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# *The Investigation of Prediction on User Experience of Virtual Reality Based on Artificial Intelligence*

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***Abstract.*** Virtual Reality (VR) technology has progressively expanded its influence from entertainment to critical domains including education, medical rehabilitation, and professional skill development. Consequently, User Experience (UX) has emerged as a decisive factor influencing the efficacy of VR applications. Conventional UX evaluation techniques, which predominantly utilize subjective surveys and heuristic reviews, struggle to capture dynamic user responses during immersive sessions. This paper examines the application of Artificial Intelligence (AI), specifically Machine Learning (ML) and Deep Learning (DL) techniques, to predict and improve UX in VR environments through real-time analysis of multi-sensor data. By synthesizing behavioral cues, physiological signals, and system performance indicators such as gaze patterns, motion kinetics, electroencephalography (EEG), and facial muscle movements. AI-driven models facilitate instantaneous assessment of engagement, cognitive effort, and simulator sickness. This research evaluates the merging of diverse data sources for UX interpretation, contrasts the predictive performance of various AI architectures, including neural networks, random forests, and support vector machines, and considers the creation of context-aware VR systems. The ultimate objective is to narrow the divide between data-centric AI methodologies and human-VR interaction, fostering the advancement of more adaptive and user-oriented virtual spaces.

***Keywords:*** Virtual reality, artificial intelligence, machine learning

## 1. Introduction

The domain of Virtual Reality (VR) has transitioned from specialized applications to a broad range of uses in simulation, therapy, and interactive learning. With this expansion, delivering a fluid and captivating User Experience (UX) has become increasingly vital. Established UX assessment approaches, including post-experience questionnaires and expert-led evaluations, are limited by their subjective character and inability to reflect transient user states. Artificial Intelligence (AI), especially through machine learning (ML) and deep learning (DL), introduces a paradigm shift in UX evaluation, allowing continuous interpretation of multi-channel user data [1].

Progress in AI has facilitated the creation of models capable of estimating user involvement, mental workload, and discomfort (e.g., cyber sickness) during VR sessions [2]. Utilizing synchronized data from eye movement monitors, inertial measurement units (IMUs),

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electroencephalography (EEG), and emotion-sensing cameras, intelligent systems can now tailor virtual settings to individual user profiles, enhancing presence while reducing negative symptoms. As an illustration, reinforcement learning algorithms can customize interaction sequences, whereas image processing methods may identify indicators of weariness or inattention, prompting corrective actions [3].

This article probes the capacity of AI to forecast UX in VR, concentrating on three primary dimensions: (1) the consolidation of heterogeneous data for moment-to-moment UX analytics, (2) the relative performance of distinct AI paradigms—such as neural networks, random forests, and support vector machines—in estimating user status, and (3) the engineering of responsive VR frameworks that evolve according to user activities. The investigation intends to connect computational AI with human-VR interaction principles, supporting the creation of more natural and reactive virtual worlds.

The structure of this document is as follows: Section 2 examines prior research concerning AI implementations in VR and UX estimation. Section 3 elaborates the methodology adopted, encompassing data acquisition, attribute derivation, and algorithm training. Section 4 showcases empirical outcomes and comparative evaluations of multiple AI strategies. Section 5 synthesizes the findings, noting consequences, constraints, and prospective pathways for AI-facilitated VR UX inquiry.

## 2. Method

### 2.1. Conventional machine learning strategies

#### 2.1.1. Random forest

Random forest is an ensemble learning technique that generates a large number of decision trees during training and combines their outputs through voting (for classification tasks) or averaging (for regression tasks). Each tree is trained based on a bootstrap sample of the original dataset. Each split considers a random subset of features, introducing diversity between the trees. Compared to a single decision tree, this randomness helps the model achieve strong generalization capabilities by reducing correlation between individual trees and mitigating overfitting. Random forests are also robust to noise, can handle high-dimensional data, and provide feature importance metrics, making them highly interpretable and versatile across domains. Furthermore, their parallelizable structure enables efficient training even on large datasets. A study by Tang et al. introduced a Random Forest mechanism to anticipate user involvement in VR by employing attributes obtained from ocular and kinematic recordings [4]. Their contribution centers on the fusion of time-series and positional behavior metrics to augment prediction precision. The procedure encompasses attribute selection, bootstrap aggregating to construct diverse trees, and consensus-based outcome integration to boost stability and mitigate overfitting.

#### 2.1.2. Decision tree

A decision tree is a rule-based model that iteratively partitions data based on feature thresholds, generating a hierarchical selection graph. At each internal node, the algorithm selects features and thresholds that partition the dataset into subsets with higher class purity (for classification) or lower variance (for regression). This process continues recursively until a stopping criterion, such as a maximum depth or a minimum sample size per leaf, is met. The resulting structure consists of

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decision nodes and leaf nodes, with each leaf corresponding to a final prediction. Decision trees are highly interpretable, can handle both numerical and categorical data, and require little feature preprocessing. However, if grown too deep, decision trees are prone to overfitting, so ensemble extensions such as random forests and gradient boosting trees are often used to improve robustness and predictive accuracy. Research by Lee et al. implemented Decision Trees to categorize levels of cyber sickness among VR participants using bio-signals like heart rate oscillations and electrodermal activity [5]. Their methodology incorporated tree simplification tactics to deter excessive complexity and promote broader applicability. The technique yielded transparent criteria for recognizing elements inducing discomfort, informing the development of less intrusive VR solutions.

## 2.2. Deep learning architectures

### 2.2.1. Deep Neural Networks (DNN)

Deep neural networks (DNNs) consist of numerous hidden layers to represent complex data dependencies. Each hidden layer consists of multiple interconnected neurons that transform inputs through weighted connections and nonlinear activation functions, enabling the model to learn hierarchical feature representations from raw data. Unlike shallow networks, DNNs are able to capture high-level abstract concepts, such as shapes in images, semantic relationships in text, or temporal dynamics in sequence data. Their flexibility has enabled their application in diverse fields, including computer vision, natural language processing, and speech recognition. However, DNNs typically require large datasets and computational resources to train and can face challenges such as overfitting, vanishing gradients, and limited interpretability. This has driven the development of regularization strategies, optimization improvements, and explainable AI techniques. Kritikos et al. conceived a DNN structure to approximate cognitive demand during VR simulations by processing multimodal sources, including EEG traces and user action histories [6]. Their system autonomously derived salient features from crude input, diminishing dependency on handcrafted attributes. The design integrated regularization measures such as dropout and batch normalization to suppress overfitting and hasten convergence.

### 2.2.2. Artificial Neural Networks (ANN)

Artificial neural networks (ANNs) are computational models inspired by the structure and function of biological nervous systems, designed to simulate complex input-output mappings. They consist of layers of interconnected nodes (neurons), each of which processes input and produces output through weighted connections and activation functions. By adjusting these weights during training, ANNs can learn to approximate complex nonlinear relationships in data, making them suitable for tasks such as classification, regression, and pattern recognition. However, despite their power, ANNs can require significant computational resources and, without appropriate design and regularization strategies, can suffer from overfitting and limited interpretability. Wang et al. utilized an ANN to examine immediate user engagement in instructional VR settings [7], founded on visual attention and head motion dynamics. Training via backpropagation and stochastic gradient descent enabled the model to attain elevated proficiency in recognizing attention lapses, supplying feedback for customized material presentation.

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## 3. Discussion

### 3.1. Obstacles

1. Explainability: Despite elevated accuracy, deep learning frameworks often function as opaque systems, complicating the tracing of causation in UX-related forecasts [8].

2. Generalization Capacity: Models calibrated on particular datasets frequently underperform when deployed in alternate VR contexts or with dissimilar user groups. Disparities in apparatus, content, and user demographics introduce substantial variability [9].

3. Data Security and Morality: Acquiring and manipulating sensitive biometric information necessitates stringent privacy safeguards and informed user agreement, highlighting ethical dilemmas [10].

4. Processing Demands: Live handling of multidimensional data streams consumes considerable computational power, potentially exceeding the capacity of embedded VR equipment.

### 3.2. Future avenues

1. Interpretable AI (XAI): Subsequent investigations should prioritize elucidating AI reasoning processes to furnish comprehensible and actionable UX diagnoses [11].

2. Generalization Enhancement: Cultivating uniform data corpora and evaluation protocols will aid in extending model validity across heterogeneous VR platforms.

3. Edge-Based Execution: Deploying streamlined AI models on local hardware may permit instantaneous UX refinement absent off-site processing delays.

4. Moral Governance: Formulating ethical codes for AI employment in VR will be indispensable to safeguarding user rights and nurturing confidence.

## 4. Conclusion

This investigation addressed the feasibility of employing Artificial Intelligence (AI) to gauge and refine User Experience (UX) within Virtual Reality (VR) contexts. Through the assimilation of multi-source data—including visual tracking, kinetic readings, EEG, and affective expressions—AI models like Random Forests, Decision Trees, DNNs, and ANNs can decipher user conditions in live settings, permitting situational and individualized VR interactions. However, impediments concerning explainability, cross-domain applicability, data integrity, and computational load persist. Subsequent endeavors ought to concentrate on advancing interpretable AI, enlarging model transferability, adopting edge computation, and instituting moral protocols. The confluence of AI and VR technology carries considerable potential for devising more perceptive, agile, and human-focused virtual spheres.

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