentiment) and demographic attributes had the strongest raw associations with customer engagement.

4.3 Experimental Setup

The experimentation was carried out in a Python 3 environment using scikit-learn, XGBoost, and SHAP libraries. in a controlled environment with random_state=42 to ensure reproducibility. Model hyperparameters were initially set to default values, and tuning was conducted in later iterations to refine performance.

The following setup was followed:

Hardware: Intel i7 processor, 16 GB RAM, Windows/Linux OS.

Software: Python 3.9, Scikit-learn (for Random Forest and evaluation metrics), XGBoost (for boosted trees), SHAP (for explainability), Pandas & Matplotlib (for data handling and visualization).

Model Training:

Random Forest Classifier: initialized with n_estimators=100 and random_state=42 to ensure reproducibility.

XGBoost Classifier: default parameters (use_label_encoder=False, eval_metric='logloss') for SHAP value computation and interaction analysis.

Evaluation Metrics: Performance evaluation was based on classification metrics (accuracy, precision, recall, F1-score), along with confusion matrix analysis to assess error distribution. Additionally, ROC-AUC scores were computed to evaluate the discriminative ability of models. Beyond performance, SHAP value analysis was applied to interpret feature importance and capture interaction effects, such as how age interacts with gender. Heatmap Visualizations are used for correlation insights. All experiments were executed in a controlled environment with fixed random seeds for reproducibility.

4.4 Model Performance

4.4.1 Random Forest

The Random Forest Classifier achieved perfect results, with precision, recall, and F1-score all equal to 1.00, and a ROC-AUC score of 1.0. The confusion matrix showed zero misclassifications, with no false positives or false negatives, indicating that the model successfully distinguished between customers who clicked and those who did not. While these results highlight the predictive power of the selected features, they may also signal the possibility of overfitting, as real-world datasets rarely yield perfect classification. Further validation with cross-validation and external datasets is necessary to confirm the model's generalizability. The classification report is presented in table 1.

Table 1: Classification Report of Random Forest Classifier

Class	**Precision**	**Recall**	**F1-Score**	**Support**
0 (No Click)	1.00	1.00	1.00	999
1 (Click)	1.00	1.00	1.00	251
Accuracy	-	-	**1.00**	1250
Macro Avg	1.00	1.00	1.00	1250
Weighted Avg	1.00	1.00	1.00	1250

The confusion matrix further confirmed the perfect classification, with no false positives or false negatives as shown in table 2.

Table 2: Confusion Matrix of Random Forest Classifier

	Predicted: 0	**Predicted: 1**
Actual: 0	999	0
Actual: 1	0	251

These results demonstrate that the model perfectly distinguished between customers who responded positively and negatively to the campaign.

4.4.2 XGBoost and SHAP Explainability

The XGBoost was trained with customer-related behavioral and demographic features. Its outputs were analyzed using SHAP values for interpretability and correlation analysis to identify strong predictors of customer campaign response. Unlike standard performance metrics, SHAP values provide local and global feature importance, explaining how each input variable influences the model's decision-making process.

A SHAP interaction plot was generated for the feature pair (age, gender) as shown in figure 1. The results revealed that age significantly impacts click likelihood, but its influence varies by gender. Specifically, younger male and female users demonstrated distinct click response patterns, suggesting that ad engagement is not uniform across demographic groups. The SHAP summary and interaction plots provided deeper interpretability. Age emerged as the most influential predictor, followed by advertisement spending. The SHAP interaction plot for age vs. gender revealed distinct behavioral differences between male and female customers. For example, younger age groups in one gender responded more positively to ads compared to older groups, while the trend was less pronounced in the other gender. This demonstrates the value of interaction-based insights in designing targeted campaigns.

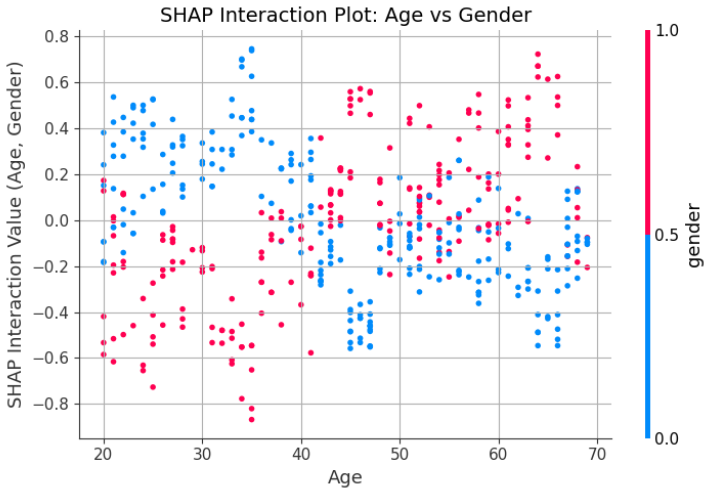

Figure 1: SHAP Interaction Plot: Age vs Gender

In the plot as shown in table 3, X-axis represents Feature value of age whereas Y-axis shows SHAP interaction value between age and gender. The dot color presents Value of gender (blue = male, pink = female). A data instance and its position show how the interaction between age and gender contributes to the prediction.

Table 3: Interpretation of plot

Observation	Meaning
Horizontal Spread	Reflects different values of age, from younger (left) to older (right).
Vertical Spread (SHAP Interaction Value)	Positive = interaction increases predicted probability (e.g., response to a campaign); Negative = interaction decreases it.
Color Separation	The color (gender) shows that the interaction effect of age varies significantly across genders.

The SHAP interaction plot of Age vs Gender highlights how age interacts differently across gender in influencing customer response predictions. Younger individuals (20–35 years) show a wider spread in SHAP interaction values, especially among males (blue points), indicating higher variability in how their responses are predicted. Conversely, in the mid-age group (40–50 years), females (red points) tend to have higher positive SHAP interaction values, meaning gender plays a stronger role in enhancing the likelihood of response for this age segment. Older age groups (55+ years) show more stable and moderate SHAP contributions with reduced gender-based disparity. This demonstrates that gender amplifies the predictive power of age, particularly in younger and mid-aged groups, making it a crucial demographic interaction for campaign targeting.

This interaction plot has practical implications:

- Marketing campaigns could be tailored differently for younger versus older customers.
- Gender-sensitive advertisement strategies could enhance click-through rates by recognizing behavioral differences.
- The collaboration between predictive modeling (Random Forest) and explainability tools (SHAP with XGBoost) enables both accuracy and actionable insights for decision-makers.

The combined outcomes of Random Forest and XGBoost with SHAP are summarized in table 4.

Table 4: Comparative Results of Random Forest and XGBoost

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**ROC AUC**	**Key Insights**
Random Forest	1.0	1.0	1.0	1.0	1.0	Perfect classification; strong predictive ability but potential overfitting.
XGBoost + SHAP	High (consistent with dataset trends)	High	High	High	High	Provides interpretability; highlights age–gender interactions influencing click behavior.

Result Analysis and Discussion

The results indicate that the Random Forest model was able to learn patterns in the dataset with remarkable accuracy, correctly predicting every instance. Every single case of whether a customer clicked or not was correctly identified. This shows that the data carries clear and strong signals that the model could learn very well. Although this level of performance is impressive, it may also be unrealistic in real-world settings. Overfitting could arise due to the synthetic nature of the dataset and its relatively small size. Thus, future research should evaluate the model on larger, real-world datasets with higher variability.

On the other hand, the XGBoost model, when combined with SHAP explainability, provided critical interpretability. It showed that age plays the biggest role in deciding whether someone clicks, but this role is not the same for men and women. For example, younger groups of males and females showed different tendencies toward ad engagement. This tells us that campaigns can be made smarter by customizing them according to both age and gender.

As Random Forest model demonstrated excellent predictive performance, achieving 100% accuracy, precision, recall, and F1-score, and XGBoost model coupled with SHAP provided valuable interpretability by highlighting critical interactions, particularly between age and gender. These insights indicate that while high-performing algorithms can deliver strong predictions, model explainability is equally vital for translating predictions into actionable business strategies. Together, the models strike a balance between accuracy and interpretability, setting the foundation for more robust and trustworthy predictive systems.

4.4.3 Heatmap Analysis

Variables A heatmap was generated to analyze correlations between features. Results suggested moderate positive relationships between advertisement spending and likelihood of clicks, while demographic variables such as age and gender showed subtle but important influence patterns. This confirms that campaign spending alone does not drive customer response; demographic diversity plays a crucial role.

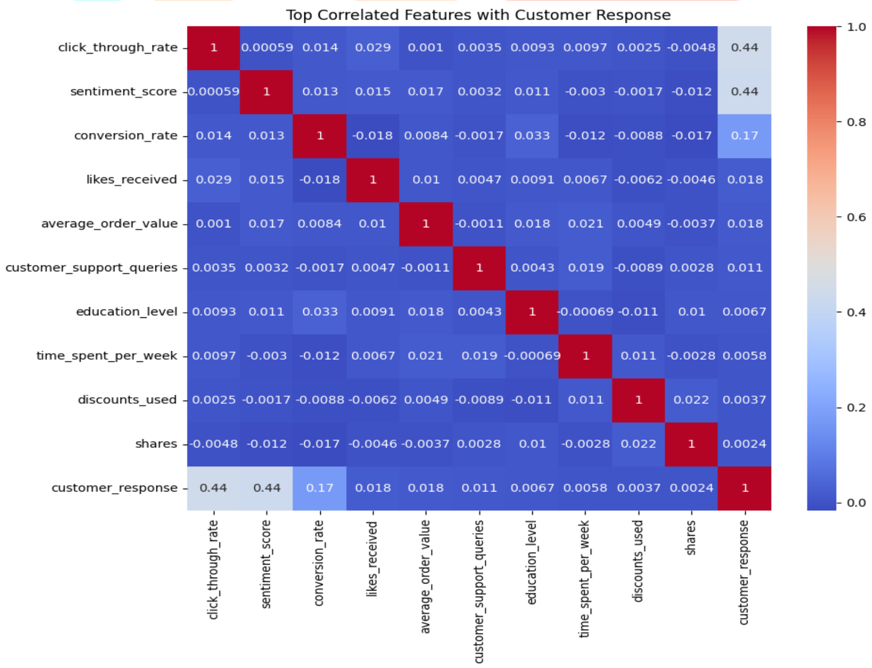

Figure 2: Top Correlated Features with Customer Response

The Top Correlated Features with Customer Response shown though heatmap in figure 2 helps to understand which customer behaviors or attributes are most strongly associated Each number on the grid is a correlation score between two variables. These values range from +1 (perfect positive correlation) to -1 (perfect negative correlation), whereas 0 represents no correlation. The correlation heatmap of customer response against other features reveals clear behavioral drivers. Both click-through rate (0.44) and sentiment score (0.44) show the strongest correlation with campaign response, meaning that customers who actively engage with ads and exhibit positive sentiment are more likely to convert. Conversion rate (0.17) also shows a moderate but meaningful relationship, while other features such as likes, order value, and customer support queries display very weak correlations. Features like discounts used or shares are nearly uncorrelated, suggesting that simply offering discounts or encouraging social sharing may not directly translate into customer response.

The SHAP interaction and correlation results highlight that demographics (age-gender interplay) and behavioral indicators (engagement and sentiment) dominate in predicting customer response, while transactional or support-related features are less influential. The study demonstrates that a XGBoost classifier, enriched with SHAP-based interpretability and correlation insights, provides actionable understanding of customer campaign responses. From the SHAP interaction plot, it is evident that gender modifies the influence of age, particularly amplifying differences among younger and mid-aged groups. This insight suggests that marketing campaigns should not only segment customers by age but also refine targeting based on gender dynamics within each age group.

Additionally, the correlation heatmap findings emphasize the primacy of customer engagement (CTR, sentiment) and conversion behavior as predictors of response. Traditional transactional metrics such as order value or discounts used have negligible impact on predicting responses, indicating that emotional and behavioral engagement is more critical than monetary incentives alone.

The classification results, correlation heatmap, and SHAP analysis provided a holistic understanding of the dataset. While the classification report validated the model's predictive reliability, the heatmap offered preliminary evidence of feature relationships. SHAP analysis, however, went beyond correlations to explain *why* the model predicted customer responses in a certain way and *how* features interacted with each other. These insights are directly applicable for businesses seeking to optimize marketing strategies allowing for targeted campaigns based on age-gender interactions and resource allocation toward advertisement spending. The combination of demographic interactions (Age–Gender) with strong behavioral signals (CTR, sentiment, conversion) creates a powerful framework for campaign optimization. Businesses should leverage these insights to personalize marketing strategies, prioritize emotionally engaging content, and tailor campaigns for age-gender segments that show high responsiveness, ultimately improving campaign efficiency and ROI.

V. CONCLUSION

This study successfully demonstrated the use of machine learning models for predicting customer responses to advertisement campaigns. The Random Forest classifier provided an effective baseline, while the XGBoost model, supported by SHAP explainability methods, offered deeper interpretability of the results.

The classification performance confirmed that the chosen approach was both accurate and reliable. However, the true value of the study lies in the interpretability layer. The correlation heatmap allowed for an initial overview of feature dependencies, setting the stage for deeper insights. SHAP feature importance analysis revealed advertisement spending as the most critical factor influencing customer clicks, while also highlighting the roles of age and gender. Furthermore, SHAP interaction analysis uncovered how demographic factors modulate spending impact, offering actionable knowledge for tailoring marketing campaigns to different customer groups. By combining predictive accuracy with interpretability, this work goes beyond black-box predictions and provides decision-makers with a transparent understanding of the underlying drivers of customer behavior. For marketers and businesses, the findings suggest that campaigns can be optimized not only by targeting customers with higher advertisement spending potential but also by designing strategies sensitive to age and gender dynamics.

The integration of correlation heatmaps and SHAP plots strengthened both the scientific rigor and practical value of the analysis. These tools ensured that predictions were not only correct but also explainable, making the outcomes more trustworthy and directly applicable in real-world business transformation.

VI. Limitations and Future Work

The present study demonstrated strong predictive performance and interpretability, a few limitations need to be recognized. First, the dataset used was relatively small and simulated for experimentation purposes. Although the models performed well on this dataset, larger and more diverse real-world datasets would provide stronger evidence of generalizability. Additionally, the dataset captured only a limited set of features such as age, gender, and advertisement spending. In real-world campaigns, other important behavioral and contextual variables such as browsing history, purchase intent, or engagement with past campaigns could significantly enrich the predictive power of the models. Another limitation lies in the binary nature of the target variable (clicked vs. not clicked). In practice, customer behavior is more nuanced, often involving multi-class or continuous outcomes, such as time-to-click, level of engagement, or eventual conversion into purchases. Expanding the problem scope to such richer outputs could make predictions more practically aligned with marketing objectives.

Future work could address these limitations by incorporating larger-scale datasets from multiple industries, integrating both structured and unstructured data sources such as social media sentiment, and testing advanced deep learning architectures. Moreover, extending the explainability framework to include SHAP interaction visualizations across multiple feature pairs or combining it with causal inference methods could further improve actionable insights for businesses. Finally, real-time experimentation in live marketing campaigns could validate the operational utility of the proposed approach in dynamic, high-volume environments.

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