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ORIGINAL

Research on the effect model of immersive design in interactive advertising

Investigación sobre el modelo de efecto de diseño inmersivo en publicidad interactiva

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ABSTRACT

Introduction: the impact of immersive design in interactive advertising focuses on how visuals in Virtual Reality (VR) and interactive elements influence user engagement. With the growing adoption of immersive technologies, advertisers seek innovative ways to enhance ad performance and optimize user interaction. A high grade of Deep Learning (DL) was used towards the enhancement and prediction of advertisement (ad) performances yet the limitations include insufficient consideration of dynamic user behavior, challenges in analyzing complex multi-modal ad content, and difficulties in generalizing findings across diverse ad formats and user demographics.
Objective: the research aims to develop a model that analyzes and predicts the impact of immersive design elements in VR interactive advertising on user engagement. The goal is to leverage innovative DL approaches to focalizing advertising efficiency and improving results of interactions with users.
Method: a novel Momentum Search-Driven Intelligent ResNet Architecture (MS-IRA) is proposed, combining an enhanced ResNet model with momentum-based optimization techniques. The dataset comprises engagement measurements, including clicks, time spent, and conversion rates throughout multiple types of ads, as well as interactive and visual ads. Through enhanced persistent associations, the IRA technique improves the feature extraction, and preprocessing enabling it possible to recognize complicated trends in immersive VR ads. Furthermore, by adjusting parameters, MS accelerates up training, assuring faster convergence and improved modeling correctness.
Results: the suggested MS-IRA approach accurately facilitates the optimization of immersive advertising designs and improves the interactive advertising efficiency and user interaction results by improving the convergence and model accuracy (AUC with 0,98) in predicting user engagement and ad effectiveness.
Conclusions: by leveraging DL techniques, the research offers valuable insights into immersive design strategies, contributing to the evolution of interactive advertising and user-centered engagement approaches.

Keywords: Immersive Design; Interactive Advertising; Ad Effectiveness; Momentum Search-Driven Intelligent ResNet Architecture (MS-IRA); Virtual Reality (VR).

RESUMEN

Introducción: el impacto del diseño inmersivo en la publicidad interactiva se centra en cómo las imágenes en realidad Virtual (VR) y los elementos interactivos influyen en la participación del usuario. Con la creciente adopción de tecnologías inmersivas, los anunciantes buscan formas innovadoras de mejorar el rendimiento de los anuncios y optimizar la interacción del usuario. Se utilizó un alto grado de aprendizaje profundo (DL)

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para mejorar y predecir el rendimiento de los anuncios, aunque las limitaciones incluyen la consideración insuficiente del comportamiento dinámico de los usuarios, los retos en el análisis del contenido de anuncios multi-modal complejo y las dificultades para generalizar los resultados en diversos formatos de anuncios y datos demográficos de los usuarios.
Objetivo: la investigación tiene como objetivo desarrollar un modelo que analiza y predice el impacto de los elementos de diseño inmersivos en la publicidad interactiva VR en el engagement del usuario. El objetivo es aprovechar enfoques DL innovadores para focalizar la eficiencia publicitaria y mejorar los resultados de las interacciones con los usuarios.
Método: se propone una nueva arquitectura de ResNet inteligente impulsada por búsqueda de momento (MS-IRA), que combina un modelo ResNet mejorado con técnicas de optimización basadas en momento. A través de asociaciones persistentes mejoradas, la técnica IRA mejora la extracción de características y el preprocesamiento, lo que permite reconocer tendencias complicadas en anuncios VR inmersivos. Además, al ajustar los parámetros, MS acelera el entrenamiento, asegurando una convergencia más rápida y una mejor corrección del modelado.
Resultados: el enfoque MS-IRA sugerido facilita con precisión la optimización de diseños publicitarios inmersivos y mejora la eficiencia de la publicidad interactiva y los resultados de la interacción del usuario mediante la mejora de la convergencia y la precisión del modelo (AUC con 0,98) en la predicción de la participación del usuario y la eficacia de los anuncios.
Conclusiones: al aprovechar las técnicas DL, la investigación ofrece una valiosa visión de las estrategias de diseño inmersivas, contribuyendo a la evolución de la publicidad interactiva y los enfoques de compromiso centrado en el usuario.

Palabras clave: Diseño Inmersivo; Publicidad Interactiva; Efectividad de Anuncios; Impulso Impulsado por Búsqueda Inteligente Arquitectura ResNet (MS-IRA); Realidad Virtual (VR).

INTRODUCTION

Virtual environment and concept design are making a huge impact on the advertising field, where ideas and technology converge for new experiences.(1) With the help of innovations like virtual and Augmented Reality (AR) to which users can actively interact with the content in real-time, watching has been replaced with a more powerful impact and ready multimedia. All these innovations make remarkable genuine interactions that improve emotional appeal, leading to better recall and thus better impact.(2) This design approach will allow the audience to interact with products or services of their interest in a practical and customized manner. For example, virtual tools enable users to build a sense of place that items occupy in the environment, something which cannot be done with traditional tools.(3) Because immersive techniques cut across the monotony of normal ads, it helps ensure that campaigns are interesting and real.(4) The impact model of immersive design measures the influences of the design approach on customers' behavior and attitudes.(5) Some of them are the extent of brand familiarity, advertising execution as well as appeal and decision rationality used in assessment of its success. Such assist marketers to come up with different techniques that suit the current market needs by providing the consumer with the content they would wish to access.(6) In addition to improving response, the use of immersive design resolves critical issues in the advertisement market, such as the problem of audience boredom, and the problem of the excess of information.(7) Brands are aware that when this occurs, they will not only attract attention but also be able to sustain it through efficient interaction and information sharing that differs from traditional media and advertising. The relationship between brand and customer is enhanced, as both parties will easily trust each other.(8) Hence, the effects of the amusement of design are examined regarding case studies and quantized values in the interactive advertising system. The way these techniques rework communication strategies with the help of advertisers was examined to create appealing campaigns as the audience.(9) Immersive design concept offers marketers an opportunity to generate value for the targeted consumers in order to help them achieve their branding objectives. The objective is to develop and validate a Momentum Search-Driven Intelligent ResNet Architecture (MS-IRA) that will optimize immersive design elements, predict user engagement, and enhance the effectiveness of interactive advertising campaigns.

Artificial intelligence (AI)-driven chatbots were mimicking human speech patterns, increasing their efficacy in advertisements.(10) According to an investigation comparing resembling chatbot profiles, message interaction, and ad type, story commercials encourage bot marketing while high messaging interaction cultivates favorable sentiments. Ad persuasion was increased by a great deal of interaction and storytelling style, which also heightened social presence and facilitated discussion of theoretical and practical consequences. Profitability for companies was greatly impacted by advertising in the digital age, with a well-executed, data-driven strategy producing notable benefits.(11) When determining return on investment, variables like ad expenditure, conversion rates, and client lifetime value were essential. Video advertising was special because it draws viewers in, makes them want to delay closing, lowers defensive opinions about it, and offers managerial insights for e-commerce incorporation and profitable operations.[12]

Using color and transcendental multimedia situations, brand activism advertising engaged consumers and promoted social change.[13] Advertisements that use Black and White (BW) imagery and promotion-framed messaging increase the efficacy of brand activism by inciting transcendent experiences in consumers and influencing their propensity to buy. Online advertising was potentially impacted by the General Data Protection Regulation (GDPR) which could lower revenue.[14] Ad publishers can lessen the detrimental effects on performance, bid prices, and income, nevertheless, by utilizing pay-per-click models and high consent rates. Background on a web page can make up for lost info. Investigation addresses the ignorance of consumers' mental reactions by investigating the purpose of physiology and neurophysiological research in marketing. Using the PRISMA paradigm, relevant publications were retrieved and global trends in neurological marketing and marketing were examined.[15]

The research emphasized how crucial reactions, perception, reward, memory, and focus were in advertisements. The impact of in-game advertisements' congruence, intrusiveness, and engagement on players' opinions and intent to purchase was examined using the Stimulus-Organization-Response (SOR) paradigm.[16] The results suggest that attitude has a moderate impact on the relationship between advertisement intrusiveness, interaction, and harmony. Using the theories of planned behavior, technological acceptance, and uses and gratifications, the research project investigated how digital natives view and respond to internet advertising.[17] The findings indicate that while certainty has little effect on intentions, simplicity of use, utility, entertainment value, authority, design, and customization all have a beneficial impact on attitudes. The notion of present as a basis investigated how users' methods and online marketing interaction mediate perceived customization and good electronic word-of-mouth.[18]

Key contributions:

- A novel method of Momentum Search-Driven Intelligent ResNet Architecture (MS-IRA), incorporating an enhanced ResNet with momentum-based optimization to forecast user engagement in VR interactive ads.
- BY utilizing a suitable data gathering process encompassed different user engagement metrics, IRA technique for feature extraction and the preprocessing mechanisms facilities the identification of complex patterns.
- A enhanced predication accuracy is achieved in MS-IRA representing a significant improvements in optimizing immersive ad designs and enhancing interactive advertising efficiency.

The remaining part of the investigation is structured as, part 2 offers the recommended MS-IRA technique that comprises the suitable pre-processing and normalization techniques which is tested on interactive advertisement the dataset to analyze the user engagement in VR ads. While part 3 focused on the obtained findings proved the enhanced effectiveness of interactive advertising together with better rates of convergence and accuracy along with necessary visualizations and part 5 briefly discussed the overall outcomes. Finally, the conclusion is provided in part 6.

METHOD

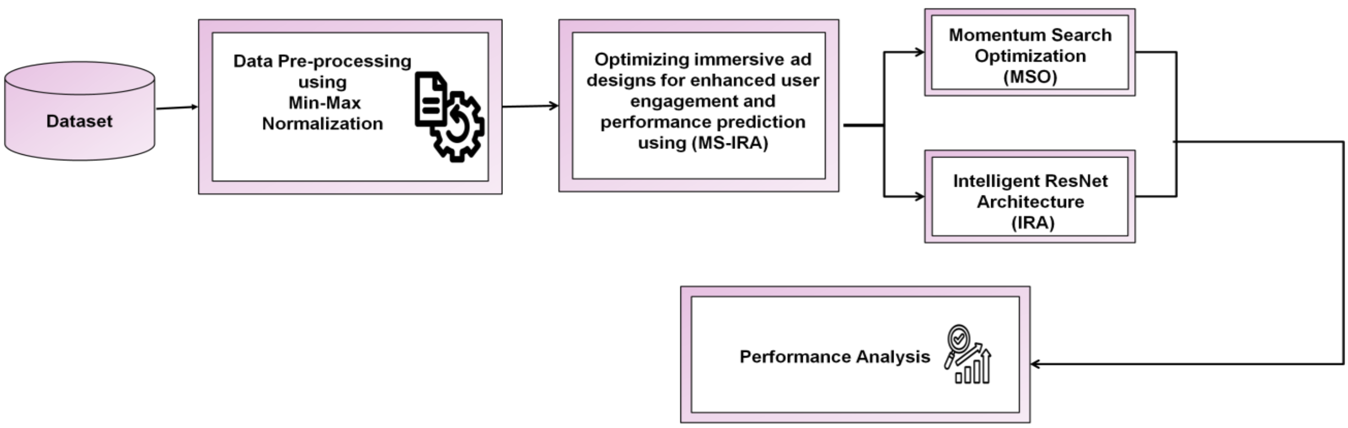

Figure 1. Proposed Methodology

In the initial stage, the dataset of interactive advertisements is collected, including ad types, user engagement metrics, and device details then the data preprocessing is performed using min-max normalization technique improves the efficiency and stability of the MS-IRA. The Momentum Search Optimization (MSO) is applied to

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fine-tuning of hyper parameters which also accelerates the convergence of the process. The Intelligent ResNet architecture (IRA) is used for efficient prediction of user engagement. Figure 1 illustrates the MS-IRA approach detailed process in analyzing the user interaction in ads.

Dataset

The dataset provides comprehensive user interaction data from diverse immersive ad formats, including 3D, AR, and 2D ads.[19] Some of these are clicks, time spent, engagement scores, conversion, bounce rate, age, gender, mobile, desktop and tablets, among others. Additional details include visual complexity and user movement data (e.g., gaze, movement), enabling analysis of immersive elements' influence on user engagement. Built for a predictive modeling environment, it helps to optimize ad designs by looking into ad types and users' behaviors. This dataset is important in providing useful information to digital marketers, advertisers, and researchers in interactive advertising technology.

Pre-processing using Min-Max Normalization

Min-Max normalization scales dataset features to a uniform range, typically [0, 1], to eliminate discrepancies caused by varying scales. This pre-processing step is essential for interactive advertising datasets, which include features like clicks, time spent, and engagement scores using equation (1).

$$W_{new} = \frac{W - Min(W)}{\max(W) - Min(W)} \qquad (1)$$

The original value, W which represents the feature to be modified, is the source of the normalized value, Wnew. max(W) is the maximum value of the feature in the dataset, and Min(W) is the minimum value. Normalizing feature consistency across the dataset, improving model accuracy, and eliminating scale biases, which is crucial for optimizing interactive advertising performance.

Momentum Search-Driven Intelligent ResNet Architecture (MS-IRA) for enhanced user engagement

The MS-IRA unifies the effective momentum-based optimization from the MS with the DL functionality of ResNet to improve the efficiency and interactivity of advertisements. MS-IRA improves the hyperspace of immersive ads that analyses shapes, color, textures, and other visual properties of ad interfaces to accurately forecast engagement and conversions such as clicks, time, and conversion rates. It increased convergence rate, reduced model errors, and enhanced interactive ad design, thereby improving user interaction.

Intelligent ResNet Architecture (IRA)

The IRA is used to improve the interactive advertising design and Quadratic DL techniques for increasing user attention via integrated Ad Interactive Features. ResNet is well-suited for this task as it can train very deep networks efficiently by using residual influences, which allow the model to skip certain layers, reducing the vanishing gradient problem and refining training competence. Interactive ads, ResNet are utilized to excerpt complex visual features from numerous ad mechanisms like images, animations, and text. These key features are to understanding user interactions and the learning process in ResNet is governed by a set of optimization equations that help improve user engagement predictions such as click-through rates, time spent, and conversion rates. Equation (2) is used to describe the learning process in ResNet is the activation function.

$$Z = e(WX + a) \qquad (2)$$

Where, W is the input data, W represents weights, a is the bias, and e is the activation function (like ReLU). This equation allows the network to learn representations of features. Equations (3 and 4) govern the residual connection.

$$Z_{res} = W + E(W) \qquad (3)$$

In the above instance E(W) is the output of the residual block, and W is the input. This residual connection ensures that the network can learn identity mappings, helping to mitigate the vanishing gradient problem. The loss function is critical to optimizing the design, as it guides the network's parameters.

$$\mathcal{L} = \sum_{j=1}^{M} \left(z_j - \hat{z}_j\right)^2 \qquad (4)$$

Where z_j represents the true value of engagement metrics, and $\hat{z}_j$ is the predicted engagement value. This equation (4) helps in estimating the difference between real and forecasted user engagement rates. With these equations, the Intelligent ResNet architecture works to optimize the interactive ad design during convergence

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and enhances the engagement of the user during the training phase. It maintains a high level of ad targeting, thereby enhancing interaction with the users, which comprise a fast convergence when optimizing.

Momentum Search Optimization (MSO)

The MSO is used in interactive advertising design to increase the user experience of the interactive medium and to gain improved results through the use of visual and interactive elements. This method uses the MS-based search techniques to achieve the best search space in interactive ads obtaining the fine hyper parameters and visual features. The algorithm increases efficiency in selecting the most important visual cues and forecasting user interactivity, enhancing the creative designs further towards delivering higher interactivity in immersive ads and achieving convergence more quickly. The optimization is done based on a fitness function that measures different ad elements that capture the user's attention and translates it to activity, including clicks, time spent on the campaign, and conversion rate. The fitness function in equations (5 and 6) to determine the effectiveness of an ad's design.

$$E_d = Min(O) \qquad (5)$$

Here, E_d represents the fitness parameter that correlates with user engagement. The position of each solution body in the search space is represented as follows.

$$W_J(s) = \left(W_{(J)}^{(1)}(s), \dots, W_{(J)}^{(C)}(s), \dots, W_{(J)}^{(M)}(s)\right) \qquad (6)$$

Where $W_{(J)}^{(M)}$ is the position in the jth dimension, capturing the visual feature of the ad in question using equation (7) defines the boundary constraints for each design variable is defined as follows.

$$W_{Min}^{(I)} \le W_{(J)}^{(I)}(s) \le W_{Max}^{(I)}, J = 1, \dots, N;\ I = 1, \dots, M \qquad (7)$$

In equation (8), the mass of a solution body is updated according to its fitness.

$$N_J(S) = \frac{Fit_J(S) - Worst(S)}{Best(S) - Worst(S)} \qquad (8)$$

The best and worst fitness values are calculated using equations (9 and 10), which identify the optimal and least favorable solutions.

$$Best(S) = \underset{I=1,\dots,N}{\mathrm{Min}} Fit_J(S) \qquad (9)$$

$$Worst(S) = \underset{I=1,\dots,N}{\mathrm{Min}} Fit_J(S) \qquad (10)$$

The momentum of the external body, representing a change in the design space, is computed in equation (11).

$$N(S) = 1 - \frac{S-1}{s-1} \qquad (11)$$

Equations (12-14) calculate the speed and momentum of the external body that influences the design's position.

$$v_J^{(C)}(S) = Q_1\left(1 - \frac{S-1}{s-1}\right) u_{max} \times sign\left(W_{Best}^{(C)}(S) - W_J^{(C)}(S)\right) \qquad (12)$$

$$O_J^{(C)}(S) = n(S) v_J^{(C)}(S) \qquad (13)$$

$$n(S) v_J^{(C)}(S) = N_J(S) U_J^{(C)}(S) + n(S) V_J^{(C)}(S) \qquad (14)$$

MSO provides valuable final configuration of the ad's visual characteristics and the layout to stimulate usage, considering not only the static and dynamic aspects of usage. As a result of momentum-based optimization approaches, the model obtains a solution upgrading user involvement with outstanding innovative design in a short time while making quick changes to the design based on the user behavior data. Algorithm 1 offers the recommended MS-IRA technique to forecast user engagement in VR interactive ads.

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Algorithm 1 : MS-IRA

$$W_{new} = \frac{(W - Min(W))}{}(Max(W) - Min(W))$$

Store W_new in Normalized_Dataset
Step 3: Intelligent ResNet Architecture (IRA) for Feature Extraction
def ResNet_Forward_Propagation(W, weights, bias):
Z = activation_function(W * weights + bias)
Z_res = W + Residual_Block(W)
return Z_res
For each Ad in Normalized_Dataset:
 Features = Extract_Features(Ad, ResNet_Forward_Propagation)
 Store Features in Feature_Set
Step 4: Momentum Search Optimization (MSO) for Hyperparameter Tuning
Initialize Population of Solutions W_J(s)
Evaluate Fitness Function for each solution:
E_d = Min(O)
While Stopping Criterion is not met:
For each Solution W_J(s):
Update Position
Apply Boundary Constraints
Compute Momentum
Compute Speed and Velocity
Evaluate New Fitness Function
Update Best and Worst Solutions
Step 5: Model Training with Optimized Parameters
Train MS-IRA Model using optimized hyperparameters and extracted features:
 Loss_Function = Sum((z_j - predicted_z_j)^2)
 Optimize Weights using Backpropagation and Gradient Descent
 Evaluate Performance using AUC, Click-Through Rates, and Engagement Scores
Step 6: Prediction & Performance Evaluation
For each New Interactive Ad:
 Extract Features using ResNet
 Predict Engagement Metrics (Clicks, Time Spent, Conversions)
Step 7: Output Optimized Ad Designs for Better User Engagement
Return Best Performing Ad Configurations

The MSO-IRA method refines ad targeting, enhances the conversion rates, and revolutionizes digital advertising strategies through innovative optimization and feature extraction approaches by analyzing visual and interactive elements. The suggested technique ensures an adaptive, high-impact ad strategies that made the user's more interactive.

RESULTS

The effectiveness of using advanced DL techniques to optimize immersive advertising design. By combining momentum-based optimization with a DL model, the approach efficiently extracts visual features and predicts user engagement metrics, such as clicks, time spent, and conversion rates. The results illustrate the enhanced effectiveness of interactive advertising together with better rates of convergence and accuracy in the behavioral prediction of users. MS-IRA augments the efficiencies of the design of the immersive advertisement, improving the outcome of interaction for the users. Table 1 shows the experimental setup.

Table 1. Experimental Setup

Category	Details
Operating System	Windows 7 OS
Processor	Intel i7-7700 CPU
Graphics Card	GeForce GTX 960 GPU
Memory	16GB RAM
Storage	512GB
Receiver Devices	HUAWEI WATCH 1, HUAWEI Nexus 6P
Software Libraries	Python (OpenCV, TensorFlow, Keras)

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Figure 2 ROC curve shows the performance of the MS-IRA model in identifying the sorts of user engagements for interactive advertising. Plotting the true positive rate versus the false positive rate yields an AUC of 0,98, indicating excellent performance. The model's capability to differentiate among negative and positive results improves with the curve's nearness to the top-left angle. The high AUC implies accurate predictive accuracy in the context of interactively assessing the engagement of users in advertisement materials.

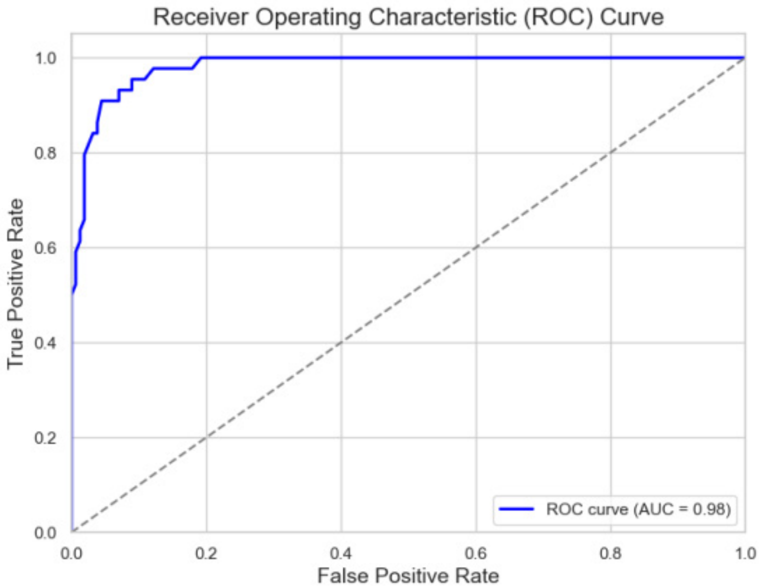

Figure 2. ROC curve

Figure 3 depicts correlation matrix, visualizing relationships between different variables in the dataset related to interactive advertising. Values range from -1 to 1, where 1 designates a perfect positive relationship among ad features and user engagement, and -1 characterizes a perfect negative correlation, showing an inverse effect. This analysis helps identify key factors that influence interactive advertising performance, such as clicks, time spent, and engagement scores. Strong correlations are observed between engagement score and engagement binned (0,98), indicating a significant alignment. Other variables, such as clicks and conversion rate, show weak or negligible correlations. This analysis highlights key variables influencing user engagement, aiding in feature selection and model development.

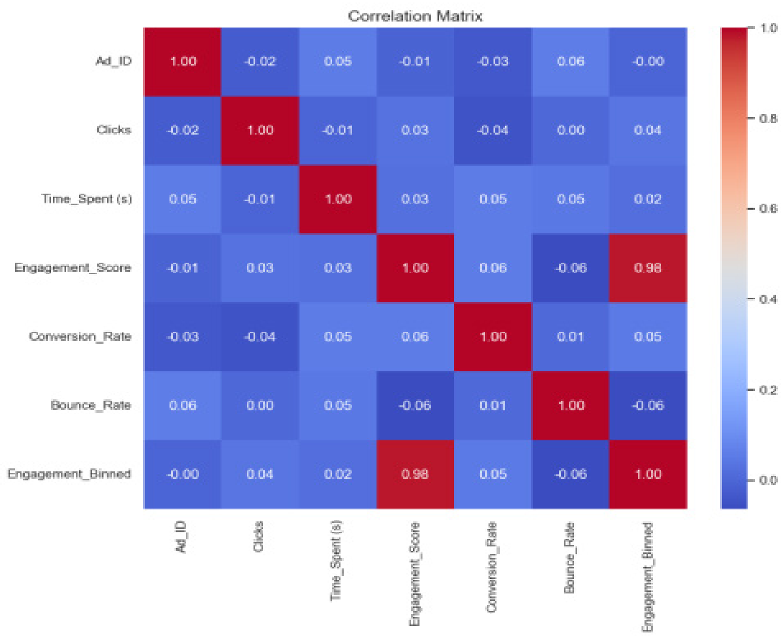

Figure 3. Correlation Matrix

Figure 4 analyses ad performance metrics across different ad types (AR, 2D, and 3D) using three visualizations. The first plot shows the relationship between clicks and time spent (in seconds) with a trendline. Figure 4 (a)

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reveals no significant trend, as the flat red line indicates that the number of clicks is not strongly influenced by the time spent viewing the ad. This suggests that time spent is not a primary determinant of user clicks. Figure 4 (b) examines the relationship between engagement score and clicks. While higher engagement scores generally align with more clicks, the variability across ad types highlights that engagement is influenced by additional factors beyond click numbers. Figure 4 (c) compares the average engagement scores for AR, 2D, and 3D ads. AR ads demonstrate the highest engagement, followed closely by 2D and 3D ads, suggesting that AR ads foster stronger user interaction compared to other formats.

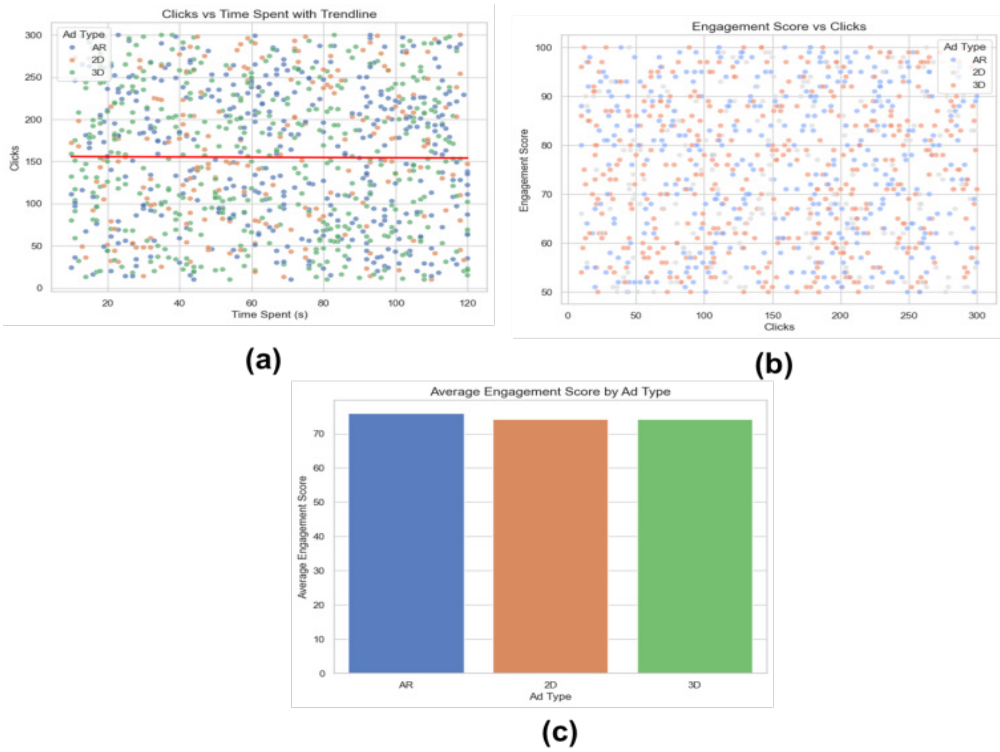

Figure 4. Advertisement Performance Metrics across Ad Types (a) Clicks vs. Time Spent with Trendline, (b) Engagement Score vs. Clicks, (c) Average Engagement Score by Ad Type

Figure 5 illustrates conversion rates across various age groups, highlighting user engagement patterns in interactive advertising. A line graph shows a steady decline in average conversion rates from the 18–24 age group (highest engagement) to 45–54 (lowest engagement), followed by a slight increase for the 55+ group. These findings suggest that younger audiences are more responsive to immersive advertising designs, emphasizing the importance of tailoring interactive strategies to specific age demographics for maximum effectiveness.

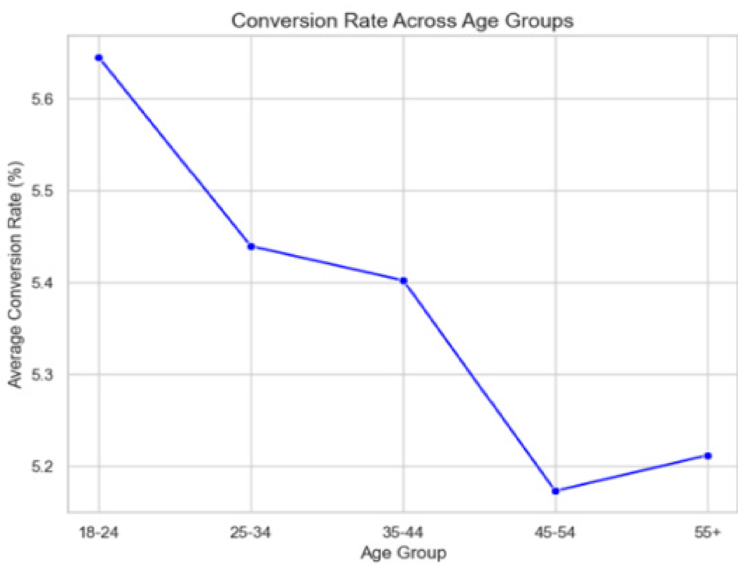

Figure 5. Conversion Rates across Age Groups in Interactive Advertising

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Figure 6 provides insights into ad performance across device types. Figure 6 (a) shows the distribution of interactions for 2D, 3D, and AR ads across desktop, mobile, and tablet devices. Mobile devices dominate user engagement, especially with AR ads, followed by desktops and tablets. Figure 6 (b) highlights the variability in clicks across device types. While desktop devices have the highest variability in clicks, mobile devices demonstrate consistent performance with a stable median. Tablet engagement is lower but exhibits minimal variability. These findings emphasize the importance of tailoring ad formats to device preferences to maximize user interaction.

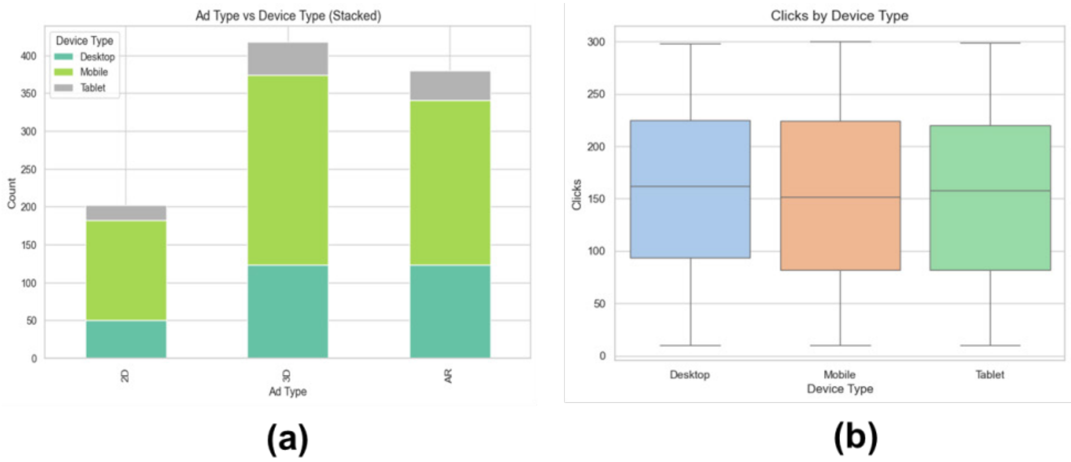

Figure 6. Ad Engagement across Devices (a) Ad type-device interaction, (b) Click variability by device

Figure 7 visualizes the relationship between clicks on ads and user engagement scores. Each point represents an observation, showing how engagement varies for different click levels. The spread of points suggests diverse engagement outcomes, with no clear linear relationship. The dense clustering highlights consistent engagement trends, while occasional peaks imply other influencing factors. This analysis provides insights into user behavior, suggesting that while clicks are important, additional variables likely play a significant role in determining engagement levels.

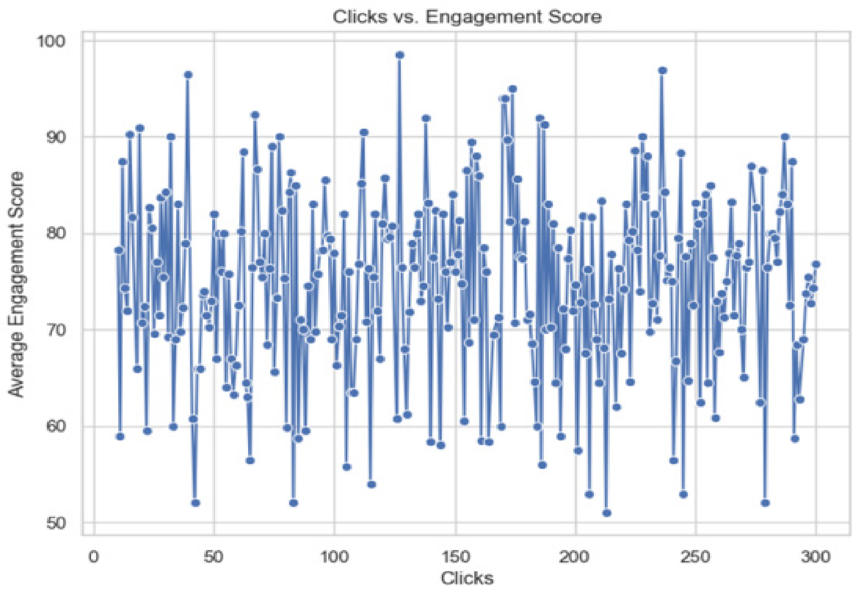

Figure 7. Clicks and Engagement Relationship across Ads

DISCUSSION

The findings of the research revealed a critical insight into how user engagement with interactive advertisements is influenced by ad type, age, device, and other behavioural factors. The high value for AUC in the ROC curve suggests that the model can predict user engagement superiorly increased than deep learning neural networks (DNN)[20] which points towards the fact that accurate predictive tools are possible in immersive ad campaigns. MS-IRA model not only confirmed the benefits of AR in enhancing user engagement, as offered

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in[21] but also extends the analysis by incorporating a wider array of engagement metrics, ad formats, and demographic factors, leading to a more comprehensive understanding of interactive advertising effectiveness. The strong correlation between engagement score and engagement binned emphasizes the need for attentive feature selection, as these metrics closely align in decisive engagement success. The variable performance across ad types (AR, 2D, 3D) demonstrates that immersive formats like AR offer superior engagement, reinforcing the importance of exploring immersive advertising for higher user interaction. The decrease in conversion rate with age also infers that there is a high likelihood of the young generation to respond to interactive ads, hence age-segmented strategies. Moreover, where mobile interactions are most prevalent in ads, it is clear that mobile-first advertising approaches are the right way to go. The findings show the importance of considering various aspects of user behavior to enhance advertising results in diverse contexts.

CONCLUSIONS

The investigation effectively established a novel approach for analyzing and predicting the impact of immersive design elements in Virtual Reality (VR) interactive advertising on user engagement. The model's capability in forecasting user engagement was validated through the comprehensive evaluation of engagement metrics, including clicks, time spent, and conversion rates, across diverse ad formats. The preprocessing improves the standard the information by guaranteeing optimal inputs for deep learning models, removing inconsistencies, and regulating engagement metrics. Through the incorporation of advanced ResNet architecture, with MSO the proposed approach effectively predicted the user engagement by adapting to dynamic interactive advertising environments that influence ad performance. The findings delivered that the best optimization of ad features, achieved an impressive AUC score of 0,98, which indicates excellent model performance in classifying user interaction outcomes. Also, the MSO-IRA showed that the AR could create even more engaging interactive ads and more effective than 2D and 3D. The trends in the volume of engagement observed for diverse age ranges and devices were also reported which offered the young people and mobile devices demonstrated higher levels of activity. While the MSO-IRA act as a preferable technique some limitations are exists. The vague incorporation of dynamic modes of user behavior and difficulties in applying observed trends across various forms of advertisement are considered. Further research can be implemented by using the interaction data in real-time, collecting data from more users, including those who do not belong to the millennial generation, the quality of models is improved and better performance is achieved in different platforms.

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