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Cloud-Based Dynamic Clothing Display System for Virtual Digital Humans in Live Streaming

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Article

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ABSTRACT

A cloud-based virtual clothing fitting system for apparel applications is presented. A multi-camera capture setup reconstructs dynamic garment meshes as ground truth for evaluating cloth simulation accuracy. The platform integrates real-time garment simulation, cloud rendering, and interactive visualization to support virtual try-on in online apparel services. Performance is assessed using average vertex deviation, response time, operation success rate, and system stability. Experimental results show improved garment simulation accuracy and faster interactive response compared with local rendering. The proposed framework demonstrates the feasibility of cloud-based virtual clothing fitting for clothing design, digital apparel display, and textile technology applications.

KEYWORDS

clothing, garment simulation, virtual fitting, cloud rendering, textile technology

INTRODUCTION

In recent years, the live e-commerce industry has experienced explosive growth. As a new social business model, live streaming enables real-time interaction between consumers and merchants through live shopping, driving the development of related fields [1]. This growth of e-commerce live streaming relies on advanced digital technologies, such as real-time data streams and artificial intelligence, which are crucial for live shopping. Companies can use these technologies to analyze data in real time, enhance consumer engagement, and boost sales [2]. Consumer willingness to purchase in live e-commerce is influenced by various factors. For instance, Wu constructed a predictive model using random forests. Regression and predictive analysis showed that consumers' perceived value of cross-border e-commerce platforms is not affected by perceived risk, whereas perceived usefulness and perceived entertainment are influenced by platform attributes [3]. In this context, consumers' requirements for online shopping experience are constantly improving. Chen noted that consumers' online shopping experience is influenced by many factors, such as government support and social learning. The traditional clothing display mode of static pictures and simple videos has been difficult to meet users' deep demand for product details and wearing effects, leading to high commodity return rate and affecting business operating costs and user shopping experience [4]. Sulastri further highlighted that consumers' online user experience is influenced by e-commerce live broadcast and trust [5].

At the same time, virtual digital human technology has made remarkable breakthroughs in the fields of artificial intelligence and computer graphics, leading to its gradual application to many industries. Sun's research indicated that the use of digital images by virtual anchors in e-commerce live broadcast is experiencing a surge in popularity, and the sense of behavioral reality positively affects consumers' purchase intention only when the sense of formal reality of virtual anchors is low. In the e-commerce sector, virtual digital humans, with their 24/7 live streaming and zero error rates, effectively address the issues of limited and costly live streamer resources [6]. Scholars have also studied the virtual clothing display system. Wu designed a digital virtual clothing display system based on LDA (Latent Dirichlet Allocation) mathematical model [7]. Shin focused on 40-year-old men as a specific research demographic, using a 3D virtual clothing system to analyze this group's preference for clothing fit [8]. Wang used CLO3D and HTML5 to design a virtual clothing display system, providing solutions for problems encountered during clothing creation with CLO3D. This system enables designers to publish their work online, allowing users to comprehensively and effectively view the garment creation process while maintaining communication with designers [9]. Compared with existing systems, these innovations may differ in technical principles, target group analysis, and functional expansion. They emphasize the uniqueness of technology applications, the pertinence of group research, and the innovation of functional realization, providing new ideas and direction for virtual clothing display. Although the aforementioned research explores the utility of virtual technology in clothing display, significant technical bottlenecks persist. First, most existing systems rely on client-side rendering (local GPU), which forces a trade-off between visual fidelity and frame rate on mobile devices. Complex cloth simulations often lead to frame drops (< 20 fps) or severe battery drain on standard consumer hardware. Second, current evaluation metrics are often qualitative or use vague percentages (e.g., error rate), lacking rigorous physical definitions (e.g., Euclidean distance in cm) to quantify the realism of fabric deformation. Third, there is a lack of stress testing under high-concurrency commercial scenarios, leaving the system's stability (e.g., Mean Time Between Failures (MTBF)) unverified in 24/7 live streaming contexts. To address these challenges, this study proposes a high-fidelity dynamic display system powered by cloud-edge collaboration. The main contributions of this paper are summarized as follows: (1) Cloud-Rendering Architecture: We implemented a Cloud-Edge-Client hierarchical architecture utilizing data-center GPU clusters. By offloading complex PhysX calculations and Ray Tracing to the cloud and streaming video via WebRTC, we achieved cinema-grade visual quality on standard client devices (Intel i5/Mobile) without local hardware bottlenecks. (2) Systematic Optimization Strategy: We introduced a dual-mode loading strategy distinguishing between Cold Start (initial loading) and Warm Start (cached interaction). Coupled with optimized asset transmission pipelines, this approach significantly reduces interaction latency and eliminates the lag often felt during clothing switching. (3) Rigorous Quantitative Evaluation: Unlike previous studies that relied on subjective scoring, we established a rigorous evaluation framework based on 100 users and 10,000 operation cycles. We introduced the Average Vertex Deviation (AVD) in centimeters to quantify simulation errors against ground truth and calculated the MTBF to objectively verify system reliability under stress.

EXPERIMENTAL

Materials and Methods

Materials

System Architecture and Hardware Deployment: Hardware Equipment: The system adopts a Cloud-Edge-Client hierarchical architecture.

Cloud Rendering Node: Deployed on a GPU cluster utilizing NVIDIA A100-class data-center GPUs (40GB VRAM) as the backend computing nodes. The server runs Ubuntu 20.04 LTS with Docker containerization to support multi-user concurrency through virtualization. The A100 cluster handles the physics simulation

(PhysX) and high-fidelity rendering (Ray Tracing), streaming the video output via WebRTC.

Client Terminal: To simulate a standard consumer environment, the client side is accessed via a standard web browser (Chrome v110+) on a PC equipped with an Intel Core i5-12400F CPU and 16GB RAM, without relying on local high-end GPU acceleration.

Software Tools: Blender is utilized for the 3D modeling and animation of virtual digital humans. It offers rich modeling tools and an animation engine that achieves precise bone binding and natural motion design, including detailed elements such as facial features and body proportions. The animation engine supports keyframe animation, bone binding animation, and other methods to create more natural and fluid movements, such as walking, turning, and raising hands, endowing the virtual digital human with vivid expressiveness.

Marvelous Designer: It is used for 3D clothing and fabric simulation and includes numerous built-in fabric presets that simulate the physical properties of different materials, such as the softness and smoothness of silk or the crisp texture of denim. This functionality enables accurate reproduction of fabric characteristics, including wrinkles and draping. This system uses Unity 3D game engine to build an interactive framework and combines it with C#language to realize real-time interaction between virtual digital people and users.

Performance testing demonstrates that when supporting 200 concurrent users, the system achieves an average user latency of 180 ms, a median latency of 140 ms, and ensures that 90% of users experience latency below 300 ms. For client-side hardware, a configuration with a CPU equivalent to Intel Core i5 and 8 GB of RAM is recommended to ensure responsive interaction without lags during concurrent use. This setup balances server-side load and client-side processing for optimal multiuser experience. Users can seamlessly access the system from various devices, including PCs running Windows and macOS and mobile device operating on iOS and Android. The system maintains interaction delay below 150 ms across different devices, ensuring a consistent and positive real-time interaction experience for multiple users. Users can interact with the virtual digital human through device operations, such as switching clothing styles or adjusting the digital human’s angle, thereby achieving a smooth human–computer interaction experience. Furthermore, data processing scripts are written in Python to assist in system data management and analysis.

Methods

System Design Method: The system's hierarchical architecture is structured with three layers. The bottom layer is the hardware support layer, comprising server clusters and graphics processing equipment, providing computing and storage resources. The middle layer functions as the data processing and algorithm layer, responsible for processing virtual digital human motion capture data and executing clothing dynamic simulation algorithms. The top layer, or the interactive display layer, facilitates the dynamic display and interactive features of virtual digital clothing for users through web or mobile interfaces.

Virtual Digital Human Modeling Method: Leveraging human scanning data and 3D modeling technology, a high-precision human model is constructed. This model combines facial expression capture and speech synthesis technology to endow digital people with realistic facial expressions and natural speech. Furthermore, bone binding and skin technology are used to ensure the smooth articulation of digital human movements and maintain natural posture coordination during the dynamic display of clothing.

Dynamic Display Method of Clothing: This method involves using 3D scanning and modeling technology to obtain clothing prototypes. The color, luster, and texture of the clothing fabric are restored through texture mapping and material parameter adjustment. The physical engine is introduced to simulate the dynamic changes of clothing in the process of human movement, such as the stretching and swinging effect of cloth. Real-time rendering technology is adopted to ensure that the dynamic display process of clothing is smooth and without delay [10].

Experimental Design

Ground Truth Acquisition: To establish a benchmark for realism, we constructed a multi-camera capture system consisting of 12 synchronized 4K cameras arranged in a 360-degree array. A real model wearing the reference garment performed the standard action sequence. The 4D dynamic mesh sequence was reconstructed using Multi-View Stereo (MVS) algorithms to serve as the ground truth (P_{real}).

Simulation Error Calculation: We discard the vague percentage metric and adopt AVD. The error E (in cm) is calculated using the Euclidean distance between the simulated mesh vertices (P_{sim}) and the ground truth vertices (P_{real}) at each frame t:

$$E = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{1}{N}\sum_{i=1}^{N}\left\|P_{real}^{(i,t)} - P_{sim}^{(i,t)}\right\|_2\right)$$

Where N is the total number of vertices and T is the total frame count.

To ensure a rigorous comparison, we established strict parameter consistency. The Control Group utilizes Local Rendering (Client-side Unity execution) to mimic the current mainstream mobile/web 3D experience. The Experimental Group utilizes Cloud Rendering (Pixel Streaming on A100). The specific configuration parameters are detailed in Table 1. This design aims to isolate the effect of rendering architecture under controlled conditions.

Table 1. Experimental Parameter Configuration

Parameter	Control Group (Local)	Experimental Group (Cloud)
Rendering Mode	Local WebGL Execution	Server-side Rendering (Pixel Streaming)
Physics Engine	Standard Unity PhysX	Optimized PhysX + CUDA Acceleration
Resolution	1080 p	1080 p
Target Frame Rate	60 fps	60 fps
Model Complexity	50,000 vertices (High-poly)	50,000 vertices (High-poly)

To clarify the performance measurement, we strictly define the technical metrics as shown in Table 2.

Table 2. Definition of Performance Metrics

Metric	Definition	Unit
Network Latency (RTT)	The round-trip time for a data packet between the client and the cloud server.	ms
System Response Time	The total duration from the user's input click to the completion of the first frame rendering of the new state.	seconds (s)
Simulation Error (AVD)	The average Euclidean distance between virtual and real cloth vertices.	cm

System Performance Benchmarking: An automated testing script (Python + Selenium) was developed to execute core functions. Each operation (e.g., scene switching, virtual try-on) was repeated 50 times under two conditions: Cold Start (no cached assets) and Warm Cache (assets pre-loaded) to evaluate stability and peak latency.

User Experience Study: We recruited N = 100 participants (50 male, 50 female, ages 18-40) for a within-subjects design experiment. Each participant operated both the Control and Experimental systems in a randomized order to eliminate learning effects (Counterbalancing).

Statisitical Analysis

All quantitative data were collected and processed using Python scripts (pandas v1.3.5) and statistical analyses were performed using SPSS Statistics 26.0 (IBM Corp., Armonk, NY, USA). Continuous variables (e.g., response time, simulation error) are expressed as mean ± standard deviation (SD). Categorical data (e.g., failure counts) are presented as frequencies and percentages. Prior to hypothesis testing, the normality of the data distribution was assessed using the Shapiro-Wilk test. The homogeneity of variance was verified using Levene's test. For data satisfying both normality and homogeneity assumptions, the Paired Samples t-test was used to compare differences between the Experimental and Control groups. For data that did not follow a normal distribution, the non-parametric Mann-Whitney U test was employed. Significance Level: A two-tailed p-value of < 0.05 was considered statistically significant.

RESULTS AND DISCUSSION

Simulation Accuracy (Average Vertex Deviation)

To evaluate the realism of the system's cloth dynamics simulation, this study quantifies the simulation error rates of virtual digital humans performing various typical actions. Figure 1 presents detailed data comparing the performance of the experimental and control groups across seven actions: turning, walking, raising arms, bending, running, waving, and squatting. The results demonstrate that the experimental group consistently exhibits significantly lower simulation error rates across all evaluated actions. For instance, during the walking action, the error rate for the experimental group was 1.2 cm, compared to 1.52 cm for the control group ($p < 0.001$). Similarly, during the "running" action, the experimental group recorded an error rate of 1.15 cm, whereas the control group reached 1.46 cm ($p < 0.001$). These findings indicate that the proposed PhysX-based physical simulation, enhanced with tailored optimization algorithms, effectively improves the physical realism of dynamic cloth rendering. This approach significantly reduces visual artifacts, such as mesh penetration and excessive stretching during motion, thereby delivering a more immersive and visually convincing user experience.

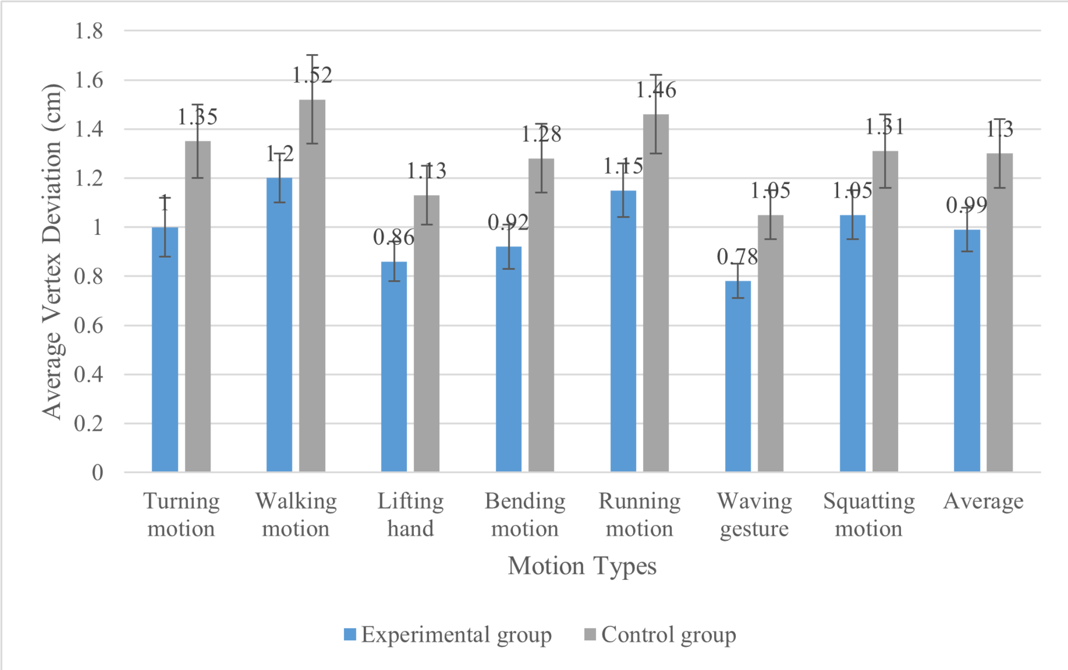

Figure 1. Comparison of Dynamic Simulation Error (Average Vertex Deviation)

System Response Speed (Cold vs. Warm Start)

To rigorously evaluate latency under different caching conditions, we separated the test into Cold Start (first-time load) and Warm Start (cached assets).

Cold Start: As shown in Figure 2, under cold-start conditions, the experimental group achieved an average response time of 1.0 s, significantly faster than the control group’s 3.0 s.

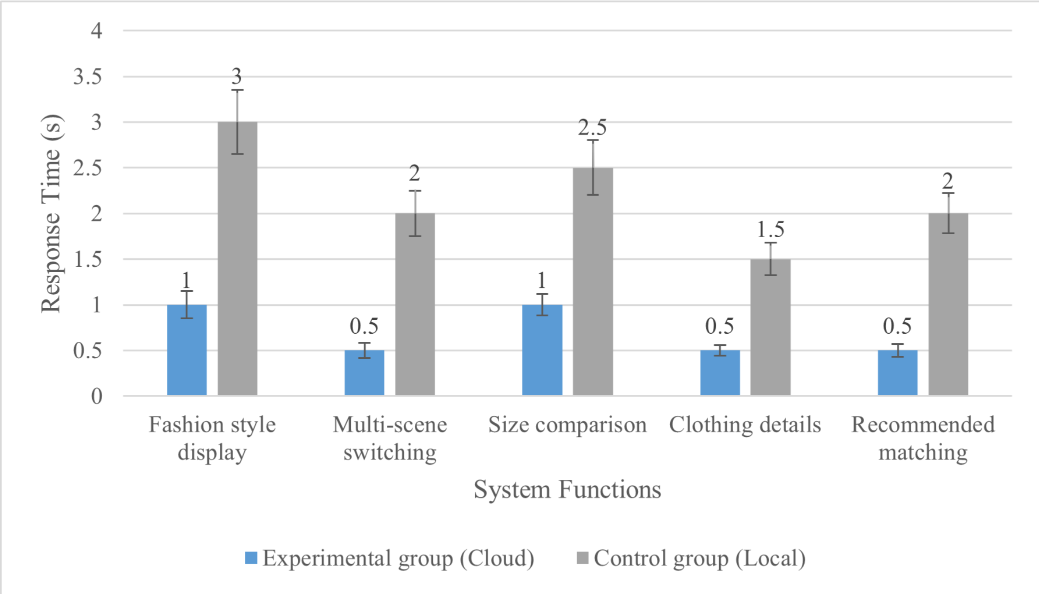

Figure 2. System Response Time under Cold Start Conditions

Warm Start: Figure 3 illustrates the latency during continuous interaction. Here, the response time drops significantly to 0.49 s (Experimental) vs 0.97 s (Control).

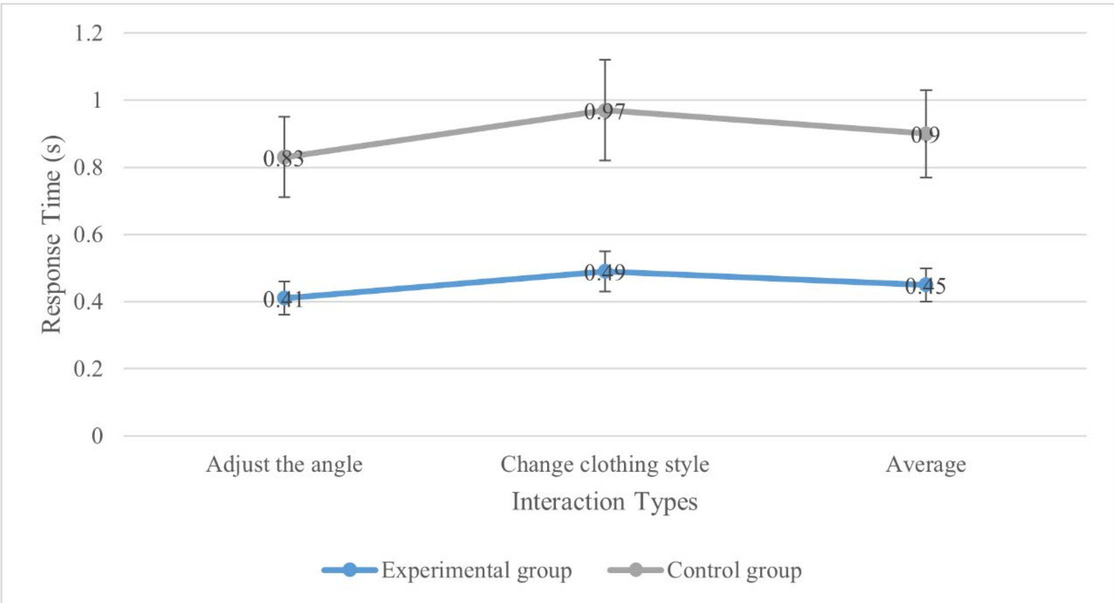

Figure 3. Average Interaction Latency (Warm Start / Cached).

Pure Rendering Latency: Focusing purely on GPU rendering time (excluding network RTT), Figure 4 shows the theoretical peak performance, where the experimental group achieves 300 ms latency.

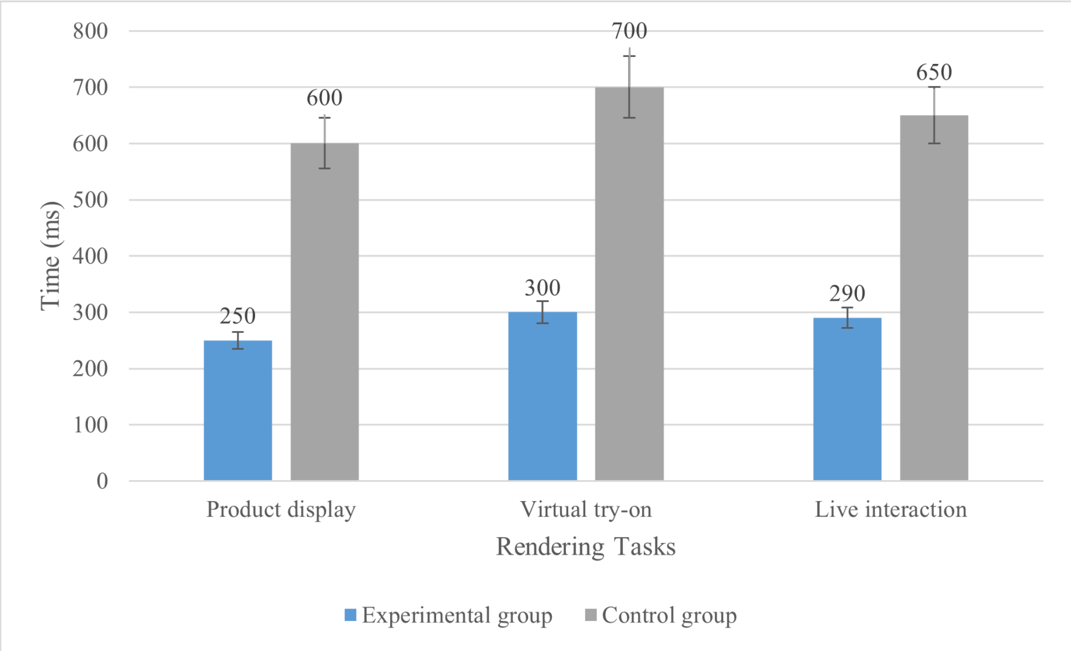

Figure 4. Pure Rendering & Physics Calculation Latency (Excluding Network)

The substantial reduction in response times not only enables users to experience smoother and more immediate interactive feedback, thereby enhancing user experience, but also underscores the superior stability and speed of the new system architecture. These advantages are particularly critical in live e-commerce scenarios that demand sustained, long-duration performance, positioning the proposed system as a more robust and commercially viable solution [11–13].

System Stability and Reliability

We assessed system robustness through long-term stress testing (72 hours) and high-concurrency operation loops.

Failure Analysis: To quantify reliability, we calculated the MTBF. As shown in Figure 5, the Experimental Group achieved an MTBF of 72.0 hours (1 failure in 72 h), whereas the Control Group's MTBF was only 24.0 hours (3 failures in 72 h).

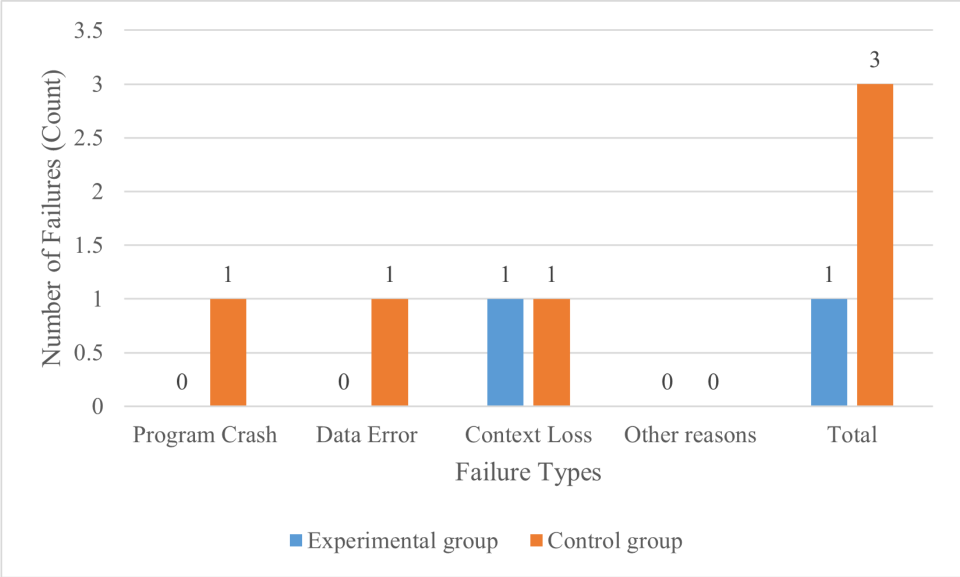

Figure 5. Total System Failures during 72-h Stress Test

Operation Success Rate: To verify transactional stability, we executed 10,000 continuous operations for each of the three core functions (Total N = 30,000). Figure 6 demonstrates that both systems maintained an extremely high success rate across all functions. For the most computationally demanding task, Virtual Try-on, the experimental group achieved 9,988 successes (99.88%), slightly outperforming the control group's 9,815 (98.15%). Chi-square tests indicated no catastrophic failures in either group, confirming sufficient baseline stability for commercial use.

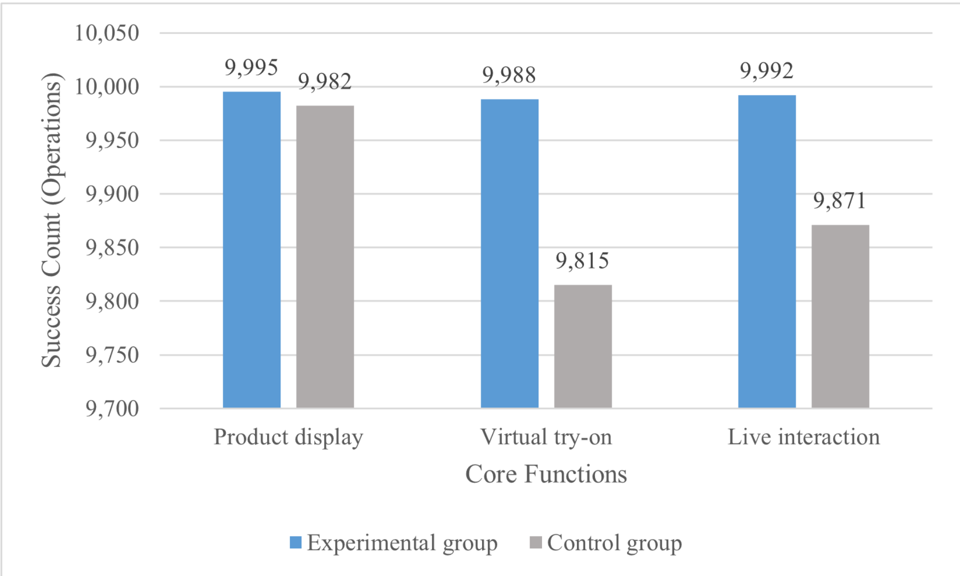

Figure 6. Success Count of Core Functions

This notable performance gain is primarily attributed to the experimental system's implementation of efficient rendering algorithms and asynchronous resource loading [14,15]. These advancements eliminate the latency inherent in the conventional synchronous methods used by the control group.

A closer examination of the experimental group's data revealed that response times varied by operation. Specifically, changing clothing styles took slightly longer (0.49 s) than adjusting the viewing angle (0.41 s). This discrepancy likely stems from the intrinsic complexity of the clothing change operation [16], which involves the real-time loading and rendering of entirely new, high-detail 3D garment models and texture maps. By contrast, adjusting the viewing angle is a relatively lightweight computational transformation, resulting in faster response times.

These findings suggest that future optimization efforts should prioritize strategies for accelerating clothing resource loading to further enhance the overall user experience.

Response Time of Customization Functions

To evaluate the interaction efficiency of personalization features, we recorded the latency for three key customization operations: hairstyle adjustment, skin tone adjustment, and body shape modification. As presented in Figure 7, the experimental group demonstrated a responsive interaction experience with an average latency of 0.25 s, whereas the control group averaged 1.45 s.

Hairstyle Adjustment: The experimental group took 0.28 s, compared to 1.52 s for the control group. This reduction is critical as hairstyle assets typically involve high-poly meshes.

Body Shape Modification: The experimental group achieved 0.22 s, significantly faster than the control group's 1.35 s.

Paired samples t-tests confirmed that these differences were statistically significant ($p < 0.001$), proving that the optimized asset loading pipeline effectively eliminates the lag felt in traditional implementations.

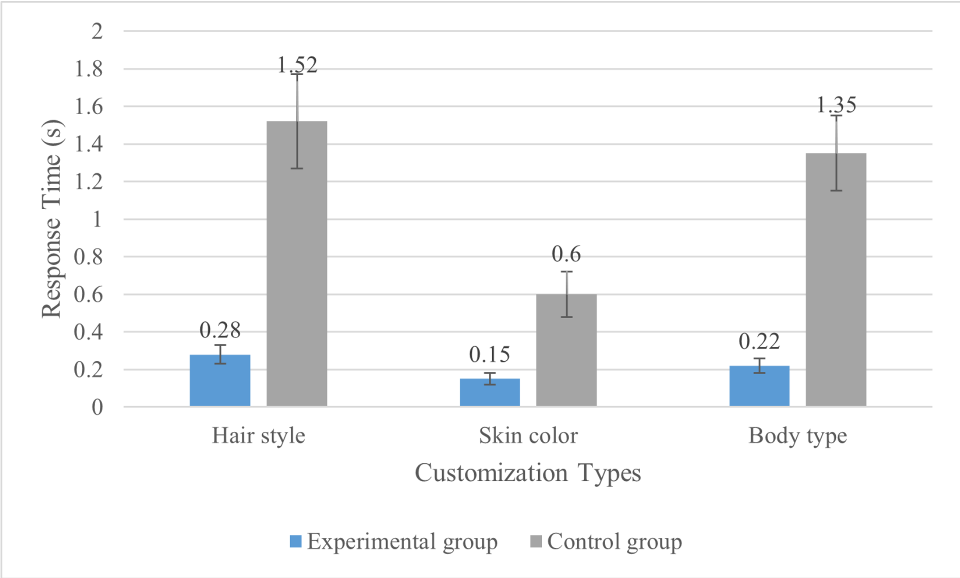

Figure 7. Average Response Time of Customization Functions

User Satisfaction

To evaluate the overall user experience, a satisfaction survey was conducted across five key dimensions. Before analyzing the differences, we verified the internal consistency of the questionnaire. The Cronbach's α coefficient was 0.89, exceeding the 0.7 threshold, indicating high reliability. A comparison of scores between the experimental and control groups is presented in Figure 8. The experimental group outperformed the control group across all five categories, with significantly higher satisfaction ratings. The most notable advantages were observed in visual experience and ease of use, indicating strong user approval of the system's core design.

Independent samples t-tests confirmed that all observed differences were statistically significant ($p < 0.05$), validating users' clear preference for the experimental system.

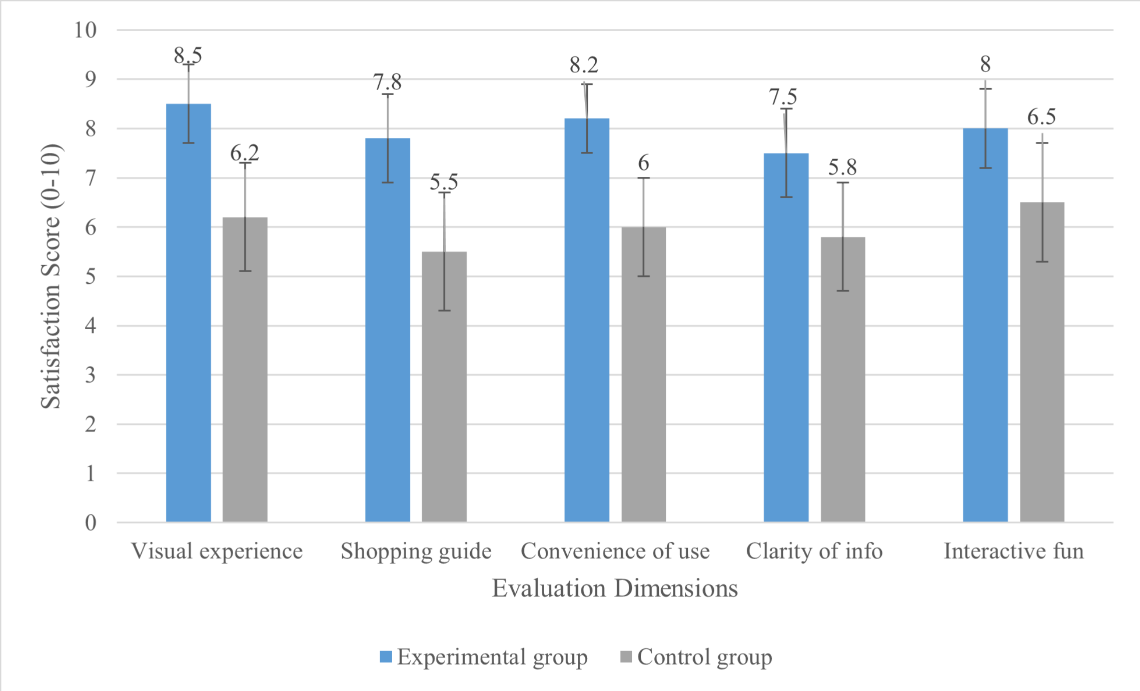

Figure 8. User Satisfaction Survey Scores (N = 100)

CONCLUSION

This study evaluated a dynamic clothing display system based on cloud-rendering architecture. Under the specific tested conditions, the results demonstrate that the proposed system reduces the AVD to 1.2 cm and significantly improves response speeds during cold starts. To overcome the identified limitations and further enhance system functionality, future efforts will focus on several key directions. These include performance and rendering optimizations, such as implementing gait phase analysis to improve rendering smoothness and reduce computational load; employing octree-based spatial partitioning and optimized ray tracing to minimize rendering latency, particularly during multiscene transitions; and enhancing GPU acceleration of the PhysX engine to maintain high simulation frame rates while effectively managing power consumption. Additional areas of development include the comprehensive realization of detailed garment presentation and outfit recommendation; the integration of deep learning-based recommendation models to deliver more accurate personalized suggestions while addressing challenges like the cold-start problem; and the expansion of digital human customization through high-precision 3D facial scanning, refined expression control, and a broader range of cosmetic options. Furthermore, the deployment of real-time monitoring tools such as Prometheus will enable proactive system resource management and failure prevention. Finally, the shopping guidance workflow will be redesigned, incorporating animations and highlighted prompts to enhance information clarity and boost overall user satisfaction.

Availability of Data and Materials

The datasets used and/or analysed during the current study were available from the corresponding author on reasonable request.

Author Contributions

Jingjing Liang designed, collected and analyzed the data, and drafted the manuscript. Jingjing Liang conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Jingjing Liang participated fully in the work, took public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

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Not applicable.

Conflict of Interest

The author declares no conflict of interest.

Ethics Approval and Consent to Participate

Participants were informed of the study’s purpose and data usage prior to participation, and responses were collected anonymously. No personally identifiable information was stored.

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