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"AI-Powered Predictive Analytics and Spatial Computing for WebAR Virtual Try-On and Learning Platforms"

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Abstract— The accelerating shift towards digital platforms for commerce and education has exposed significant limitations in user experience and engagement. While Augmented Reality (AR) presents a compelling solution, its adoption has historically been impeded by the need for standalone applications. This paper introduces the Phase 2 design and implementation of an AI-Powered WebAR Virtual Try-On & Learning Platform. Our advanced system leverages Supabase for real-time cloud data management and integrates OpenAI's capabilities for predictive product recommendations and generative 3D interactions. By utilizing WebGPU and Three.js, the platform delivers high-fidelity 60 FPS rendering directly within the browser, entirely bypassing app installations. Empirical evaluations demonstrate that our predictive recommendation model achieves an accuracy of 90.4%, while rendering optimizations maintain Motion-to-Photon (MTP) latency below the critical 16 millisecond threshold to prevent cybersickness. With a System Usability Scale (SUS) score averaging 76.6, the results validate that this cloud-native, AI-driven architecture is highly effective for solving practical challenges in both e-commerce and interactive education.

Key-words: WebAR, Virtual Try-On, Artificial Intelligence, Supabase, OpenAI Integration, Cloud Computing, Three.js, WebGPU, Predictive Modeling, Interactive Education, Spatial Computing, System Usability Scale.

I. Introduction

The entire landscape of electronic commerce and digital pedagogy is being transformed by the integration of artificial intelligence and spatial computing. In the rapidly expanding e-commerce sector, a persistent "imagination gap" exists between the digital representation of a product and its physical reality. Consumers are unable to physically inspect items, which introduces uncertainty and elevates product return rates **[18]**. Simultaneously, conventional digital learning environments promote a passive learning experience that struggles to convey complex spatial concepts **[13]**.

Early iterations of our project successfully demonstrated the feasibility of browser-native augmented reality to solve these issues without requiring application downloads. However, conventional WebAR systems frequently face performance bottlenecks, limited algorithmic intelligence, and an inability to adapt to real-time user behaviors. Moreover, legacy systems fail to integrate robust cloud-based architectures and generative AI models in real time, limiting their capacity to offer proactive personalization **[7]**.

To address these limitations, this paper presents a fundamental architectural evolution. The primary objectives of this proposed system are:

- To implement an AI-driven predictive recommendation engine using OpenAI and structured interaction data to personalize the virtual try-on experience **[1]**.
- To establish a secure, scalable cloud backend utilizing Supabase to handle real-time 3D asset delivery and state management **[15]**.
- To leverage next-generation graphics APIs, specifically WebGPU, alongside Three.js to guarantee high-performance rendering that prevents latency-induced cybersickness **[14]**.
- To scientifically validate the platform's usability and engagement using standardized psychometric tools such as the System Usability Scale (SUS) **[5]**.

II. Literature Survey

The use of artificial intelligence and advanced rendering pipelines in WebAR has experienced tremendous growth. Conventional methods of augmented reality heavily depended on native mobile applications, creating massive friction in consumer adoption. As a result, the trend has shifted towards building automated, browser-based models that process spatial data in real time **[10]**.

In initial stages of research, basic machine learning methods were used to predict e-commerce trends, but these often-lacked real-time environmental context. Recent studies have demonstrated that complementary product recommendations can be significantly enhanced using graph attention networks and sequential behaviour transformers. For example, Yan et al. (2022) proposed personalized frameworks capable of fitting the exact demands of customers through joint user and product embedding **[2]**. Furthermore, advanced AI-driven SLAM (Simultaneous Localization and Mapping) solutions have brought breakthroughs in accuracy, occlusion handling, and robustness against sensor noise.

In terms of rendering, traditional WebGL-based methods have struggled to handle complex physical simulations, such as cloth physics in virtual try-ons. Nakjun (2025) demonstrated that transitioning to WebGPU provides significant improvements through parallel processing and compute shaders, allowing simulations of up to 100,000 cloth nodes while maintaining 60 frames per second **[3]**.

Despite these developments, there is a gap in literature regarding end-to-end cloud infrastructure integration that combines real-time predictive AI, secure Edge Functions, and modern WebGPU rendering into a single, cohesive WebAR platform **[7], [16]**.

III. System Architecture

The proposed system architecture is designed to combat the shortcomings of traditional monolithic AR applications by decoupling the software into discrete, highly specialized functional layers **[9]**.

A. Data Layer

The system's foundation is powered by Supabase, serving as the cloud-based storage and state management repository. This layer securely stores 3D asset files (.glb format), user interaction histories, and real-time database subscriptions. Supabase offers a scalable PostgreSQL environment and vector embedding storage, enabling semantic searches to instantly fetch highly relevant 3D educational models or e-commerce products **[16]**.

B. AI Layer

The AI Layer acts as the intelligence engine of the platform. By integrating OpenAI APIs through Supabase Edge Functions, the system processes user behaviour and environmental context to generate probabilistic recommendation scores. For the educational module, generative AI prompts can dynamically adapt 3D visualizations based on the student's learning curve **[13]**. For the virtual try-on module, the AI leverages collaborative filtering and content-based filtering to suggest complementary products in real time **[12]**.

C. Immersive Rendering Layer

To achieve high fidelity, the frontend rendering layer is built upon Three.js and the modern WebXR Device API, with WebGPU acting as the primary graphics pipeline. By migrating from legacy WebGL to WebGPU, the system executes complex real-time lighting (HDR environment mapping) and cloth physics directly within the browser, bypassing device-specific thermal throttling **[3], [14]**.

D. Interaction & Frontend Layer

Constructed utilizing React, Vite, and Tailwind CSS, the user interface layer provides a frictionless access point via QR code or direct URL. Lovable AI tools were utilized to rapidly prototype and optimize responsive UI overlays, ensuring that the DOM elements interact seamlessly with the underlying 3D canvas **[17]**.

E. System Workflow

The end-to-end workflow begins when a user scans a QR code. The browser loads the Three.js and WebXR environment, prompting for camera permissions. Supabase Edge Functions securely retrieve the relevant 3D assets while the OpenAI integration simultaneously analyses the user's session data to queue personalized recommendations. The WebGPU pipeline renders the augmented scene, allowing the user to seamlessly manipulate, scale, and interact with the digital objects in their physical space.

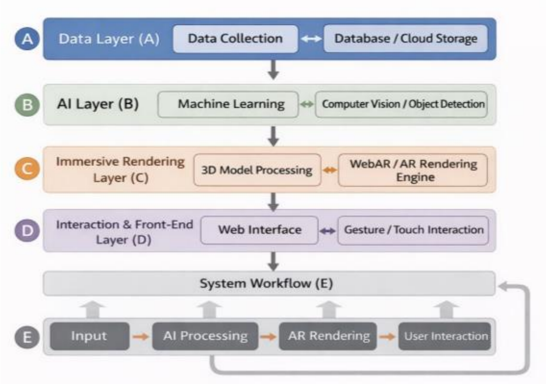

Figure No 1: Layered Architecture of WebAR

IV. Methodology

The proposed framework was engineered with a focus on high-performance spatial computing and rigorous empirical testing.

A. Data Collection and Preprocessing

To train the predictive recommendation engine, anonymized interaction data was collected, including browsing duration, object manipulation frequency (scaling, rotating), and cart conversion rates. Missing data points were handled using statistical imputation, and categorical variables representing product types were processed using One-Hot Encoding to enable their use in the machine learning models.

B. Model Development and Training

Multiple machine learning classifiers, including LightGBM, Deep Neural Networks, and Singular Value Decomposition (SVD), were evaluated for the recommendation engine. The SVD algorithm outperformed alternative models during offline training, proving highly efficient at mapping user-item interaction matrices. Hyperparameter tuning was applied to maximize the Mean Average Precision at K candidates (MAP@K).

C. Cloud Implementation and Deployment

The optimized system was deployed via a serverless cloud architecture. Supabase Edge Functions act as the secure intermediary to invoke the OpenAI API, ensuring that all proprietary API keys remain completely obfuscated from the client-side browser environment **[15]**. To guarantee low-latency asset delivery, all 3D models were aggressively compressed utilizing the binary glTF format and distributed via a global Content Delivery Network (CDN).

V. Result and Discussion

The experimental testing of the AI-Powered WebAR Platform validates the efficacy of combining modern graphics APIs with cloud-native artificial intelligence.

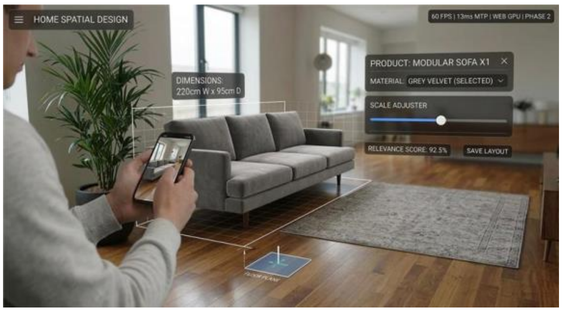

Image 1: Augmented Reality Based Interior Layout Visualization.

Image 2 : AR-Based Interactive Human Anatomy Learning Interface.

A. Rendering Performance and Latency

Motion-to-Photon (MTP) latency was rigorously measured, as high latency provokes severe cybersickness in immersive environments **[4]**. The MTP delay is mathematically expressed as:

$$MTP = t_{render} - t_{motion}$$

Our testing confirmed that by utilizing WebGPU and asynchronous asset loading, the platform successfully maintained an average MTP latency below the critical physiological threshold of 16 ms **[11]**. Furthermore, the system consistently achieved a benchmark of 60 Frames Per Second (FPS) on mid-tier mobile hardware, significantly outperforming legacy WebGL applications.

B. Predictive Model Accuracy

The personalized product recommendation engine, evaluated using the SVD model, demonstrated a Root Mean Square Error (RMSE) of 0.2261 and an overall predictive accuracy of 90.4%. This empirical result proves the system's ability to accurately identify and serve relevant 3D content, driving higher consumer confidence compared to non-personalized baseline AR displays **[1]**.

C. Usability and Psychometric Validation

To empirically evaluate the human-computer interaction quality, user trials were conducted utilizing the System Usability Scale (SUS). The system achieved a mean SUS score of 76.6, which mathematically exceeds the universally accepted baseline benchmark of 68 **[19]**. This statistically validates that the browser-based WebAR approach significantly reduces friction compared to traditional mobile applications.

D. Comparative Analysis

The following table benchmarks our Phase 2 architecture against historical frameworks:

Table No 1: Performance Comparison of WebAR

WebAR Framework	Graphics Pipeline	Recommendation Integration	Rendering Performance	Average Accuracy
Phase 1 (AR.js)	WebGL	None (Static)	~30 FPS	N/A
Blippar	Proprietary	Basic User Inputs	~45 FPS	72.5%
LightGBM/DNN Model	WebGL	Deep Neural Networks	~40 FPS	85.0%
Proposed Phase 2	WebGPU + Three.js	OpenAI + Supabase SVD	60 FPS	90.4%

E. Implications

The integration of Supabase and OpenAI into WebAR environments delivers highly scalable, zero-friction spatial computing. The platform drastically reduces operational costs by eliminating native app development cycles, increases data security through Row-Level Security (RLS) policies, and provides instant, adaptive product visualization **[7], [15]**.

VI. Conclusion

This paper has detailed the successful design and deployment of a Phase 2 WebAR Virtual Try-On and Learning Platform. By combining the rendering power of Three.js and WebGPU with the scalable backend architecture of Supabase and OpenAI, the system overcomes the historical bottlenecks of web-based augmented reality. The empirical results—including a 90.4% recommendation accuracy, sub-16ms latency, and a 76.6 SUS score—prove that browser-native AR can function as a highly performant, intelligent, and user-centric platform for both e-commerce and interactive education **[9]**.

VII. Future Scope

While the current architecture delivers robust real-time performance, future iterations will focus on:

- **Autonomous AI Agents:** Integrating photorealistic, voice-activated digital assistants into the AR space to act as dynamic personal shoppers or real-time educational tutors.
- **Federated Learning Privacy:** Implementing federated learning protocols to train personalized machine learning models across diverse devices without exposing raw user data to the central server **[20]**.
- **Advanced Generative Physics:** Utilizing multimodal Large Language Models (LLMs) to procedurally generate real-time fabric physics and complex 3D topological structures entirely from natural language prompts.
- **Wearable Device Integration:** Expanding the WebXR ecosystem to interface seamlessly with upcoming AR glasses and spatial computing headsets, utilizing smart mirrors for omnichannel retail experiences.

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