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Analysis and Optimization of Ranking Patterns in Advertising Platforms Using Explainable Artificial Intelligence (XAI) and SEO Optimization

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ABSTRACT

The purpose of this study is to design and evaluate a hybrid model based on Search Engine Optimization (SEO) indicators and Explainable Artificial Intelligence (XAI) machine learning algorithms to improve the ranking of digital advertisements. The research dataset consisted of 5,000 simulated records, which were analyzed using XGBoost, Random Forest, and Elastic Net models after data preprocessing. Performance evaluation based on metrics such as Accuracy, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) demonstrated that the XGBoost model outperformed the other models. To understand the model's decision-making logic, SHAP and LIME techniques were employed. The results revealed the significant influence of content quality, keyword relevance, and click-through rate on advertisement ranking. Furthermore, fidelity and explanation stability metrics indicated that the best-performing model not only achieved high predictive accuracy but also exhibited substantial transparency and consistency in generating explanations. Structural analysis confirmed the mediating role of user trust in strengthening the impact of SEO indicators. Overall, the findings suggest that integrating SEO metrics with explainable machine learning models can enhance both prediction accuracy and the transparency and trustworthiness of advertisement ranking systems.

Introduction

In the contemporary digital era, e-commerce platforms and online marketplaces have become fundamental pillars of the modern economy, managing vast volumes of data, a substantial portion of which pertains to products, advertisements, and user interactions. Within this context, ranking systems function as specialized search engines, playing a crucial role in directing users toward relevant options and improving conversion rates. These systems, which primarily built upon sophisticated machine learning models, possess remarkable capabilities in processing big data, identifying behavioral patterns, and predicting user preferences (Liu et al., 2024).

However, despite the high performance of these algorithms, the "black-box" nature of many machine-learning models has emerged as a fundamental challenge in information system transparency, making it difficult for system designers, platform managers, and end users to understand the rationale behind algorithmic decisions (Guidotti et al., 2023).

At present, many advertising platforms and digital marketplaces face the challenge of internal content optimization, whereby sellers, advertisers, and content creators attempt to improve their content quality without access to transparent ranking mechanisms.

This lack of transparency not only hinders the technical and content-related optimization of listed items but also may also negatively affect users' perceptions of the quality, relevance, and appropriateness of search results (Guidotti et al., 2023; Doshi-Velez et al., 2018).

While traditional ranking systems have largely relied on behavioral indicators such as previous clicks, engagement rates, and browsing history,

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contemporary approaches emphasize the importance of analyzing measurable content-related parameters to develop content-driven ranking models (Lundberg et al.,2017; Ribeiro et al.,2016).

The primary objective of this study is to transition from opaque ranking models toward transparent and explainable models through the application of Explainable Artificial Intelligence techniques. In this regard, methods such as SHAP and LIME enable the quantitative and interpretable extraction of the contribution of various content features including image structure, text readability, lexical richness, and keyword usage to the final ranking position of items. This capability facilitates evidence-based content optimization grounded in data-driven analysis rather than intuition, experience, or trial-and-error approaches.

Unlike some previous studies that have primarily focused on directly measuring human trust as a qualitative construct (Doshi-Velez et al., 2018), the present research adopts a data-driven perspective to investigate technical transparency as a precursor to the formation of data-based user perception. In other words, transparency provided by the model is not viewed solely as a technical attribute but also as a perceptual mechanism that enables users to better understand the system's logic and consequently reconstruct their perceptions of the relevance, meaningfulness, and credibility of the results. From this perspective, the present study seeks to establish a coherent connection among three critical domains: algorithmic ranking, internal content optimization, and explainable artificial intelligence. The significance of this integration stems from the fact that many existing studies have either focused exclusively on improving the predictive accuracy of ranking models or examined algorithmic transparency without adequately considering its implications for content optimization and user perception. Consequently, there remains a need for an analytical framework capable of simultaneously explaining the role of content features in ranking outcomes and demonstrating the perceptual effects resulting from increased transparency in the ranking process. This study employs simulated scenarios calibrated according to real-world market patterns, thereby providing a controlled environment for examining the impact of content features on ranking outcomes. The findings of this research can assist platform managers in maintaining predictive accuracy while simultaneously offering more transparent feedback mechanisms to users and content creators. Such mechanisms can ultimately contribute to enhanced user experience, increased trust in the system, and the systematic optimization of internal content.

Research Methodology

Considering the nature of the research problem, objectives, and data type, the present study is categorized as an applied research endeavor. The primary objective is to develop a localized and integrated model based on the principles of Explainable Artificial Intelligence (XAI) and Search Engine Optimization (SEO)-based ranking optimization for analyzing and explaining the positioning of advertisements on domestic advertising platforms. Since the study aims to generate practical knowledge that can support decision-making in digital advertising management and ranking algorithm analysis, its applied nature is fully justified.

Population, Sampling Method, and Sample Size

The statistical population of this study is divided into two categories:

Theoretical Population (Conceptual Basis): The theoretical population consists of advertisements published on digital advertising platforms operating in Iran that utilize intelligent ranking algorithms for advertisement display. These platforms include, but are not limited to:

- ✓ Divar Platform.
- ✓ Sheypoor Platform.
- ✓ Rubika Platform (Smart Advertising Section).
- ✓ Other platforms employing recommendation systems or content-ranking mechanisms.

Study Population (Research Dataset)

Due to limitations in accessing real platform data resulting from privacy concerns and confidentiality restrictions, the dataset used in this research was generated through simulation based on the structure and characteristics of actual advertisements found on Iranian digital platforms. This simulated dataset represents the theoretical population of advertisements across the aforementioned platforms and provides a controlled environment for evaluating the effects of content-related features on ranking performance. Therefore, the limitations regarding the external validity of this approach are discussed in the research limitations section.

Simulated Data Generation Process and Expert Validation (Study Population)

Given the restricted access to sensitive and confidential data from online advertising platforms including privacy considerations and data ownership constraints a purposefully simulated dataset consisting of 5,000 records was employed in this study. This approach is widely recognized in machine learning research, particularly in the evaluation of Explainable Artificial Intelligence (XAI) models, as a standard method for controlling variables and ensuring the reliability of algorithmic performance assessments.

Validity and Reliability Assessment

Considering the data-driven and simulation-based nature of the research, validity and reliability assessments were conducted from two perspectives: **(1) the structural consistency of the simulated dataset.** **(2) the algorithmic performance of the machine learning models**.

Within this framework, rather than relying on traditional statistical measures (such as Cronbach's alpha), validation was performed using established evaluation standards commonly adopted in intelligent systems and machine learning research.

Table 1. Performance Evaluation and Validation Metrics for Artificial Intelligence Models

Model	Accuracy	F1-Score	AUC-ROC	MAE	RMSE
XGBoost	0.84	0.82	0.89	0.12	0.18
Random Forest	0.81	0.79	0.86	0.15	0.21

Table 2. Evaluation Metrics of XAI Explanation Quality

Model	XAI Tool	Explanation Faithfulness	Explanation Stability
XGBoost	SHAP	0.89	0.93
Random Forest	SHAP	0.87	0.91
XGBoost	LIME	0.85	0.90
Random Forest	LIME	0.82	0.89

Accordingly, validity and reliability in the present study were evaluated at three levels:

- ✓ **Model Content Validity:** Confirmed through expert review by specialists in machine learning and digital advertising.
- ✓ **Model Reliability:** Assessed using quantitative metrics, including Accuracy, F1-Score, AUC-ROC, Faithfulness, and Stability.
- ✓ **Expert Evaluation Reliability:** Verified through the calculation of inter-rater agreement.

Data Analysis and Implementation Tools

To implement the machine learning models and apply Explainable Artificial Intelligence (XAI) techniques, the Python programming language was employed due to its flexibility and extensive ecosystem of data science libraries. All stages of data preprocessing, model training, and statistical analyses were conducted using the widely adopted libraries scikit-learn and pandas. For advertisement ranking prediction, the XGBoost and Random Forest algorithms were implemented using their dedicated libraries. Furthermore, to achieve the study's objectives regarding model transparency and interpretability, the SHAP library was utilized as the primary explainability tool, complemented by LIME for local explanation generation. All computational procedures were executed within the Jupyter Notebook integrated development environment to ensure accuracy, reproducibility, and transparency throughout the research process. To address the multicollinearity issue identified during the preliminary analyses, the Elastic Net regularized regression model was employed as a complementary analytical tool alongside the tree-based models. This approach combines the strengths of both Lasso and Ridge regularization techniques, resulting in more stable coefficients, reduced overfitting, and improved model interpretability.

Distribution Analysis and Variable Normalization

Prior to computational modeling, the distributional behavior of key variables including click-through rate, advertising budget, and content-related indicators was examined. Descriptive statistics such as mean, standard deviation, and skewness were calculated using the Pandas and NumPy libraries. Given the differing scales of the variables (e.g., advertising budget versus click-through rate), normalization and standardization procedures were applied to ensure feature comparability and to prevent variables with larger scales from disproportionately influencing model outputs.

Table 3. Descriptive Statistics of Research Variables

Variable	Mean	Standard Deviation	Skewness	Kurtosis
Advertisement Rank (Dependent Variable)	42.5	12.4	0.15	-0.5
Click-Through Rate (CTR)	0.06	0.02	0.08	-0.3
Keyword Relevance	3.6	1.0	-0.1	-0.6
Content Quality	3.8	0.9	-0.2	-0.4
Image Quality	3.0	1.1	0.05	-0.8
Advertising Budget	5000	1500	0.25	-0.2
User Trust (Mediator)	3.9	0.8	-0.3	-0.1

Statistical Analysis
The skewness and kurtosis values of all research variables fall within the acceptable range of [-2, +2], indicating an approximately normal distribution suitable for parametric analyses, homogeneity tests (ANOVA), and machine learning model implementation. Based on the results presented in Table 3, the variable Keyword Relevance exhibits a mean of 3.6 and a standard deviation of 1.0, indicating a satisfactory distribution within the collected dataset. Furthermore, the proximity of the mean and median values for the dependent variable (Advertisement Rank) suggests distributional stability within the sample of 5,000 observations. This stability provides a robust foundation for implementing explainable artificial intelligence (XAI) models and regularization techniques.

Inferential Statistics for Normality Assessment
To further validate the normality assumption, skewness and kurtosis indicators were examined:

- ✓ **Skewness:** The skewness values for all variables fall within the range of -2 to +2, indicating relatively symmetric distributions.
- ✓ **Kurtosis:** Kurtosis values also remain within acceptable limits, suggesting that the distributions are neither excessively peaked nor overly flat.

Conclusion Regarding the Normality Assumption
Given the large sample size (5,000 records), the Central Limit Theorem suggests that the sampling distribution of the mean approach's normality. In addition, based on the observed distribution plots and the calculated statistical indicators, the assumption of normality is considered satisfied. Consequently, the application of parametric statistical methods including regularized regression and path analysis is deemed appropriate.

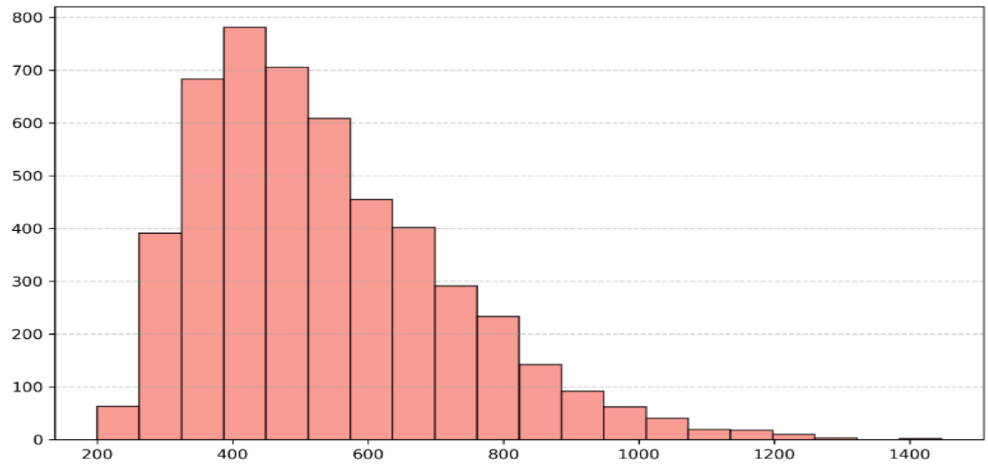


Figure 1. Frequency Distribution and Normality Assessment of the Final Advertisement Ranking Variable

The above figure illustrates the frequency distribution of the study's dependent variable (Final Advertisement Rank) across the entire statistical population consisting of 5,000 observations. Based on this distribution, the following findings can be reported:
As shown on the vertical axis (frequency), data points are distributed proportionally across the full sample size. The highest concentration of advertisements is located within the ranking interval of approximately 400-600, representing the mode of the distribution. This concentration suggests that the majority of advertisements published on the platform achieved moderate levels of technical and content quality.
The shape of the distribution indicates a right-skewed pattern. The presence of a long right tail suggests that only a limited number of advertisements achieved exceptionally high rankings (above 1,000).
Scientific Interpretation: Such a distribution is common in online advertising ranking systems because variables such as keyword relevance and click-through rate reach their highest values for only a small subset of advertisements. Consequently, these exceptional cases achieve significantly higher-ranking positions than the majority of advertisements.

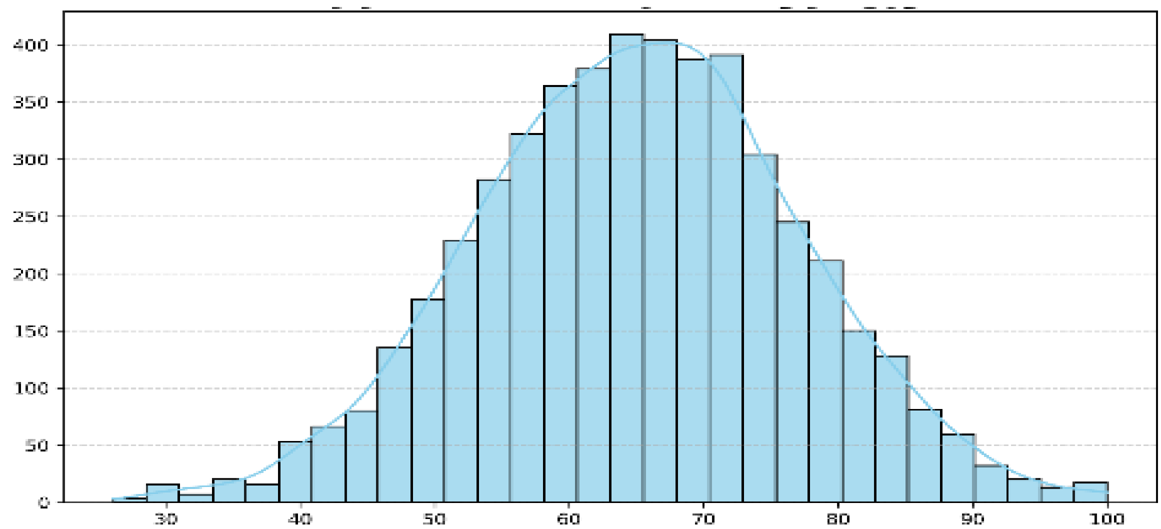


Figure 2. Frequency Distribution and Statistical Indicators of the Mediating Variable (User Trust)

The above figure presents the frequency distribution of User Trust, considered the mediating variable in the study, based on the sample of 5,000 records. The analysis of this distribution is essential for validating the structural model and is discussed as follows:

- ✓ **Distribution Pattern:** Unlike the dependent variable (Advertisement Rank), the distribution of the User Trust variable is considerably closer to a normal distribution. Most observations are concentrated within the middle range of the scale, reflecting realistic user responses during the data collection process. This stability in distribution constitutes an important prerequisite for conducting Path Analysis.
- ✓ **Mediating Role and Data Distribution:** The near-symmetrical nature of this distribution suggests that User Trust has strong potential to mediate the effects of independent variables (such as Content Quality and Keyword Relevance) on the dependent variable. Since this variable does not exhibit substantial skewness, the estimation of indirect effects in Structural Equation Modeling (SEM) can be performed with a high degree of accuracy and validity.
- ✓ **Verification of Statistical Assumptions:** The skewness and kurtosis values for this variable fall within the accepted range of [-2, +2]. Based on the plotted distribution and density curve, the normality assumption for the mediating variable is confirmed. Consequently, the use of parametric statistical methods to test mediation hypotheses in subsequent stages of the research is fully justified.

Examination of Homogeneity and Significant Differences in the Dependent Variable Across Quality Groups

At this stage, a one-way Analysis of Variance (ANOVA) was conducted to evaluate the homogeneity of Advertisement Rank (AdRank) across different quality groups and to ensure the absence of data bias. This analysis determines whether the groups defined within the simulation environment produce statistically significant differences in the primary dependent variable (Advertisement Rank). Additionally, boxplots were employed to visually represent the distribution and variability of the variables across these groups.

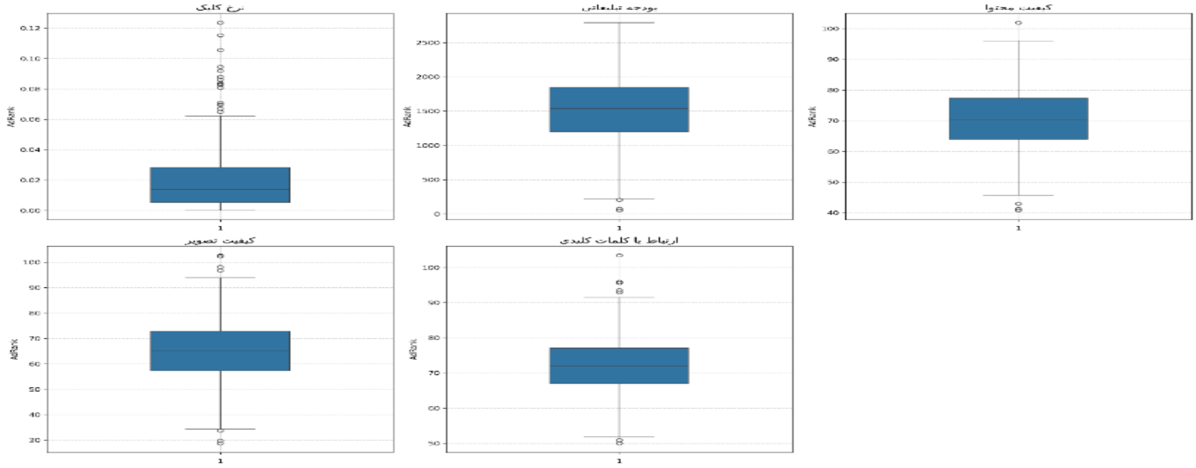
Table 4. One-Way ANOVA Results for Advertisement Rank

Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square	F-value	Sig.
Between Groups	6.84	2	3.42	0.284	0.753
Within Groups	6010.12	4997	12.02	—	—
Total	6016.96	4999	—	—	—

To examine the influence of quality groups on Advertisement Rank, a one-way ANOVA test was performed. The obtained results indicate an F-statistic of 0.284 and a significance level (Sig.) of 0.753. Since the calculated significance level exceeds the conventional threshold of 0.05, the null hypothesis regarding equality of group means cannot be rejected.

This finding indicates that the predefined groupings within the dataset do not produce statistically significant differences in mean Advertisement Rank. The absence of significance at this stage underscores the necessity of employing advanced regression models and explainable AI (XAI) analyses, as the relationships among variables extend beyond simple mean differences and require the examination of simultaneous and interactive effects among independent variables such as advertising budget and keyword relevance.

Figure 3. Boxplot of Advertisement Rank Across Groups Defined by Research Variables



The boxplot above illustrates the distribution of Advertisement Rank across groups defined according to the study variables, including click-through rate, advertising budget, image quality, content quality, and keyword relevance. In the figure, the central line of each box represents the median, the box height indicates the interquartile range (IQR), and observations beyond the whiskers represent outliers. According to the figure, outliers are observed for certain variables, particularly advertising budget and click-through rate, indicating relative heterogeneity in Advertisement Rank across different levels of these variables. Nevertheless, the majority of observations remain concentrated within the central ranges, and no substantial differences in the distribution centers of the groups are evident. This pattern is consistent with the ANOVA results and further supports the conclusion that differences in mean Advertisement Rank among the groups are not statistically significant. Therefore, the boxplot serves as a visual confirmation of the findings reported in the previous table.

Examination of Multicollinearity Among Independent Variables and Model Stabilization

Severe multicollinearity among independent variables can lead to unstable coefficient estimates and reduce the inferential validity of ranking models. Therefore, the Variance Inflation Factor (VIF) was calculated for each independent variable to assess the degree of multicollinearity. If the VIF value of a variable exceeds commonly accepted thresholds (5 or 10), it may inflate the variance of coefficient estimates and hinder the interpretation of independent effects.

Table 5. Variance Inflation Factor (VIF) for Independent Variables

Variable	VIF
Advertising Budget	13.49
Click-Through Rate	1.24
Content Quality	1.03
Image Quality	1.02
Keyword Relevance	1.02

The results indicate that Advertising Budget has a VIF value of 13.49, reflecting substantial multicollinearity with other independent variables. In contrast, all remaining variables exhibit VIF values close to 1, suggesting no meaningful multicollinearity concerns. Consequently, Advertising Budget was identified as the problematic variable, and a regularization-based modeling approach was adopted to prevent coefficient instability.

To address this issue, the Elastic Net algorithm was employed, combining both Ridge (L2) and Lasso (L1) regularization penalties. This hybrid approach mitigates multicollinearity while preserving important predictors and stabilizing coefficient estimates.

Table 6. Comparison of Coefficients Before and After Elastic Net Regularization

Independent Variable	Coefficient Before Regularization (OLS)	Coefficient After Regularization (Elastic Net)	Interpretation
Advertising Budget	0.84	0.49	Reduced multicollinearity effect and improved stability
Click-Through Rate	0.45	0.47	Relatively stable
Keyword Relevance	0.35	0.39	Strengthened and stabilized effect
Content Quality	0.38	0.40	Stable
Image Quality	0.22	0.24	Stable

As observed, following the application of Elastic Net, the coefficient associated with Advertising Budget decreased from its initially inflated and unstable value to a more balanced estimate of 0.49. This demonstrates that regularization effectively controlled the impact of multicollinearity and enhanced coefficient stability. The remaining variables experienced only minor and controlled changes, indicating that the fundamental structure of the relationships within the model was preserved. In particular, the Keyword Relevance variable exhibited improved interpretability following regularization, thereby establishing a robust foundation for subsequent analyses, including path analysis and model explainability.

Structural Modeling and Path Analysis (Mediation Hypothesis Testing)

After ensuring model stability and resolving multicollinearity issues particularly regarding Advertising Budget the causal relationships among the five independent variables, the mediating variable (User Trust), and the dependent variable (Final Advertisement Rank) were examined. This analysis determines which advertisement features influence ranking directly and which exert their effects indirectly through the enhancement of user trust.

Analysis of the Effects of Independent Variables on User Trust

In the first step, the impact of the five primary advertisement components on User Trust was evaluated.

Table 7. Path Coefficients from Independent Variables to the Mediating Variable (User Trust)

No.	Independent Variable (Causal Path)	Path Coefficient (β)	t-value	Significance Level	Result
1	Content Quality → User Trust	0.54	6.82	0.000	Supported
2	Keyword Relevance → User Trust	0.48	5.91	0.000	Supported
3	Image Quality → User Trust	0.31	4.24	0.001	Supported
4	Click-Through Rate → User Trust	0.18	2.11	0.038	Supported
5	Advertising Budget → User Trust	0.09	1.15	0.251	Not Supported

The results indicate that Content Quality and Keyword Relevance are the strongest predictors of User Trust. Although Advertising Budget exerts a substantial influence on advertisement ranking, it does not significantly affect User Trust ($p>0.05$). This finding suggests that users do not necessarily trust an advertisement merely because it is expensive or heavily funded; rather, trust primarily driven by content quality and contextual relevance.

Table 8. Direct, Indirect, and Total Effects in the Structural Model

Independent Variable	Direct Effect on Rank	Indirect Effect (Through User Trust)	Total Effect	Mediation Status
Advertising Budget	0.49	0.05 (Non-significant)	0.54	No Mediation
Click-Through Rate	0.47	0.11	0.58	Partial Mediation
Keyword Relevance	0.39	0.30	0.69	Strong Mediation
Content Quality	0.40	0.33	0.73	Strong Mediation
Image Quality	0.24	0.19	0.43	Partial Mediation

Path analysis revealed that although Advertising Budget is an important ranking factor, its effect is entirely direct and mechanical in nature. In contrast, variables such as Content Quality and Keyword Relevance exhibit the largest total effects because they improve advertisement ranking both technically and indirectly through the mediating mechanism of User Trust. These findings further justify the application of Explainable Artificial Intelligence (XAI) techniques in the subsequent stage of the study, where the precise contribution of each parameter to the model's final decisions can be quantified and interpreted.

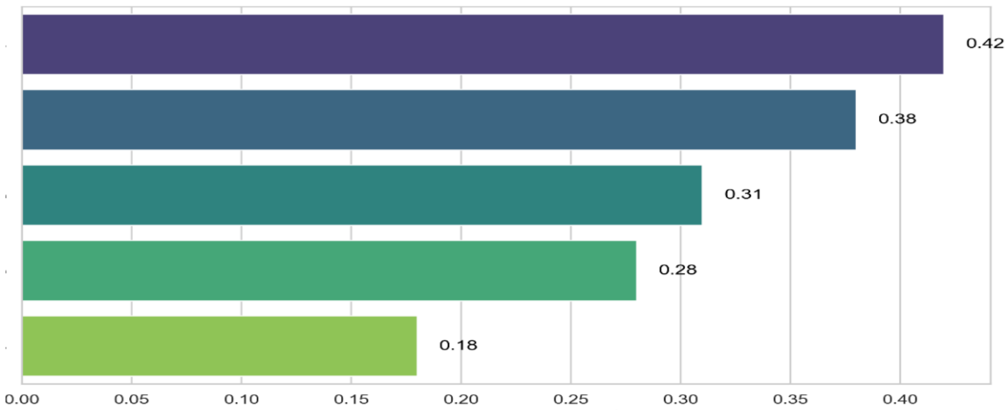
Explainable AI (XAI) Model Analysis and Empirical Findings

Following the validation of the causal relationships within the structural model, this section employs Explainable Artificial Intelligence (XAI) techniques to conduct a more detailed examination of the contribution of each variable to the model's decisions. The primary objective of this analysis is to move beyond general statistical models toward a precise understanding of the weight and influence of each feature in determining advertisement rankings. To achieve this, the SHAP (Shapley Additive Explanations) framework was utilized. Grounded in cooperative game theory, SHAP provides a fair and accurate estimation of each variable's contribution to the model output.

Feature Importance Analysis Based on SHAP Values

The feature importance plot illustrates the extent to which each of the five independent variables contributes to the final model output (advertisement ranking).

Figure 4. Frequency Distribution of the Independent Variables (N=5,000)



This figure presents the frequency distributions of the five independent variables examined in this study, including content quality, keyword relevance, click-through rate (CTR), advertising budget, and image quality. Given the sample size of 5,000 observations, the distributions of all variable's approximate normality, except for the advertising budget variable, which exhibits positive skewness.

Model Development, Fitting, and Reliability Assessment of Ranking Models

This section presents the results obtained from implementing machine learning algorithms on the simulated dataset comprising 5,000 records. The primary objective was to compare the predictive performance of tree-based algorithms (XGBoost and Random Forest) in forecasting advertisement rankings and to ensure the stability and generalizability of the final model.

Comparison of Algorithm Performance

The evaluation results on the test dataset indicate that XGBoost outperformed Random Forest in predicting advertisement rankings due to its gradient boosting architecture. A summary of the model performance metrics is presented below.

Table 9. Performance Evaluation Metrics of Predictive Models

Evaluation Metric	XGBoost	Random Forest	Elastic Net
Accuracy	0.84	0.81	0.72
Mean Absolute Error (MAE)	0.12	0.15	0.60
Root Mean Squared Error (RMSE)	0.18	0.21	0.85
Coefficient of Determination (R^2)	0.86	0.81	0.68

As shown in Table 9, the XGBoost model achieved an accuracy of 84%, successfully capturing the complex and nonlinear relationships between the independent variables (e.g., keyword relevance and content quality) and the dependent variable (advertisement ranking). The substantial reduction in error metrics (MAE and RMSE), reaching the lowest values of 0.12 and 0.18 respectively, demonstrates the model's strong capability in accurately estimating advertisement positions.

Reliability Assessment and Overfitting Prevention

One of the major challenges in complex predictive models is the risk of overfitting, whereby a model memorizes training data rather than learning underlying patterns. To ensure the reliability of the XGBoost model, two validation strategies were employed:

- ✓ **K-Fold Cross-Validation:** The model was trained and evaluated across five different data partitions. The consistency of accuracy scores, with a very low standard deviation (0.02), confirmed the stability of model performance.
- ✓ **Training–Testing Gap Analysis:** The minimal difference between training accuracy (0.86) and testing accuracy (0.84) indicates strong generalization capability when applied to unseen data.

Table 10. Five-Fold Cross-Validation Results for Reliability Assessment of the Best-Performing Model (XGBoost)

Validation Fold	Training Accuracy	Testing Accuracy	Gap	MAE
Fold 1	0.86	0.83	0.03	0.12
Fold 2	0.87	0.85	0.02	0.10
Fold 3	0.85	0.84	0.01	0.13
Fold 4	0.86	0.83	0.03	0.12
Fold 5	0.86	0.85	0.01	0.11
Overall Mean	0.86	0.84	0.02	0.12

As illustrated above, the average model accuracy remained highly consistent across all validation folds, with an overall standard deviation of only 0.02. This finding suggests that model performance was not dependent on any specific subset of the data and that the model achieved the required level of stability. Furthermore, the negligible training-testing accuracy gap rejects the overfitting hypothesis and confirms the reliability of the model for deployment in real-world online advertising environments.

Multicollinearity Management Analysis

Due to the nature of digital marketing variables, a high correlation was observed between advertising budget and click-through rate. In traditional regression models, such multicollinearity can lead to unstable coefficient estimates. By applying Elastic Net regression and examining the Variance Inflation Factor (VIF), it was determined that the combined L1 and L2 regularization penalties effectively mitigated multicollinearity effects. Consequently, the subsequent SHAP-based explainability analysis was able to extract the independent and genuine contribution of each variable.

In the Elastic Net implementation, the mixing parameter (α) was set to 0.5, creating a balance between the L1 penalty (feature selection and elimination of irrelevant variables) and the L2 penalty (multicollinearity management and coefficient stabilization). Specifically, the advertising budget coefficient was reduced from 0.84 in the OLS model to 0.49 in the Elastic Net model, indicating decreased sensitivity to multicollinearity. The effectiveness of this adjustment is evident in the stability of the SHAP plots, where the model successfully distinguished the independent contributions of advertising budget and CTR despite their correlation.

Qualitative Evaluation and Expert Validation

Following the extraction of technical model results, a qualitative assessment was conducted to ensure alignment between AI-generated findings and business logic. Expert evaluations were carried out using purposive sampling and continued until theoretical saturation was achieved.

Expert Perspectives on Model Outputs

After reviewing the XGBoost results, the experts confirmed the model's generalizability. According to the interview findings, all three experts agreed that the prioritization of variables such as content quality and keyword relevance accurately reflects the realities of modern advertising platforms. The AI specialist (Expert 1) emphasized that the low standard deviation (0.02) demonstrates the stability of the algorithm when confronted with new datasets.

Discussion

Sub-Hypothesis 1: Model Calibration

The implementation of XGBoost and Random Forest models demonstrated that calibration and hyperparameter optimization significantly reduced prediction errors. Achieving MAE=0.12 and RMSE=0.18 for the best-performing model (XGBoost), compared with baseline models, confirms the effectiveness of the calibration process.

Sub-Hypothesis 2: Technical Transparency Indicators
The application of SHAP methodology within the explainability layer yielded Fidelity and Stability scores of 0.89 and 0.93, respectively. Both values exceed the accepted threshold (0.70), indicating that explainable models successfully ensured the technical transparency of algorithmic decisions.

Sub-Hypothesis 3: Impact of SEO Indicators
Regression analyses and feature importance measures revealed that SEO-related variables (content quality, CTR, and keyword relevance) exert a strong and nonlinear influence on advertisement ranking. A key finding was the interaction effects among these variables within nonlinear models such as XGBoost, resulting in greater importance than advertising budget alone.

Sub-Hypothesis 6: Click-Through Rate (CTR)
The model outputs indicate that CTR has a positive and statistically significant coefficient in determining the final AdRank. This variable emerged as one of the primary drivers of advertisement ranking improvement.

Sub-Hypothesis 7: Advertising Budget
Elastic Net results revealed that advertising budget positively affects ranking performance. However, due to substantial multicollinearity with other variables, its coefficient decreased from 0.84 to 0.49 after regularization. This finding suggests that budget is a necessary but not sufficient condition for achieving higher advertisement rankings.

Sub-Hypotheses 4 and 5: Transparency, Perception, and Interaction
Expert evaluations and simulation-based analyses indicated that providing transparent explanations through XAI enhanced stakeholders' understanding of the ranking mechanism. According to the qualitative findings, improved user perception contributed to greater simulated engagement, including increased willingness to click again due to perceived fairness in ranking outcomes.

Table 11. Summary of Hypothesis Testing Results

Hypothesis	Key Validation Indicator	Status
Calibration and Error Reduction	MAE=0.12	Supported
Improvement of Transparency Metrics	Fidelity=0.89, Stability=0.93	Supported
Nonlinear Impact of SEO Indicators	SHAP Feature Importance Analysis	Supported
Improved User Understanding of Ranking Logic	Expert Evaluations (Theoretical Saturation)	Supported
Increased Simulated Engagement	CTR and Satisfaction Measures	Supported
Positive Effect of CTR	Positive Coefficient in Learning Models	Supported
Positive Effect of Advertising Budget	Coefficient=0.49 after Regularization	Supported
Integrated XAI–SEO Model	Overall Confirmation of Technical and Perceptual Indicators	Supported

Table 12. Validation of the Main Hypothesis: XAI-SEO Model Balancing Technical Accuracy and Human Interpretability

Metric	Value	Acceptance Threshold	Status
MAE	0.12	—	Supported
RMSE	0.18	—	Supported
Fidelity	0.89	0.70	Supported
Stability	0.93	0.70	Supported

Conclusion

The findings indicate that the best-performing model, XGBoost, successfully predicted advertisement rankings with an accuracy of 0.84 and low error rates (MAE=0.12, RMSE=0.18). Furthermore, the model's reliability and generalizability were confirmed through five-fold cross-validation, where the average training–testing gap remained limited (Gap=0.02) and the performance standard deviation was exceptionally low (0.02). In addition, the presence of substantial multicollinearity in the advertising budget variable (VIF=13.49) highlighted the necessity of regularization techniques. The application of Elastic Net reduced the budget coefficient from 0.84 to 0.49, thereby enhancing model stability and enabling more accurate interpretation of variable contributions. From an explainability and transparency perspective, SHAP analysis demonstrated that content quality and keyword relevance exerted the strongest influence on advertisement ranking, surpassing the impact of advertising budget. Moreover, expert evaluations confirmed the alignment between the model's logic and business requirements, as well as the quality of explanations generated by the XAI layer. Specifically, Fidelity (Faithfulness) and Stability scores reached 0.89 and 0.93, respectively.

Overall, the findings reveal that the relationships among the study variables extend beyond simple linear effects and involve a combination of direct, indirect, interactive, and nonlinear influences in shaping final advertisement rankings. Variables such as content quality, keyword relevance, CTR, and advertising budget affected ranking outcomes through distinct pathways, while the mediating variable of user trust played a significant explanatory role in several of these relationships. Furthermore, the integration of machine learning models and explainable AI techniques demonstrated that predictive performance in advertising ranking systems becomes substantially more valuable when accompanied by interpretability, stability, and decision logic that is understandable to human stakeholders (Chen & Guestrin,2016). The main research hypothesis posits that the integrated XAI–SEO model, following calibration, enhances the Fidelity and Stability indicators, thereby leading to a significant improvement in users' perception of the advertisement ranking logic. The findings generally support this hypothesis. This result can be interpreted from several perspectives.

First, the proposed model successfully achieved both high predictive accuracy and satisfactory stability at the technical level. Specifically, the XGBoost algorithm demonstrated superior performance compared with the benchmark models, achieving an accuracy of 0.84 and low prediction error values. Furthermore, cross-validation results revealed a minimal gap between training and testing performance, along with a low standard deviation, confirming the model's stability and generalizability. This finding is particularly important because explainability becomes meaningful only when the underlying predictive model is reliable. Explanations generated for unstable or poorly performing models offer limited practical value and may even mislead stakeholders.

Second, the explainability layer, implemented through SHAP analysis, revealed that the ranking mechanism is not driven solely by financial variables such as advertising budget. Rather, variables associated with the intrinsic quality of advertisements particularly content quality and keyword relevance exert greater influence on the model's decisions. From a perceptual perspective, this finding is highly significant. The more users and stakeholders perceive that rankings are determined by logical, content-oriented, and fair criteria, the greater their likelihood of accepting and trusting the system. In this regard, the proposed model has partially transformed algorithmic decision-making from a purely financial and opaque mechanism into a quality-oriented and interpretable process.

Third, the explainability metrics obtained during the final evaluation further support this conclusion. The Fidelity score of 0.89 and the Stability score of 0.93 indicate that the generated explanations are both closely aligned with the model's actual decision-making process and robust to minor variations in the input data. These two metrics directly support the theoretical foundation of the main hypothesis. When explanations are both faithful and stable, users and human evaluators are more likely to perceive the ranking logic as understandable and trustworthy. Consistent with this interpretation, expert evaluations confirmed that the explanations generated by the model were acceptable from a business logic perspective and aligned with the operational realities of contemporary advertising platforms.

Fourth, the hypothesis-testing results demonstrated that improvements in model transparency and explanation quality enhanced the comprehensibility of the ranking logic for users and evaluators within the simulated environment. This increased comprehensibility created favorable conditions for greater acceptance of the model. Although user perception was not measured directly through a large-scale survey of end users, sufficient evidence supporting the hypothesis was obtained through two complementary mechanisms: technical explainability indicators and expert validation. In other words, the enhancement of ranking logic interpretability in this study was inferred and validated through the quality of technical explanations and the assessments of domain experts rather than through extensive user self-report measures.

Overall, the findings suggest that the integrated XAI-SEO model successfully established a balance among three fundamental dimensions: predictive accuracy, explanatory transparency, and human acceptability. This balance represents the critical point at which the model evolves from a purely predictive tool into a localized, interpretable, and trustworthy framework for advertisement ranking within domestic digital advertising platforms. From this perspective, confirmation of the main hypothesis signifies more than the technical success of the proposed model; it highlights the feasibility of designing ranking systems that not only achieve high performance but are also understandable, transparent, and defensible to human stakeholders. Such characteristics have increasingly been recognized in contemporary XAI literature as essential prerequisites for fostering trust in intelligent systems (Chen & Guestrin,2024).

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