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Evaluating the Effectiveness of Digital Product Advertisement Type using Machine Learning and Shapley Additive Explanations Analysis

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ABSTRACT

Digital advertising continues to grow rapidly, yet advertisers face persistent uncertainty in selecting the most effective ad format for different campaign objectives and audience segments. Prior studies often rely on limited metrics or lack interpretability, making it difficult to explain why certain formats perform better. This study addresses this gap by evaluating ad format effectiveness using explainable machine learning. This study evaluates the effectiveness of image and video advertisements (ads) across five key performance indicators (KPIs): reach, impressions, link clicks, cost per click (CPC), and cost per thousand impressions (CPM). A dataset of 4,526 campaigns from Meta Ads Manager (July 2021–August 2024) was analysed using machine learning models integrated with Shapley Additive Explanations (SHAP). Model performance was assessed using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2). The results showed that video ads achieved higher reach and impressions with lower CPM. Meanwhile, image ads delivered lower CPCs and stronger click performance, particularly among users aged 13–17 and 55+. Aside from confirming established format patterns, this study made certain contributions by applying explainable machine learning in a large-scale, non-Western context and by clarifying the mechanisms behind ad performance. The findings offered actionable guidance; for example, video ads were optimal for awareness and visibility objectives. Additionally, image ads were preferable for engagement-driven campaigns.

Keywords: Ad type, digital advertising, machine learning, SHAP analysis.

INTRODUCTION

Global digital ad spending is expected to exceed $400 billion, representing over 60% growth from 2022 (Yoon, 2022). This growth showed the influence of digital marketing on consumer behaviour. In addition, image and video advertisements (ads) dominated the diverse formats, with each characterised by distinct advantages. Previous studies reported that image ads were simple and easy to process, while video ads provided valuable storytelling and emotional appeal (Grewal et al., 2021). Selecting the appropriate format was essential to maximising return on investment (ROI). It required more than surface comparisons; it demanded a thorough examination of the factors that triggered consumer responses. Traditional statistical methods were unsuccessful in analysing digital ad performance. These methods struggled with complex human behaviours, which failed to account for endogenous variables, and often introduced specification errors (Farahat & Shanahan, 2013). Outdated information bias detected during collection further undermined accuracy (Prosekov, 2020). Prior studies reported that interpreting ad platform data remained a challenge due to limited ability to draw actionable insights (Braun et al., 2023).

Aside from being foundational, traditional analytics were unable to keep pace with the complexity of modern digital data, which includes high-dimensional variables, intricate interactions, and non-linear relationships. These factors often obscured critical insights, creating gaps in understanding the variables that drove ad success. Additionally, there was a need for tools that could thoroughly process the complexity. Recent studies have focused on how artificial intelligence and network analytics are shaping digital marketing decisions. For example, Abu Bakar et al. (2025) reported that AI-driven social-network models effectively identified influential sellers and products in e-commerce environments, reinforcing the strategic significance of data-driven engagement measurement in online advertising contexts. In this context, machine learning (ML) offered a major advantage over traditional methods by avoiding subjective judgment. It improved precision and enabled more accurate predictions of consumer behaviour (Osakwe et al., 2023). ML models also uncovered subtle patterns and relationships in complex data, which offered a more precise evaluation of ad performance. The models helped explain the functions and performances of certain ad features.

The Shapley Additive Explanations (SHAP) analysis was conducted to evaluate and incorporate model outputs into value-based contributions from each feature, thereby improving interpretability. In addition, this method was used to translate ML results into meaningful, strategic insights. The method has also been proven useful in other fields such as public policy, energy and business, where it extracted insights from consumer satisfaction data (de Carvalho & da Silva, 2021), supported grid stability planning (Hamilton & Papadopoulos, 2023), and clarified demand forecasts in direct sales (Arboleda-Florez & Castro-Zuluaga, 2023), respectively. Furthermore, SHAP is prominent for its theoretical soundness and practical relevance, compared to tools such as Local Interpretable Model-agnostic Explanations (LIME) and permutation importance (Kedar, 2024).

Previous studies had three limitations: first, the majority focused on a single metric, namely click-through rate (CTR) or conversions, excluding visibility–cost trade-offs (i.e., reach, impressions, CPC, cost per mille (CPM)). For example, Patil et al. (2022) adopted CTR and click data to improve campaign strategies. Lakshmanarao et al. (2021) also used reinforcement learning to optimise ad positioning. Second, few studies adopted explainable ML methods to show why format effects differed across audience segments and campaign objectives. Third, most large-scale analyses were conducted in Western or platform-agnostic settings, leaving a gap in evidence from non-Western, platform-native contexts. Therefore, the present study addressed these gaps by applying ML models and SHAP analysis to evaluate image and video ads across multiple key performance indicators (KPIs), explicitly modelling interactions among format, audience, and objective. The insights guided advertisers in selecting creative formats that aligned with campaign objectives and demographics. Based on this perspective, the present study aimed to:

1. Compare the effectiveness of image and video ads across reach, impressions, link clicks, CPC, and CPM.
2. Examine how demographics interact with ad formats to affect outcomes.
3. Identify significant performance drivers and provide actionable guidance for ad optimisation.

The combination of ML and SHAP analysis enabled performance assessment and explained the associated mechanisms. These insights helped marketers match ad formats to audience preferences and campaign objectives, improving both cost efficiency and engagement.

RELATED WORKS

The combination of ML models and SHAP analysis was a promising approach for evaluating the effectiveness of image and video advertisements across various KPIs. This review synthesised studies on the application of ML to ad performance, the role of KPIs in digital advertising, the comparative effectiveness of image and video ad formats, and the interpretability provided by SHAP analysis.

Comparing Image and Video Ad Effectiveness

The effectiveness of image and video ads depended on audience engagement and campaign KPIs. Previous studies reported that video ads generally outperformed images in terms of reach, impressions, and interaction rates, making them effective for cost-efficient engagement and emotional storytelling (Grewal et al., 2021; Tavares et al., 2023). Video content enhanced brand recall and consumer interest, with emotional messaging driving stronger engagement and conversions than static images (Prihatiningsih et al., 2024; Félegyházi, 2024). In context-related settings, midroll video ads were most effective at boosting brand recall and shaping related attitudes (Stewart et al., 2023). Image ads performed better in direct engagement, particularly in transactional or community-driven campaigns. These ads often achieved higher CTR and were more cost-efficient per view (Northcott et al., 2021; Mihajlović et al., 2024). The clarity and visual simplicity prompted quick actions, such as app downloads or ticket purchases, outperforming video ads in reactions, comments, and shares (Tavares et al., 2023; Stewart et al., 2023). Ad-context congruence also influenced performance, while image ads benefited more with consistent content across digital platforms (Xie et al., 2024).

The strategic combination of both formats, based on campaign objectives and audience behaviour, maximised results. Video and image ads supported long-term brand building and immediate responses, respectively (Grewal et al., 2021; Northcott et al., 2021). Moreover, Chumwatana (2018) explored comment- and sentiment-analysis methods using Thai social-media reviews to assess customer satisfaction. This study described the relevance of linguistic and cultural factors in interpreting consumer reactions to visual content, an aspect that complemented analyses comparing the effectiveness of image and video ads. The findings described the significance of selecting ad formats based on context, audience segmentation, and marketing objectives, as shown in Table 1.

Table 1

Related Works for Image and Video Ad Effectiveness

System	Methodology	Results
Grewal et al. (2021)	Used multimedia data (video, image, text, audio) with ML and NLP fusion to analyse and predict ad outcomes.	Video ads drive stronger emotion and storytelling; image ads perform better for direct response. Combining both maximises effectiveness.
Tavares et al. (2023)	Analysed Facebook campaigns comparing video and image formats across engagement metrics (reach, impressions, CPM, cost, reactions, shares).	Video ads outperformed in reach, impressions, and CPM; image ads led in comments, reactions, and shares.
Prihatiningsih et al. (2024)	Applied quantitative survey with descriptive and inferential analysis to assess ad engagement.	Video content sustains attention longer and delivers higher engagement and conversion than static images.
Félegyházi (2024)	Conducted A/B testing of visual ad formats to evaluate engagement and performance.	Video ads achieved lower click costs and higher engagement; optimising visual content boosts campaign success.
Stewart et al. (2023)	Combined online experiment and field study comparing Facebook ad formats using vividness and fit theory.	Image ads generated more purchase clicks; video ads increased social engagement.
Northcott et al. (2021)	Compared image vs. video ads by cost efficiency and engagement (CTR, downloads).	Image ads were more cost-effective and achieved higher reach and engagement.
Mihajlovic et al. (2024)	Used A/B testing on static vs. animated images and carousel posts.	Static image ads had lower CPC and higher ROI; carousel posts outperformed video ads by ~32% ROI.
Xie et al. (2024)	Analysed 6 million Snapchat user sessions to assess ad-context and format congruence.	Content congruence increased viewing time; format congruence benefited image ads but reduced video ad views.

ML in Advertising Performance

ML has transformed digital advertising by replacing intuition-based methods with data-driven strategies. These technologies enabled precise predictions of campaign performance, audience targeting, and ad optimisation, leading to improved engagement, including ROI (Chavda & Patel, 2024). The significant applications included intelligent bidding, audience segmentation, and automated ad placements, which ensured ads reached the appropriate audiences and at the right time (Booth, 2019). Additionally, deep learning and natural language processing (NLP) enhanced personalisation by analysing sentiment and refining campaigns in real time (Nwaimo et al., 2024; Ji et al., 2024).

Yang et al. (2019) reported that tools such as Baidu's AiAds system influenced ML by refining bidding strategies and maximising performance. Furthermore, advanced algorithms such as reinforcement learning optimised ad positioning. Predictive models also forecasted essential metrics, including CTR, campaign profitability, and return on ad spending (ROAS) (Lakshmanarao et al., 2021; Jha et al., 2024). These innovations empowered advertisers to make informed decisions, allocate resources effectively, and achieve measurable outcomes. Complementing the advances, Ismail and Yusof (2022) systematically reviewed ten years of machine-learning prediction studies based on open data. It was reported that integrating open datasets and ML methods enabled more accurate, scalable forecasting across social-network and marketing applications. The findings outlined the value of transparent, data-rich environments for improving predictive accuracy and guiding marketing optimisation. The ongoing evolution of ML further enhanced the efficiency and strategic impact of advertising. Table 2 presents related work on ML in advertising.

Table 2

Related Works for ML in Advertising

Authors	Methodology	Results
Patil et al. (2022)	ML models were developed and evaluated to predict CTR and ad clicks on social media platforms.	The study developed an ML model to predict CTR and ad clicks, providing insights to optimise the effectiveness and efficiency of advertising campaigns.
Lakshmanarao et al. (2021)	The study utilised a Kaggle dataset and applied two reinforcement learning algorithms, Upper Confidence Bound and Thompson Sampling, to predict ad positions based on ad clicks, implemented in Python.	The study achieved high accuracy and demonstrated that ad placement significantly influences click rates.
Chavda and Patel (2024)	Systematic review of the existing literature on using ML to enhance online advertising ROI	Integrating ML enhances online advertising by analysing large data sets to identify target audiences, predict potential customers, and maximise ROI.
Ji et al. (2024)	The study used ML models to analyse customer behaviour data, predict user intent, and enhance personalisation in e-commerce and targeted advertising.	ML has transformed advertising by enabling precise targeting and engaging experiences through advanced data processing and analysis, surpassing traditional intuition-based methods.
Yang et al. (2019)	The study included the design, development, and implementation of the AiAds system by Baidu, leveraging ML methods to automate core components of the sponsored search process.	The AiAds system significantly enhances advertiser campaign performance, user experience, and advertising platform revenue in the sponsored search ecosystem.
Jha et al. (2024)	The study conducts experimental simulations of various RTB methods using real-world datasets and advertising campaigns, analysing its performance across metrics.	The analysis identifies that the Constrained Markov Decision Process-based model outperformed other methods across key metrics, achieving higher CTRs, CRs, and ROI, while optimising win rates, CPM, and E-CPC.
Kedi et al. (2024)	The study analyses existing literature, case studies, and tools to evaluate how ML enhances social media advertising through audience segmentation, predictive analytics, and campaign optimisation.	ML enhanced advertising efficiency and personalisation. This method helped SMEs overcome resource constraints. However, challenges such as data quality and technical expertise persisted.

SHAP Analysis in ML for Ad Interpretability

SHAP analysis is a significant tool for improving the interpretability of ML models in marketing analytics. Developed by Lundberg and Lee (2017), this tool assigned importance scores to features, offering clear insights into how each input affected model predictions. Its flexibility made it worthwhile across a range of complex models, including deep neural networks and ensemble methods (Rodríguez-Pérez & Bajorath, 2020).

In marketing and sales, SHAP helped refine demand forecasting by isolating the impact of individual features, enabling businesses to effectively integrate ML insights into decision-making (Arboleda-Florez & Castro-Zuluaga, 2023). Considering computational advertising, it clarified both global model behaviour and feature importance across categories. For example, visual content played a relevant role, with SHAP showing how its impact varied by product type and supporting more designed strategies (Santos, 2023). Regarding advertising, SHAP helped interpret the outcomes of high-accuracy models. For example, this tool was used to explain a Random Forest model that predicted user behaviour with 97.67% accuracy (Al-Khafaji & Karan, 2024). The insights enabled advertisers to understand the diverse variables, such as ad type, content, and targeting, that impact performance (Zhao & Harinen, 2019). Even when general and category-specific click models performed similarly, SHAP revealed feature patterns that supported personalised strategies (Santos, 2023). At the individual level, it also helped reduce misclassification and supported predictions aligned with business objectives.

These findings outlined the value of explainable Artificial Intelligence (AI) in marketing. Furthermore, tools such as SHAP helped marketers to strike a balance between predictive accuracy and transparency, enabling the ethical and effective applications of ML. SHAP also played a major role in building trust, driving the adoption of AI in advertising. Previous studies on online advertising reviewed three main gaps. First, the majority optimised a single outcome, such as CTR or conversions, without jointly modelling visibility and cost metrics. As a result, the trade-offs among CPM, CPC, reach, impressions, and clicks were not fully understood (Yang & Zhai, 2022; Asdemir, Kumar, & Jacob, 2012). Second, explainable ML methods, including SHAP, have been applied in other domains, but advertising analysis has not systematically used them to identify how demographic factors, budgets, and objectives interact with creative formats (Lundberg & Lee, 2017; Cunha & Barbosa, 2024). Third, the existing evidence base was dominated by Western or platform-agnostic datasets, ignoring large-scale, platform-native studies in non-Western contexts (Huang et al., 2020).

This study addressed the gaps by comparing image and video ads across five KPIs, namely *reach*, *impressions*, *link clicks*, CPM, and CPC, using an explainable ML framework. A model format-audience-objective interactions was explicitly incorporated in first-party Meta Ads Manager data from Indonesia, thereby extending the evidence base beyond Western contexts.

THE PROPOSED METHOD

This study adopted a multi-outcome modelling method that combined predictive accuracy with interpretability. ML was used to predict campaign outcomes, while SHAP values provided transparent, feature-level attributions. This integrated design allowed the (i) comparison of image and video performances across five KPIs, (ii) attributed differences to campaign features such as budget, audience age, and objective, as well as (iii) translated results into actionable recommendations for advertisers. In addition, the study advanced beyond average-effect comparisons, offering goal-conditioned prescriptions for creative choice.

The analysis used data from the Meta Ads Manager platform, designed by an educational institution in Indonesia. The dataset included 4,526 ad campaign records collected between July 2021 and August 2024. All data handling procedures adhered to ethical guidelines approved by the institution's review board, ensuring compliance with privacy regulations. Personal information was anonymised to protect individuals' privacy, thereby supporting applicable data protection laws. The analysis was conducted mainly in Google Colab for its accessibility and ease of use. Python 3.10.12 was also used with the necessary libraries preloaded for efficiency.

Dataset

The original dataset comprised 13 columns, with 2 additional features engineered to enrich the dataset. Furthermore, the campaign duration was calculated by subtracting the start date from the end date. The ad type was derived from patterns in the campaign name and ad set name, classifying each as either image-based or video-based. After feature engineering, the campaign name, ad set name, start, and end were removed from the dataset to focus the analysis on relevant variables. A detailed description of the refined dataset is shown in Table 3.

Table 3

Refined Dataset Description

Column No.	Column Name	Column Type	Description
1	Objective	Feature	The goal of the ad campaign (e.g., brand awareness, conversions, lead generation, link clicks, outcome awareness, outcome engagement, outcome leads, and outcome sales).
2	Age	Feature	The age group targeted by the ad (13-17, 18-24, 25-34, 35-44, 45-54, 55-64, 65+).
3	Gender	Feature	The gender targeted by the ad (male, female).
4	Reach	Target	The number of unique users who saw the ad at least once.
5	Impressions	Target	The total number of times the ad was shown to users (may include repeats).
6	Amount spent (IDR)	Feature	The total cost spent on the ad campaign in Indonesian Rupiah (IDR).
7	Link clicks	Target	The number of times users clicked on the ad link.
8	CPC	Target	The average cost for each link click (Amount spent/Link clicks).
9	CPM	Target	The cost of the ad per 1,000 impressions (Amount spent / Impressions × 1,000).
10	Campaign Duration	Feature	The length of time the ad campaign was active (e.g., 7 days, 14 days, 30 days, etc.).
11	Ad type	Feature	The format of the ad (image, video).

Campaigns with zero values in KPIs such as reach, impressions, link clicks, CPC, and CPM were excluded to ensure solid analysis. The removal of those with missing values reduced the dataset from 4,526 to 4,289 rows. These steps helped maintain a dataset that was both comprehensive and relevant for addressing the proposed study questions (Das et al., 2023).

Data Pre-processing

The dataset was subjected to pre-processing before analysis, with categorical variables, namely gender, age group, objective, and ad type, transformed into numerical format. It was realised using label encoding, which assigned a unique integer value to each category (Das et al., 2023). Binary variables such as gender and ad type were encoded as 0 and 1, respectively. Gender was encoded as 0 for female and 1 for male, while ad type was encoded as 0 for image and 1 for video. For multi-category features, age group (seven age ranges) and objective (eight distinct campaign objectives) were encoded sequentially as 0-6 and 0-7, respectively.

Label encoding was preferred over one-hot encoding to maintain data compactness and computational efficiency, particularly considering the presence of multiple categorical features (Kosaraju et al., 2023). This method ensured uniqueness within feature classes while minimising dimensionality (Hancock & Khoshgoftaar, 2020). Following encoding, numerical variables were normalised to standardise respective scales and enhance model interpretability, including performance (Das et al., 2023). Min-max scaling was applied to transform each feature to a [0, 1] range, using the formula in Equation 1.

$$x_{scaled} = (x - x_{min}) / (x_{max} - x_{min}) \tag{1}$$

Where x is the original data value, x_{min} denotes the minimum value of x in the dataset, x_{max} refers to the maximum value of x in the dataset, and x_{scaled} is the normalised (scaled) value of x.

This normalisation prevented features with larger magnitudes (e.g., amount spent) from disproportionately influencing the model over smaller-scale features (e.g., CPC), thereby improving learning stability and comparability (scikit-learn, 2019; mljourney, 2024). Considering alternative normalisation methods, such as Z-score standardisation, robust scaling, and log transformation, Min-max scaling was selected for two main reasons. First, the dataset lacked significant outliers, reducing the risk of distortion. Second, it preserved the original distribution shape of the features, which is important for interpretability. Before training the models, exploratory data analysis (EDA) was conducted to understand feature relationships. It included comparison charts, heatmaps, and feature-importance scores. In addition, the findings from this phase were discussed in the results section.

ML

ML was applied in two main stages, namely (i) prediction of advertising KPIs and (ii) interpretation of feature contributions using SHAP. The prediction of ad effectiveness led to splitting the dataset into training (80%) and test (20%). It followed standard practice to ensure sufficient data for model learning and unbiased evaluation (Das et al., 2023). Meanwhile, three supervised regression models were implemented, namely Linear Regression, Decision Tree, and Random Forest. These were selected for their complementary strengths in handling feature imbalances and non-linear relationships. Linear Regression served as the baseline due to its simplicity, speed, and interpretability (Das et al., 2023). This model also assumed a linear connection between features and their target, using Ordinary Least Squares (OLS) to minimise residual errors. It struggled with non-linear patterns, despite enabling the understanding of the relationship strength and direction. Linear Regression also relied on strict assumptions, including linearity, normal residuals, and low multicollinearity.

Decision Trees provided more flexibility, capturing non-linear relationships through recursive splits based on feature values (Das et al., 2023). Its structure is easy to interpret, with clear decision paths (Kovalerchuk et al., 2023). The model also handled imbalanced features effectively by prioritising more informative variables (Liu et al., 2021), and processed both categorical and numerical data without transformation. Random Forest extended Decision Tree functionality by averaging predictions across multiple trees trained on random subsets of data and features (Das et al., 2023). This ensemble method reduced overfitting and improved generalisation, specifically with imbalanced data. The model minimised feature dominance and increased model diversity by introducing randomness into sampling and feature selection (Ye et al., 2020). It also outputted feature importance metrics, thereby helping identify significant performance drivers.

These models collaboratively offered a balanced framework, realised by combining interpretability, complexity handling, and robustness. The essence was to generate meaningful insights into ad performance, even in data with feature imbalances (Liu et al., 2021; Ye et al., 2020; Balcan & Sharma, 2024). After identifying the best-performing model, SHAP analysis was conducted to enhance interpretability. The values quantified the marginal contribution of each feature to the model's predictions, thereby connecting predictive performance with actionable business insights. It led to the use of ML to improve predictive accuracy and to explain the drivers of ad effectiveness.

Evaluation Metrics

Evaluation metrics played an essential role in assessing ML models. It led to the adoption of four metrics, namely Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2). Additionally, each metric offered a distinct perspective on model performance, ensuring a comprehensive evaluation. MSE measured the average of the squared differences between predicted and actual values. The metric detected larger errors, leading to significant deviations and an overly sensitive response to outliers (Das et al., 2023). RMSE is the square root of MSE, which provides error magnitude in the same units as the target variable. Additionally, it was specifically helpful when significant errors were a concern (Das et al., 2023). MAE calculated the average absolute difference between predicted and actual values. Compared to MSE and RMSE, it does not square errors, which reduces sensitivity to outliers. The metric produced a straightforward measure of average error (Das et al., 2023), with R^2 (coefficient of determination) measuring the proportion of variance in the target variable explained by the model. Moreover, higher values within the range of 0 to 1 represented a better fit. Unlike error metrics, R^2 measures how well the model captures basic data patterns (Chicco et al., 2021). The formulas used to calculate each metric are presented in Equations 2-5.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_{actual,i} - y_{predicted,i})^2 \tag{2}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_{actual,i} - y_{predicted,i})^2} \tag{3}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_{actual,i} - y_{predicted,i}\right| \tag{4}$$

$$\text{R}^2 = 1 - \frac{\sum_{i=1}^{n}(y_{actual,i} - y_{predicted,i})^2}{\sum_{i=1}^{n}(y_{actual,i} - \bar{y})^2} \tag{5}$$

Where n is the total number of data points, $y_{actual,i}$ denotes the actual (true) value for the i^{th} data point, $y_{predicted,i}$ refers to the predicted value for the i^{th} data point, and $\bar{y}$ represents the mean of all actual target values. Each metric captured a different dimension of model performance, MSE focused on large errors, RMSE presented error in usable units, MAE offered robustness to outliers, and R^2 disclosed explanatory power. However, when combined, the metrics provided a complete view of accuracy and generalisability.

SHAP Analysis

Post hoc SHAP analysis was conducted to enhance interpretability and complement model evaluation. The analysis interpreted ML predictions by attributing contributions to individual features using cooperative game theory (Lundberg & Lee, 2017). It explained the model's prediction by distributing the difference between the output and baseline values across all input features (Das et al., 2023). The values obtained were derived using the Shapley value formula, stated in Equation 6.

$$\varphi_i = \sum_{S\subseteq F\{i\}} \frac{|S|!(|F|-|S|-1)!}{|F|!}[f(S\cup\{i\}) - f(S)] \tag{6}$$

Where φ_i is the Shapley value for feature I (representing the contribution of feature i to the model's prediction), S refers to a subset of features from F that does not include feature I, F denotes the set of all features, $f(S)$ represents the model prediction using only the features in subset S, and $f(S \cup \{i\})$ is the model prediction which adopted the features in S, including those in i.

This formula calculated the average marginal contribution of each feature across all possible subsets. Based on previous studies, the formula ensured a fair and comprehensive assessment of feature influence (Lundberg & Lee, 2017). SHAP bridged accuracy and interpretability by clearly showing how features triggered predictions. It also provided a transparent breakdown of model behaviour, helping identify which variables most influenced campaign success. It produced results that were both technically rigorous and practically valuable for optimising advertising strategies. The experimental setup consisted of training three regression models, namely Linear Regression, Decision Tree, and Random Forest, on 4,289 campaigns, using demographic and campaign features to predict five KPIs. An 80/20 train–test split was used to evaluate the models using MSE, RMSE, MAE, and R^2, while SHAP was applied to the best model for interpretation.

EVALUATION AND RESULTS

Descriptive Statistics and Preliminary Analysis

Descriptive analysis was conducted to examine the overall structure and distribution of the dataset before the application of ML models. Table 4 shows the summary statistics for all normalised numerical features. Most variables exhibited low means, such as reach (0.02), impressions (0.03), and link clicks (0.01), representing modest campaign engagement. The age distribution was skewed toward younger users, and the low mean of ad type (0.04) suggested that image ads dominated the dataset. The gender balance was evidence of equal representation (mean = 0.50, standard deviation = 0.50), reflecting equal representation of male- and female-targeted ads.

Table 4

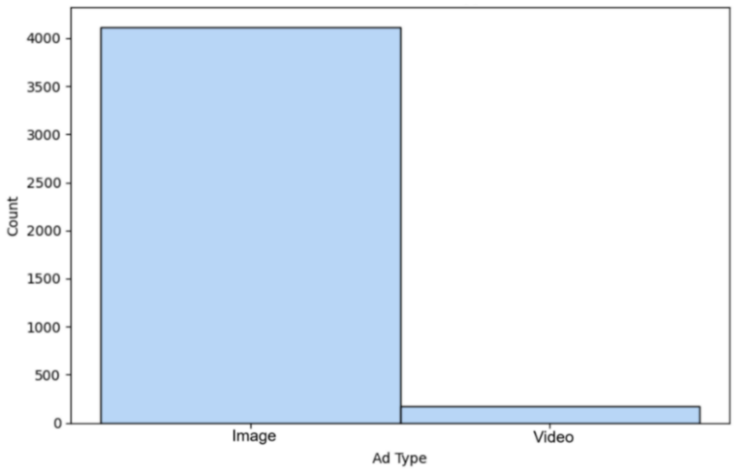
Descriptive Statistics

Statistics (n=4,289)	Mean	Standard Deviation (SD)	Min	25%	50%	75%	Max
Objective	0.55	0.36	0.00	0.14	0.43	0.86	1.00
Age	0.27	0.28	0.00	0.00	0.17	0.50	1.00
Gender	0.50	0.50	0.00	0.00	0.00	1.00	1.00
Reach	0.02	0.04	0.00	0.00	0.01	0.02	1.00
Impressions	0.03	0.06	0.00	0.00	0.01	0.03	1.00
Amount spent (IDR)	0.05	0.07	0.00	0.01	0.03	0.06	1.00
Link clicks	0.01	0.03	0.00	0.00	0.00	0.01	1.00
CPC	0.01	0.03	0.00	0.00	0.00	0.01	1.00
CPM	0.02	0.03	0.00	0.01	0.01	0.03	1.00
Campaign duration	0.36	0.19	0.00	0.20	0.39	0.49	1.00
Ad type	0.04	0.20	0.00	0.00	0.00	0.00	1.00

The descriptive statistics outlined the dominance of image-based ads. The ad type variable had a mean of 0.04 and extremely low percentiles, which confirmed a sharply imbalanced distribution. This imbalance was retained to mirror real-world campaign conditions and preserve external validity (Johnson & Khoshgoftaar, 2019; Lusito et al., 2023). Figure 1 shows the visualised distribution of ad type.

Figure 1

Distribution of Ad Type



Descriptive statistics for reach, impressions, link clicks, CPC, and CPM showed a transparent age gradient. Reach peaks in the 13 to 24 segment for video ads, comprising more than 200,000 users aged 13 to 17. However, this declined sharply in older groups, as shown in Figure 2. Impressions followed a similar pattern to Figure 3, with video ads dominating across every cohort except users aged 25 to 34, due to lower engagement.

Figure 2

Reach by Age and Ad Type

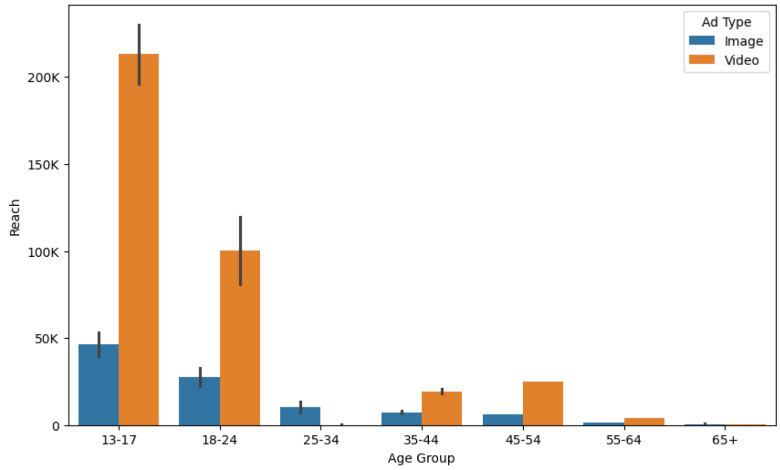
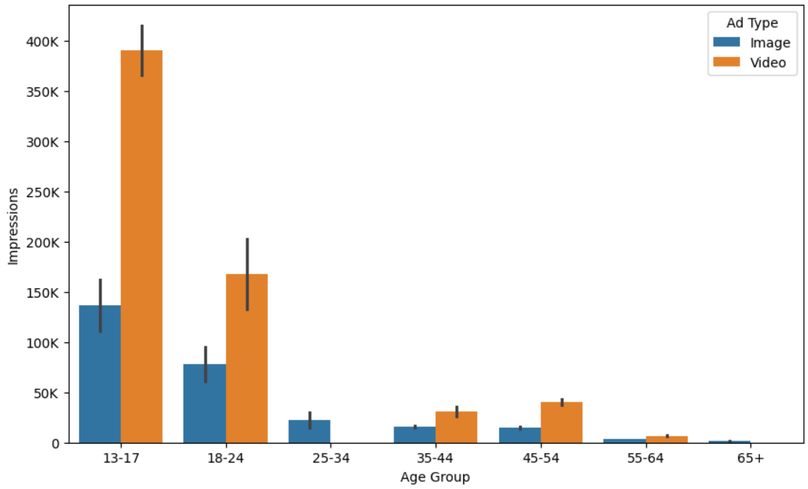


Figure 3

Impressions by Age and Ad Type



Engagement patterns diverged when examining link clicks, with video ads outperforming images among 35 to 54-year-olds. Meanwhile, image ads were for users aged 13–34, including those aged 55 and above, as shown in Figure 4. Gender played a minor role, and video ads were more effective for men, but neither was statistically significant (Figure 5).

Figure 4

Link clicks by Age and Ad Type

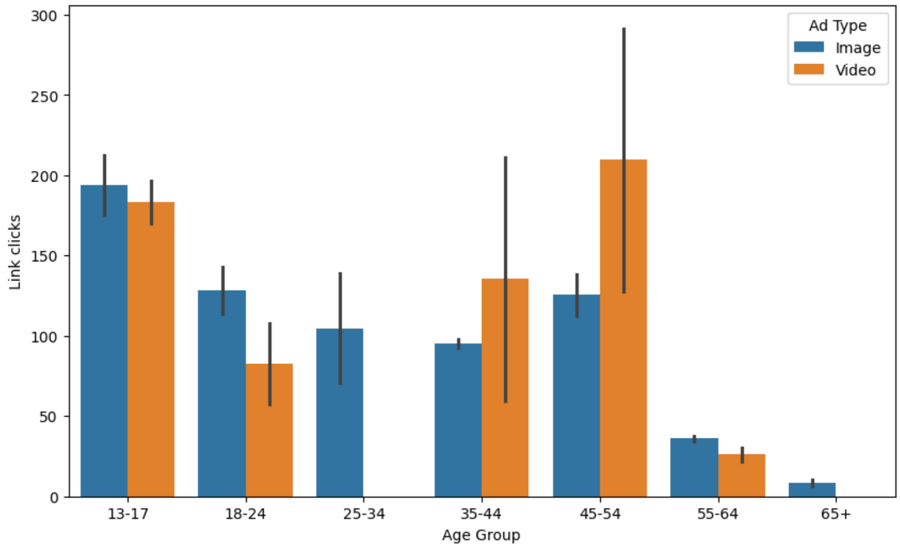


Figure 5

Link clicks by Gender and Ad Type

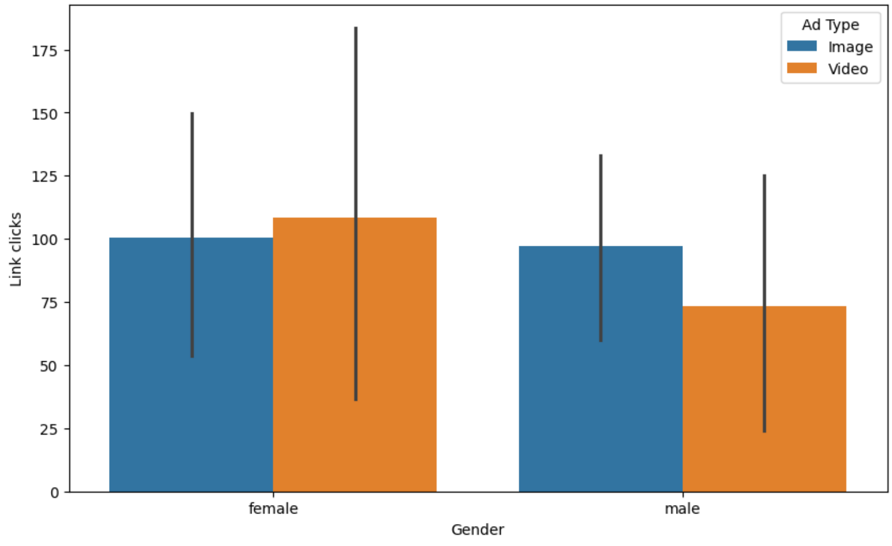


Figure 6 describes video ads' higher CPC, specifically within the 13–17 and 35–54 age ranges. Furthermore, image ads maintained more consistent and lower CPCs across age groups.

Figure 6

CPC by Age and Ad Type

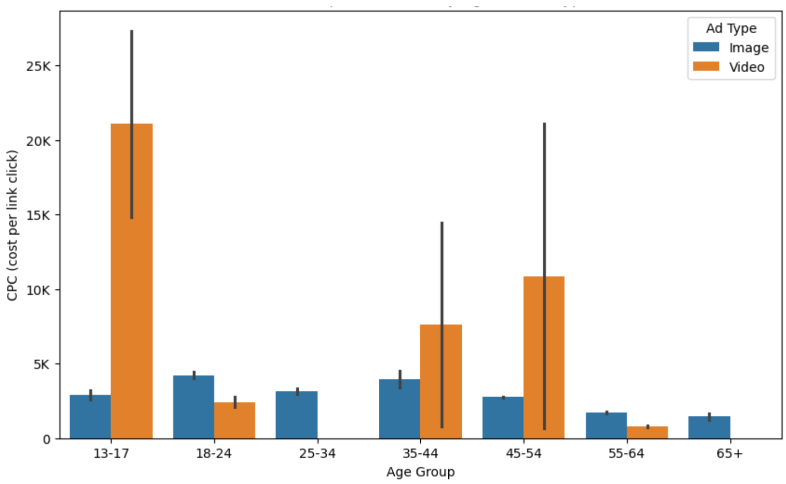
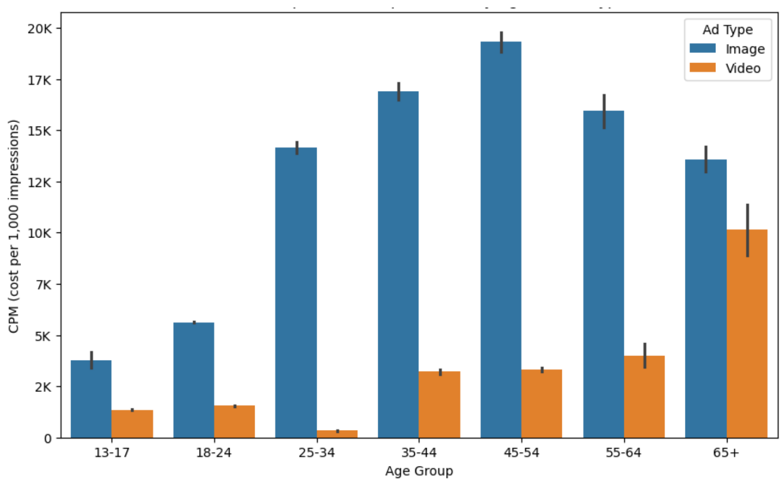


Figure 7 shows that video ads were more cost-efficient (i.e., CPM) for impressions across all age groups. The highest CPMs for image ads were recorded in the 35–64 age range, while video ads had lower CPMs in that age range. However, even in age groups with low video engagement (e.g., 25–34), video ads still achieved better CPM, suggesting efficient budget allocation in auctions.

Figure 7

CPM by Age and Ad Type



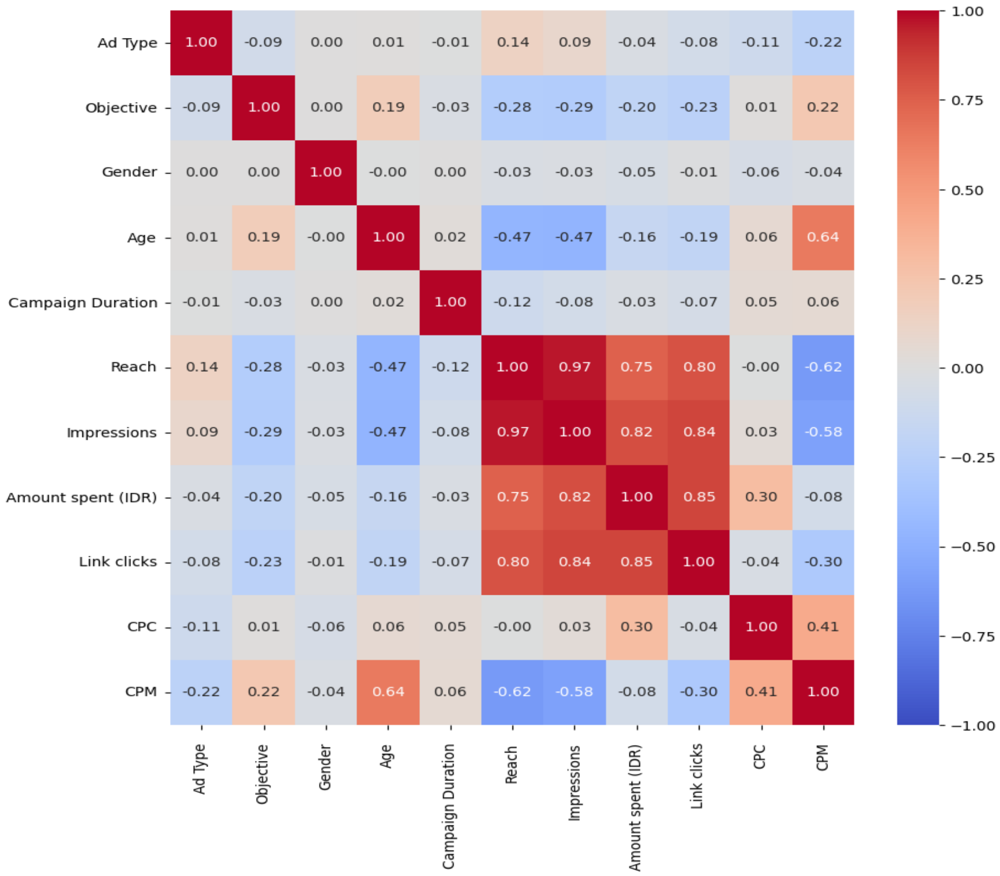
The Spearman rank correlation was used to assess the strength and direction of the variables' relationship and to better understand the relationship. The heatmap in Figure 8 visualised the strength of correlations between variables, with red indicating positive correlations and blue negative ones. The intensity of the shades reflected the strength of the correlation. Additionally, darker shades indicated stronger correlations, as discussed in detail in the following section. The initial observation was that ad type, gender, and campaign duration did not correlate with the remaining variables. It suggested that ad type, gender, and campaign duration do not significantly influence the ads' KPIs. Age showed a negative correlation with reach and impression, implying that older age groups were less engaged with ads. It was consistent with the finding that age showed a strong positive correlation with CPM, as lower engagement in older age groups was associated with higher CPM. The analysis also suggested that age does not have a noticeable influence on campaign duration, spending, or link clicks.

A significant positive correlation existed between the amount spent and several performance metrics, including reach, impressions, and link clicks. The ad type variable showed weak correlations with other metrics, suggesting that the choice between video and image ads does not strongly affect KPIs. The most significant correlation was the negative relationship with CPM (-0.22), suggesting that certain ad formats slightly influenced cost per thousand impressions. However, its correlations with reach (0.14) and impressions (0.09) were weak, showing that ad format does not significantly determine visibility. The weak correlation with the objective (-0.09) indicated that campaign objectives were not strongly influenced by the type of ad used.

The objective variable has moderate negative correlations with reach (-0.28) and impressions (-0.29), suggesting that different campaign objectives affected audience visibility. For example, objectives focused on conversions might not generate as many impressions as awareness-based campaigns. A weak positive correlation with CPM (0.22) indicated that objectives had a slight influence on advertising costs, but the overall relationship remained minor. The interpretation of this variable should be approached with caution, as the analysis does not disaggregate the eight specific objective categories. As a result, these correlations may obscure important differences between campaign goals.

Figure 8

Features Heatmap

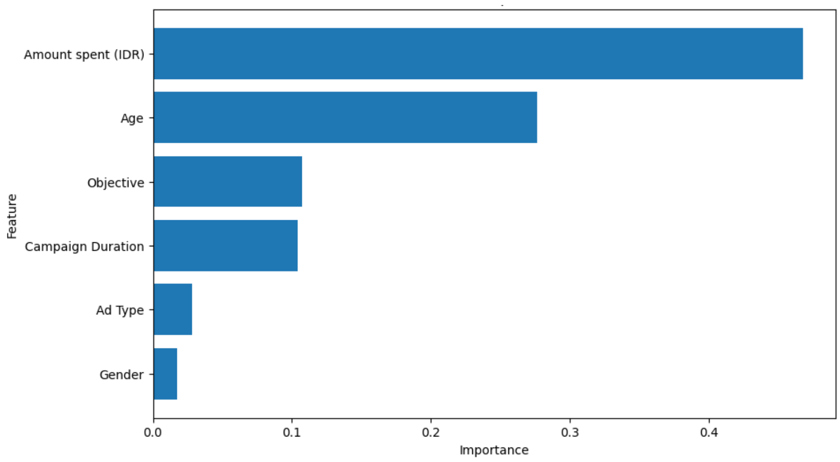


Reach showed a strong positive correlation with impressions, spend, and link clicks. This result was intuitive because as reach grew, impressions also tended to increase, leading to higher spend and more link clicks. Logically, higher reach led to lower CPM, consistent with the analysis's finding that large-scale campaigns were cost-efficient. In this context, reach does not affect CPC. Impressions and reach also had strong positive correlations with amount spent and link clicks, and a negative correlation with CPM.

Amount spent (IDR) is a significant driver of link clicks, implying that larger ad investments translate into higher visibility and user interactions. However, the increased spending does not significantly raise CPC, indicating budget efficiency. Link clicks showed no correlation with CPC; however, there was a negative correlation with CPM, suggesting cost-efficient ads. CPC also showed the strongest correlation with CPM (0.41), indicating that campaigns with higher CPCs tended to have higher CPMs. Feature importance was used to identify the most impactful factors in decision-making by quantifying each input variable's contribution to a model's predictions. Figure 9 shows the Feature Importance of the main variables used.

Figure 9

Feature Importance



The amount spent was identified as the most influential factor with a score of 0.47, which was significantly greater than the other features. It strongly demonstrated that budget drove ad performance, outlining the impact of increased spending on metrics such as reach and impressions. Age is another important feature that supports demographic targeting and strongly impacts ad effectiveness. It is consistent with findings that different age groups responded differently to image and video ads, as well as to engagement metrics. Objective and campaign duration showed moderate feature importance, implying that the specific goals of a campaign, including its duration, influenced ad outcomes. Campaign objectives prioritised conversions or engagement to influence performance results. Meanwhile, longer campaign durations improved reach and link clicks, providing ads with adequate time to be seen and reviewed. Ad type and gender have relatively low feature importance scores. Considering that ad type and gender had some impact on ad performance, they were not as critical as budget, age, or campaign characteristics. Gender had the least importance, indicating that gender-based targeting did not significantly impact the dataset's performance. Additionally, these results laid the groundwork for further analysis using ML models to identify complex patterns and interactions in the data.

ML Model Performance Comparison

The study applied three ML models, namely Linear Regression, Decision Tree, and Random Forest, to predict ad effectiveness across various KPIs. The predictive accuracy of the models was evaluated by calculating MSE, MAE, R^2, and RMSE for each KPI. Table 5 presents the calculated MSE, MAE, R^2, and RMSE for reach, impressions, link clicks, CPC, and CPM across the three models considered in this work.

Table 5

ML Evaluation Models

Metric	Model	MSE	MAE	R^2	RMSE
Reach	Linear Regression	0.00020	0.010	0.50	0.01
	Random Forest	0.00008	0.005	0.80	0.01
	Decision Tree	0.00014	0.006	0.65	0.01
Impression	Linear Regression	0.00060	0.018	0.55	0.02
	Random Forest	0.00020	0.007	0.85	0.01
	Decision Tree	0.00032	0.008	0.76	0.02
Link clicks	Linear Regression	0.00007	0.006	0.59	0.01
	Random Forest	0.00004	0.003	0.78	0.01
	Decision Tree	0.00007	0.004	0.61	0.01
CPC	Linear Regression	0.00003	0.004	0.03	0.01
	Random Forest	0.00002	0.003	0.41	0.00
	Decision Tree	0.00003	0.003	0.08	0.01
CPM	Linear Regression	0.00035	0.014	0.37	0.02
	Random Forest	0.00015	0.007	0.73	0.01
	Decision Tree	0.00023	0.008	0.59	0.02

Random Forest outperformed both Linear Regression and Decision Tree across all KPIs. For example, on reach, Random Forest improved R^2 by 30 percentage points over Linear Regression (0.80 vs 0.50), reducing MAE by half (0.005 vs 0.010). On the impressions dataset, it achieved an R^2 of 0.85, compared to 0.55 for Linear Regression, representing a 54% relative improvement. The results described the benefits of an ensemble-based architecture for capturing complex, non-linear relationships, enabling the model to achieve consistently high accuracy and robust generalisation.

Interpretive Analysis using SHAP

The SHAP values for the Random Forest model were calculated to show how features affected ad performance. These values enabled the identification of both the direction and magnitude of influence for each feature, offering a detailed prediction of ad effectiveness across KPIs. Although the objective was an influential feature in certain SHAP plots, this analysis failed to disaggregate the eight specific objective categories. The observed SHAP effects were interpreted with caution, and future studies would benefit from a more granular exploration of how distinct campaign goals influence ad performance metrics, such as reach.

Figure 10 shows the SHAP distribution, which describes how different features impact the model's prediction of reach. In addition, the amount spent was the most impactful predictor of reach. The distribution of SHAP values was skewed toward the positive side, indicating that the model predicted that reach increased with spending, as shown by the red dots. Age had a significant impact on reach, with the distribution of SHAP values centred around zero and showing a distinct pattern. Younger demographics, represented by blue dots, were clustered toward positive values, while older demographics, represented by red dots, tended toward negative values. It suggested that targeting younger demographics increased predicted reach, and the older age groups were associated with lower predicted reach. The scattered distribution of SHAP values implied that age did not consistently push the prediction towards a preferred direction. Other factors, such as ad type or campaign objective, also influenced reach.

The objective feature exhibited mixed SHAP values clustered around zero, suggesting that its influence on reach was highly context-dependent. This pattern reflected the fact that some campaign objectives were inherently aligned with reach-maximising strategies, while others prioritised alternative outcomes, such as conversions or engagement. Ad type, encoded as image and video ads, was associated with 0 and 1, respectively. The distribution of SHAP values for ad type was highly skewed toward the positive side, with Video ads dominating and represented by red dots. It implied that ad type was an effective predictor of reach, with the model suggesting that the presence of Video ads increased the likelihood of higher reach. Campaign Duration exhibited a balanced distribution of SHAP values around zero, implying that duration did not consistently drive reach. However, this variable was influenced alongside other factors, such as budget or target age group. Gender had minimal influence on reach, with SHAP values clustered near zero, suggesting it was not a significant predictor in this dataset.

Figure 10

SHAP Distribution for Reach

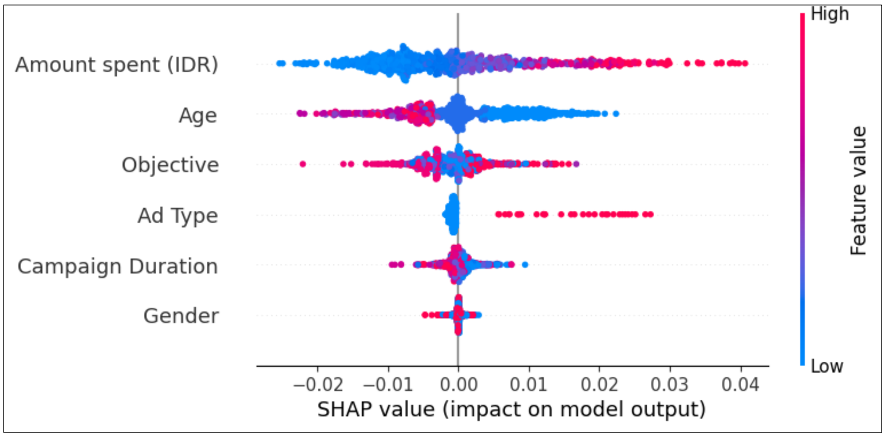
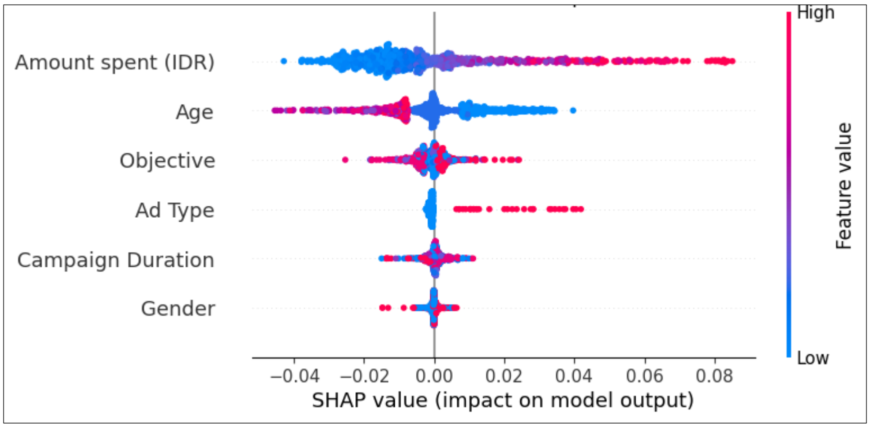


Figure 11 shows the distribution of SHAP values for impressions, alongside several similarities and certain significant differences in reach observed in Figure 10. The amount spent remained the most impactful feature, with its impact on Impressions being more pronounced. In addition, SHAP values reached approximately 0.08, compared to 0.04 for reach. It exhibited a strong relationship between budget allocation and impressions. Regarding reach, age showed a variable impact, scattered and centred around zero, with younger audiences associated with positive SHAP values. This variability suggested that age was not the sole predictor of Impressions. It is context-dependent and potentially interacts with other features, such as ad type or objective. The role of ad type was consistent with the analysis shown in Figure 10. Moreover, video ads correlated positively with impressions. Gender and campaign duration had minimal influence on impressions, with SHAP values clustered around zero. It showed that the variables were not significant predictors of impressions.

A significant difference between the charts centred on the impact of the objective was that the impressions chart showed greater variability. It suggested that campaign objectives played a slightly greater role in determining impressions than in determining reach. The overall SHAP value range is wider for impressions, reflecting more substantial or variable feature contributions in the impressions model. Given that both charts showed similar trends, the impressions model indicated that spending had a stronger influence on campaign objectives than reach did.

Figure 11

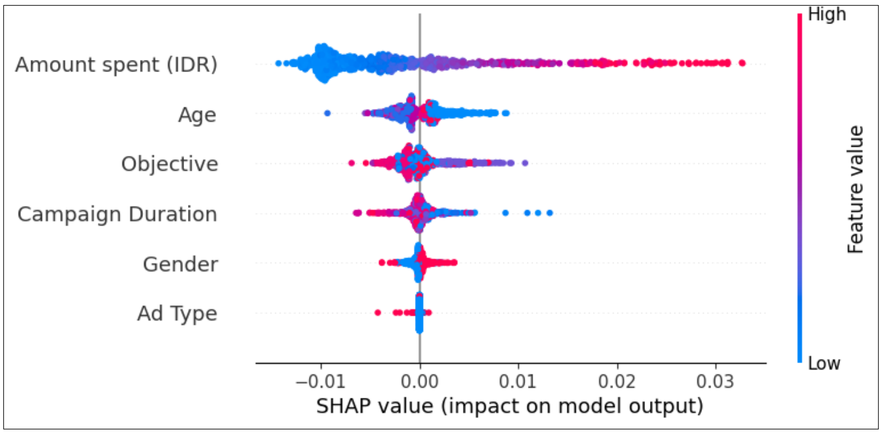
SHAP Distribution for Impressions



The distribution of SHAP values for link clicks is shown in Figure 12, and the predictions were mainly driven by the amount spent, indicating that budget was the key to engagement. Age had a weaker, less consistent impact, while campaign duration and gender had virtually no influence, as indicated by near-zero SHAP values. Ad type's effect was negligible for link clicks, suggesting that content format could not reliably predict click behaviour.

Figure 12

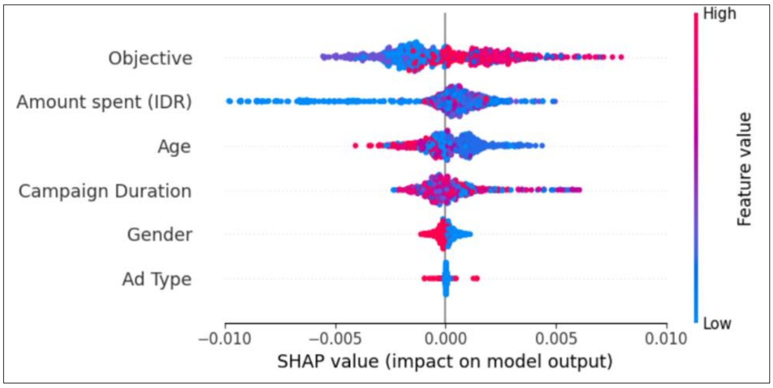
SHAP Distribution for Link Clicks



The SHAP plot for CPC is shown in Figure 13, and the maximum value was less than the previous values within the range of -0.01 to 0.01. Given the preferred directions for some features, such as amount spent and campaign duration, the overall SHAP scale was extremely narrow, making it difficult to draw meaningful inferences. The model failed to detect certain signals in the prediction with minimal impact, including bearing the weight for drawing meaningful predictions. It was inferred that CPC was insensitive to the features considered in the present study.

Figure 13

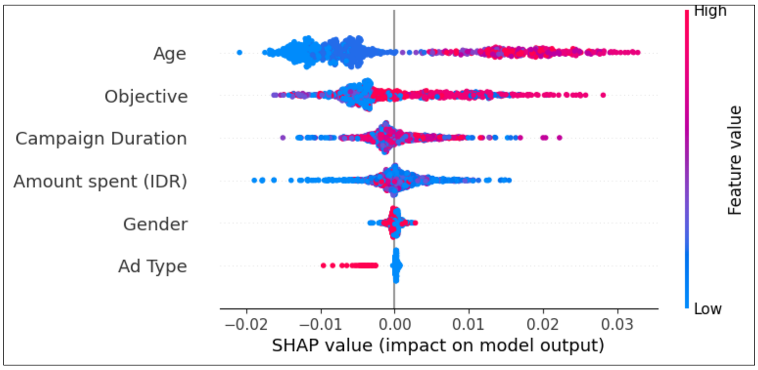
SHAP Distribution for CPC



The final metric evaluated was CPM, with the SHAP distribution shown in Figure 14. Age was the most influential factor, with older demographics (represented by red dots) associated with higher CPM. It showed that campaigns targeting older demographics were predicted to have higher CPM. Based on this perspective, objective and campaign duration had significant impacts on CPM. Positive SHAP values were realised for certain campaign objectives, namely engagement, leads, and sales, which increased CPM, due to the need for more targeted or intensive ad placements. Campaign duration exhibited a varied impact, suggesting that both brief and lengthy campaigns influenced CPM, possibly reflecting different pricing models. Amount Spent had a relatively low influence on CPM compared to other KPIs. It showed that increasing the budget did not significantly affect CPM outcomes. Gender and ad type were the least influential features, with SHAP values approaching zero. Although video ads represented by the red dots had slightly lower CPM, the overall impact remained minimal. CPM identified demographic-driven cost sensitivity and targeted older age groups, resulting in a significant increase. Compared to other KPIs, where budget allocation or campaign objectives played leading roles, CPM was strongly influenced by audience age. It showed that cost efficiency for impressions varied considerably by demographic factors.

Figure 14

SHAP Distribution for CPM



Comparison of Statistical, ML, and SHAP Findings

This section discusses insights from descriptive statistics, Spearman's correlation, Random Forest results, and SHAP interpretations to provide a comprehensive perspective on ad effectiveness. Statistical analysis showed clear performance differences between ad type and demographic groups. Video ads consistently exhibited greater reach and impressions, particularly among younger audiences aged 13-24. However, image ads excelled at generating link clicks across both younger (13-17) and older (55+) demographics, underscoring their effectiveness in engagement-driven campaigns. These findings outlined the importance of selecting an ad type based on specific campaign objectives and target demographics.

Based on this perspective, Random Forest was perceived as having the best predictive power. Furthermore, the amount spent was identified as the dominant predictor of ad performance across all KPIs. It outlined budget allocation as the main driver for campaign success. Given that age and ad type were crucial predictors, they had little influence compared to spending. The models described trade-offs among cost metrics, such as CPM and CPC, and ad effectiveness, underscoring the need for careful resource allocation to optimise outcomes. SHAP analysis provided detailed insights into how different features influenced ad performance. For example, budget is a consistent positive driver of reach, impressions, and link clicks, with its impact on CPM and CPC less pronounced. Age showed varying levels of influence, with younger demographics associated with increased reach and impressions. Ad type also exhibited context-dependent effects. It was observed that video ads tended to boost visibility metrics, namely reach and impressions.

Furthermore, image ads were more cost-efficient, contributing to lower CPC. Campaign objectives emerged as critical drivers of CPC, with engagement- and conversion-focused goals associated with higher CPC. These findings described the strategic importance of supporting campaign objectives with performance priorities. The integration of these methods showed a comprehensive picture of ad performance. Moreover, statistical analysis explored relationships and patterns among variables, with Random Forest providing predictive accuracy of the fundamental model, and SHAP offering insights into how the diverse features influenced model predictions. The amount spent, age, and ad type were identified as significant influential factors for ad performance across all analyses. Meanwhile, the delicate interplay between budget, demographics, and campaign objectives drove cost-efficiency dynamics. The analysis showed that data-driven decision-making balanced cost efficiency, visibility, and engagement to achieve campaign success. A summary of performance metrics by ad type and age groups is shown in Table 6.

Table 6

Performance Summary of Ad Type across Age Groups and Key Metrics

Ad Type	Audience	Visibility (Reach & Impressions)	Engagement (Link Clicks)	CPM	CPC
Video Ads	Younger (13–24)	High – Strong visibility due to multimedia engagement	Moderate – Less effective for clicks than image ads	Low – More cost-efficient for reaching a broad audience	High – Less efficient for engagement-driven campaigns
	Adult (25–34)	High – Maintains strong reach	Moderate – Performs well but behind image ads for clicks	Low – Cost-effective for broad visibility	High – Higher cost per click makes engagement campaigns pricier
	Midlife (35–54)	High – Strong brand awareness potential	High – Effective in engagement for this age group	Low – Keeps impression costs lower while maintaining reach	Moderate – Balanced cost-efficiency and engagement
	Older (55+)	Moderate – Lower reach than younger groups	Low – Limited engagement for clicks	Low – Remains cost-efficient for visibility campaigns	Moderate – Engagement costs remain manageable but not optimal
Image Ads	Younger (13–24)	Low – Less reach than video ads	High – Best for engagement (clicks, reactions)	High – Less cost-efficient for visibility campaigns	Low – Cost-effective for engagement-focused objectives
	Adult (25–34)	Moderate – Performs adequately but behind video ads	High – Best for direct engagement actions	High – Higher cost per thousand impressions compared to video ads	Low – Lower cost per click makes it ideal for engagement-focused goals
	Midlife (35–54)	Moderate – Visibility remains stable but not as strong as video ads	Moderate – Performs well but video ads generate more engagement in this group	High – Costs more for impressions, making it less ideal for awareness campaigns	Low – Cost-effective for driving direct engagement
	Older (55+)	Low – Least effective for visibility	Low – Struggles to drive engagement in this demographic	High – Expensive for impressions with limited reach	Low – Remains cost-effective for engagement but struggles with visibility

Discussions

This study confirmed that video ads drove higher reach and impressions, specifically among audiences aged 13–24. The findings supported previous studies, which stated video content was more engaging for younger demographics due to its dynamic nature and storytelling capabilities (Grewal et al., 2021; Tavares et al., 2023). It was further supported by Tavares et al. (2023), who analysed the effectiveness of video ads in broad engagement campaigns. The Attention, Interest, Desire, Action (AIDA) model was used to show that video ads played a significant role in the attention and interest stages due to their visual appeal and narrative strength. However, this study does not directly measure the action phase; the high engagement suggests that video content triggered desire, which eventually drove action over time. Image ads were more effective at motivating direct engagement, particularly among younger (13–17) and older (55+) users. The simplicity and low CPC made it a cost-effective option for action-driven campaigns, supporting prior findings (Stewart et al., 2023; Northcott et al., 2021). These were also consistent with the study by Xie et al. (2024), which focused on the role of ad-context congruence in enhancing engagement, specifically for image-based formats. In the AIDA framework, image ads were more effective in the desire and action stages, prompting users to click, engage, or convert.

SHAP analysis and feature importance identified budget allocation as the most influential factor in ad performance. Spending also directly impacted visibility and engagement metrics, reinforcing its strategic role in campaign success. Trade-offs detected between CPM and CPC must be managed carefully. Considering that video ads offered lower CPMs and greater visibility, higher CPCs reduced efficiency for conversion-focused goals. Image ads provided a more cost-efficient solution for engagement-driven strategies (Tavares et al., 2023; Stewart et al., 2023). These findings were in line with the studies by Félegyházi (2024) and Mihajlovic et al. (2024), which stated that video ads increased reach, while static image ads delivered better ROI during engagement. ML models, particularly Random Forest, played a significant role in identifying these patterns. Its ability to handle complex, non-linear relationships enabled accurate predictions for reach, impressions, and link clicks. SHAP analysis further enhanced these insights by showing how individual features influenced outcomes. For example, higher ad spending correlated with stronger reach and impressions for video ads targeted at younger users. Age also played a mixed role; video ads resonated more with younger users, while older demographics preferred image formats. These insights were consistent with studies by Lakshmanarao et al. (2021) and Patil et al. (2022), which described the value of ML in optimising ad performance.

This data-driven method helped marketers support ad formats with both campaign goals and audience preferences. In the AIDA framework, it enabled the design of video and image ads to different stages of the customer journey, capturing attention, building interest, triggering desire, and driving action. Video ads were suited for visibility-focused objectives, while image ads excelled in engagement-focused campaigns. The findings were in line with those of Xie et al. (2024), which highlighted the importance of format-goal support. SHAP also contributed to the growing role of explainable AI in advertising. It enabled campaign planners to make informed decisions by translating predictions into actionable insights. It was supported by Zhao and Harinen (2019) and Al-Khafaji and Karan (2024), who also described SHAP's strategic utility. The studies by Chavda and Patel (2024) and Ji et al. (2024) showed that ML enhanced ROI by enabling more precise and optimised targeting.

The contributions of this study were threefold: first, it provided large-scale confirmation in a non-Western, platform-native context. The analysis of 4,526 Meta campaigns from Indonesia (2021–2024) validated established format patterns. Video ads outperformed in terms of visibility and CPM, while image ads were more cost-efficient (i.e., CPC). The extension beyond small-scale A/B tests and Western-focused samples strengthened the generalisability of prior findings. Second, the study went beyond reporting outcomes to explain relevant occurrences. The integrated ML and SHAP analyses showed that budget allocation (amount spent) was the dominant driver of visibility. Additionally, age demographics and campaign objectives strongly influenced CPM and CPC, respectively. This multi-KPI, explainable modelling method clarified the mechanisms behind format differences, contributing both methodological and substantive insights to the literature. Third, the study translated these insights into actionable guidance, reporting the optimal nature of video ads in terms of visibility and CPM. Meanwhile, image ads were preferable for engagement and cost-efficient clicks—particularly among younger (13–17) and older (55+) audiences.

From a managerial perspective, these findings outlined the need to align creative formats with campaign objectives and audience segmentation. Advertisers should avoid reliance on average effects and instead match format choice to specific goals. Videos were used for awareness and broader reach, while images were adopted for engagement and cost-efficient clicks. Budget allocation remained the strongest driver of performance, with its influence differing across metrics. In practice, marketers treated budget as the lever for scaling visibility, allowing demographic and objective considerations guide creative decisions when optimising CPC. These designed strategies ensured more efficient resource allocation, improved ROI, and shifted campaign planning away from one-size-fits-all assumptions toward evidence-based, goal-conditioned choices.

This study offered data-driven insights into the effectiveness of image and video ads, but several limitations must be acknowledged to contextualise the findings and guide future analyses. First, the analysis was limited to data from Meta Ads Manager. The extensive dataset reflected only an advertising platform. Since audience behaviour and algorithmic mechanics differed across platforms such as Google Ads, TikTok, or Snapchat, future studies should include multi-platform data to improve generalisability. Second, the study did not account for content quality variables, such as creativity, message clarity, or design appeal. These qualitative aspects affected ad performance, which was not measured. Future studies will integrate methods, such as sentiment analysis and computer vision, to assess how creative elements influence outcomes.

Third, temporal factors, including seasonal patterns, holidays, and campaign timing, were not examined. In this context, the factors significantly affected user behaviour and ad engagement. Incorporating time-based variables allowed future studies to identify trends associated with timing. Fourth, the dataset excluded campaigns with zero values for key metrics, introducing selection bias. Excluding underperforming campaigns led the analysis to overrepresent successful ad strategies. Furthermore, including the full spectrum of campaign outcomes provided a more balanced view. Addressing these limitations in future studies enhanced the robustness and applicability of findings in digital advertising.

CONCLUSION

In conclusion, this study provided a comprehensive analysis of how video and image ads performed across key metrics, including reach, impressions, link clicks, CPC, and CPM. The findings showed that video ads were more effective at increasing visibility, particularly among younger audiences, due to their dynamic, attention-grabbing nature. Image ads were more cost-efficient for engagement, especially with older demographics, making them effective for interaction-focused campaigns under budget constraints. SHAP analysis and feature importance modelling proved that ad performance was mainly driven by budget allocation, with age and campaign duration influencing outcomes. These results outlined the value of demographic targeting when selecting ad formats, as diverse age groups responded differently to content type. For example, younger users preferred video ads, while older individuals responded to simpler, static image content.

From a strategic perspective, aligning ad formats with campaign goals and audience profiles significantly improved cost efficiency and engagement outcomes. Video ads offered broader exposure at competitive CPM during visibility-driven campaigns. Image ads tended to achieve lower CPC for action-oriented goals. SHAP analysis showed minimal feature influence on CPC, suggesting that unmeasured variables, such as content quality or audience context, shape it. These findings were consistent with the AIDA framework. Video ads strongly captured Attention and built interest, while image ads effectively generated desire, motivating action. The insights helped marketers design diverse advertising strategies to achieve optimal results. Future studies should address additional factors that shape ad effectiveness to strengthen the insights further. Content quality, including creativity, emotional tone, and visual design, was assessed using sentiment analysis or computer vision methods. Seasonal and temporal trends also prompted an investigation using time-series data to capture variations in user behaviour over time. Contextual variables, namely device type, browsing environment, or time, showed further nuances in engagement patterns.

Evolving ad formats such as short-form videos, interactive content, and augmented reality offered new opportunities for brand storytelling. Moreover, psychographic segmentation accounted for audience attitudes, values, and motivations, providing deeper insights for personalised ad experiences. Addressing these areas enabled future studies to expand on the current findings and supported the development of more adaptive, targeted, and high-performing digital advertising strategies.

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