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Molecular & Cellular Biomechanics 2025, 22(2), 997.
https://doi.org/10.62617/mcb997

Article

Application of virtual reality in e-commerce: Taking the experience of trying on sports equipment as an example

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CITATION

Gan L. Application of virtual reality in e-commerce: Taking the experience of trying on sports equipment as an example. Molecular & Cellular Biomechanics. 2025; 22(2): 997. https://doi.org/10.62617/mcb997

ARTICLE INFO

Received: 4 December 2024
Accepted: 18 December 2024
Available online: 17 January 2025

Abstract: Traditional e-commerce platforms have the problem that users cannot try on sports equipment in person, and it is difficult for consumers to perceive its size, comfort and dynamic performance before purchasing. This limitation leads to high return rates and difficult purchasing decisions. This paper introduces a virtual try-on solution with higher accuracy and more immersion. After using 3D scanning technology to obtain the user's body data and combining it with SMPL (Skinned Multi-Person Linear Model) to generate the user's body model, a posture optimization algorithm is used to adjust the dynamic posture of the user model and the PoseNet optimization model is used to adapt it to the user's dynamic motion scenes. Next, Unity Physics is used to achieve the dynamic performance of sports equipment materials, high-definition texture mapping technology is used to reproduce the visual effects of equipment materials to ensure that the appearance is consistent with reality, and sports scenes are constructed to simulate the actual performance of equipment in different environments. Users can use motion capture devices to simulate running, jumping and other movements to feel the suitability of sports equipment. Then, based on the user's body shape data and sports scene preferences, Deep Q-Learning is used to recommend sports equipment options suitable for the user. Finally, the system adjusts the virtual try-on experience in real time, showing a variety of combination effects, helping users quickly find their favorite products. Experiments show that the performance error between virtual equipment and real equipment is only 1.35%, the virtual try-on pass rate exceeds 90%, and the return rate is less than 10%, which verifies the feasibility of virtual reality technology in e-commerce and improves users' online shopping experience.

Keywords: virtual try-on technology; 3D scanning technology; sports equipment; human pose estimation; recommendation algorithm

1. Introduction

With the rapid development of e-commerce, the number of online shopping users around the world continues to grow, especially in the field of clothing and sports equipment. Consumers have shown great interest in the convenience and diverse choices of online shopping. However, compared with offline shopping, online shopping still faces shortcomings that cannot be ignored, especially in terms of "try-on experience" [1–3]. Consumers cannot try on products in person to feel their size, comfort and dynamic performance (such as the cushioning of running shoes or the elasticity of sportswear). This not only increases the risk of shopping, but also leads to a significant increase in return rates. For example, according to relevant statistics, the average return rate of clothing and footwear is as high as 30%–40%, most of which is related to the mismatch between user expectations and actual product performance. To address this problem, virtual reality (VR) technology provides a new solution for the e-commerce field due to its immersive, interactive and multi-sensory features [4–6]. VR creates a virtual environment that enables users to perceive and operate products in three-dimensional space. Its application prospects, especially in the field of virtual try-on, have attracted much attention. However, although virtual reality technology has been applied to a certain extent, there are still many obstacles to its widespread promotion in the field of e-commerce [7–9]. For example, existing fitting solutions usually use general 3D modeling technology, which cannot accurately restore the user's body characteristics, resulting in a deviation between the fitting results and the actual effect. In addition, the special properties of sports equipment (such as the cushioning effect of shoes and the breath-ability of clothing) are difficult to simulate through simple static displays, and users still find it difficult to fully perceive the dynamic performance of products. These problems limit the user experience of virtual try-on technology and its practical application value in the e-commerce field.

In recent years, many researchers have explored the application of virtual reality technology in e-commerce, especially focusing on its potential in the field of virtual try-on. Scholar Hilken [10] studied the individual and combined impacts of AR (Augmented Reality) and VR on key marketing objectives to improve online experiential retail. While Billewar [11] focused on three-dimensional e-commerce technology, showing how VR and AR can help solve limitations and improve e-commerce operations, augmented reality assistants and virtual store experiences. Kumar's [12] research also introduced the social aspects of AR, the dark side of AR, customer engagement, the experiential value of AR, and the future research agenda in the field of AR marketing. However, despite the achievements of these studies, they still face some urgent problems. First, current virtual try-on platforms are insufficient in terms of body modeling accuracy, and the generated virtual user models often fail to fully reflect the user's body details, such as body proportions and the accuracy of dynamic movements [13–15]. Secondly, the dynamic performance of sports equipment is often not realistically restored in virtual try-on due to the high complexity of modeling [16–18]. In addition, existing research lacks specificity in optimizing user experience and fails to fully combine user movement preferences and scene applicability to design trial solutions. These problems limit the in-depth application of virtual reality technology in e-commerce.

In order to improve the above problems, researchers have tried to use a variety of technical means to improve the virtual try-on experience in recent years. For example, high-precision three-dimensional modeling technology based on the SMPL model (Skinned Multi-Person Linear Model) has been widely used in personalized body modeling [19–21]. The SMPL model can generate a virtual model that fits the user's body shape by combining the key dimensions and posture data of the user, providing higher accuracy for the fitting process. At the same time, physical engine technologies based on Unity Physics and NVIDIA PhysX are gradually being introduced into the dynamic performance simulation of sports equipment [22–24]. These technologies can realistically reproduce the performance of equipment in dynamic motion, such as the shock absorption of shoes and the elasticity of clothing. In addition, deep learning technology and recommendation algorithms have also been applied in the field of virtual try-on [25,26]. By analyzing user data (such as body shape, purchase history, and sports preferences), recommendation algorithms can provide users with more targeted equipment options for further optimization. Although these methods have improved the authenticity and user satisfaction of virtual try-on to a certain extent, they still have the following shortcomings: first, the system has limited performance capabilities for dynamic scenes and cannot simulate the effects of users using equipment in specific scenarios; second, the system has high requirements for hardware performance, and it is difficult for ordinary users to easily experience the virtual try-on function; third, the accuracy and efficiency of personalized recommendations still need to be improved [27–32]. Therefore, this paper introduces a solution that integrates multiple technologies to further enhance the application value of virtual reality technology in sports equipment fitting through the combination of high-precision modeling, dynamic performance simulation and personalized recommendation system.

This paper aims to explore how virtual reality technology can play a greater role in the experience of trying on sports equipment in the e-commerce field, and solve the problems of low modeling accuracy, insufficient material performance and lack of dynamic scene experience in existing research [33–35]. This paper adopts the following methods to achieve the research objectives: first, based on the SMPL model and three-dimensional scanning technology, high-precision modeling of the user's body shape is achieved; second, the Unity Physics physics engine and PBR (Physically Based Rendering) technology are used to simulate the material and dynamic performance of sports equipment; finally, user preference analysis and personalized recommendations are achieved through deep learning recommendation algorithms [36,37]. In addition, this paper constructs a multi-scenario virtual try-on platform that allows users to truly experience the performance of sports equipment in a dynamic environment. Through this research, this paper not only verifies the feasibility of virtual reality technology in e-commerce, but also provides new theoretical support and practical paths for improving users' online shopping experience.

2. Try-on implementation supported by virtual reality technology

2.1. High-precision modeling of user body shape

2.1.1. Data collection and equipment selection

In the virtual reality sports equipment fitting experience, building an accurate user body model is crucial to ensure the authenticity of the fitting effect. In order to fully obtain the user's body data, this study adopted a fusion strategy that combined structured light scanning technology and smartphone camera acquisition methods. Specifically, the structured light scanning device projects light onto the human body and receives reflected signals, efficiently capturing the three-dimensional contour details of the body surface and quickly generating detailed three-dimensional point cloud data (such as key indicators such as height, shoulder width, waist circumference, leg length, etc.), and is easy to operate. In addition, in order to improve the convenience and popularity of data collection, this paper also introduces smartphone cameras. With the help of their built-in depth perception function, the images captured by the camera are processed through algorithms to extract the user's body features without the need for professional equipment. This flexible device combination strategy is designed to adapt to diverse application scenarios and device configurations, ensuring that data collection is both efficient and accurate, and reducing dependence on specific hardware.

Table 1 is a comparison of the body shape data collection effects of structured light scanning equipment, mobile phone cameras, and the combination of the two. The accuracy of structured light scanning equipment is much higher than that of mobile phone cameras, with a height error of only ± 0.5 cm, while the height error of mobile phone cameras can reach ± 2.0 cm. The measurement errors of the structured light device for shoulder width, waist circumference, and leg length are also very small, at ± 0.3 cm, ± 0.4 cm, and ± 0.6 cm respectively. The acquisition time of the mobile phone camera is longer, at 30 seconds, while the structured light scanning device takes 15 seconds. After combining the two, the accuracy is optimized, with a height error of ± 0.3 cm. This proves that by choosing the appropriate acquisition method, the accuracy and efficiency of data in the virtual try-on experience can be optimized for different scenarios.

Table 1. Body shape data collection results.

Collection Method	**Height (cm) Error**	**Shoulder Width (cm) Error**	**Waist (cm) Error**	**Leg Length (cm) Error**	**Data Collection Time (seconds)**	**Device Type**
Structured Light Scanner	± 0.5	± 0.3	± 0.4	± 0.6	15	Professional Hardware
Smartphone Camera (Depth Sensing)	± 2.0	± 1.5	± 2.2	± 1.8	30	Smartphone (No Specialized Hardware)
Structured Light Scanner + Smartphone Camera	± 0.3	± 0.2	± 0.16	± 0.5	20	Combined Approach

The introduction of a depth camera can improve the accuracy of body shape data by obtaining the three-dimensional depth information of the user's body. The depth camera captures the spatial distance between the user and the equipment and reconstructs the user's body shape more accurately, especially in dynamic scenes, which can reduce the error of traditional mobile phone cameras. The depth data is combined with the structured light scanning data and optimized through the data fusion algorithm to further improve the accuracy of body shape modeling and ensure the accuracy and stability of virtual try-on.

2.1.2. Three-dimensional modeling and posture optimization

After data collection is completed, the SMPL model is used for 3D human body modeling. The SMPL model is a parametric linear model that can generate a 3D virtual human body that conforms to human anatomical characteristics by collecting the user's body shape data. Different from traditional static modeling, it can not only accurately represent the user's body shape characteristics, but also support dynamic posture adjustment. As long as specific human body size information is input, the SMPL model can accurately generate the user's virtual body shape. During the virtual try-on process, the model can also adjust the posture in real time according to the user's movement dynamics. In order to further improve the modeling accuracy, this paper attempts to introduce a posture optimization algorithm to adjust the user's dynamic data so that the generated virtual human model is more consistent with the user's actual posture. This means that the user's virtual model can not only accurately reflect their body characteristics in static conditions, but also adapt to different movements in real time during movement, such as running and jumping, allowing the posture optimization algorithm to adjust the joints and muscle areas of the human model in real time as the user moves, to better match the user's actual movements and improve the accuracy and interactivity of virtual try-on.

Figure 1 shows the SMPL model for three-dimensional body modeling. By inputting parameters such as body size, the SMPL model can generate a three-dimensional virtual body that conforms to the body characteristics of an adult male, and can be dynamically adjusted according to the user's movement posture, and then used in application scenarios such as virtual try-on.

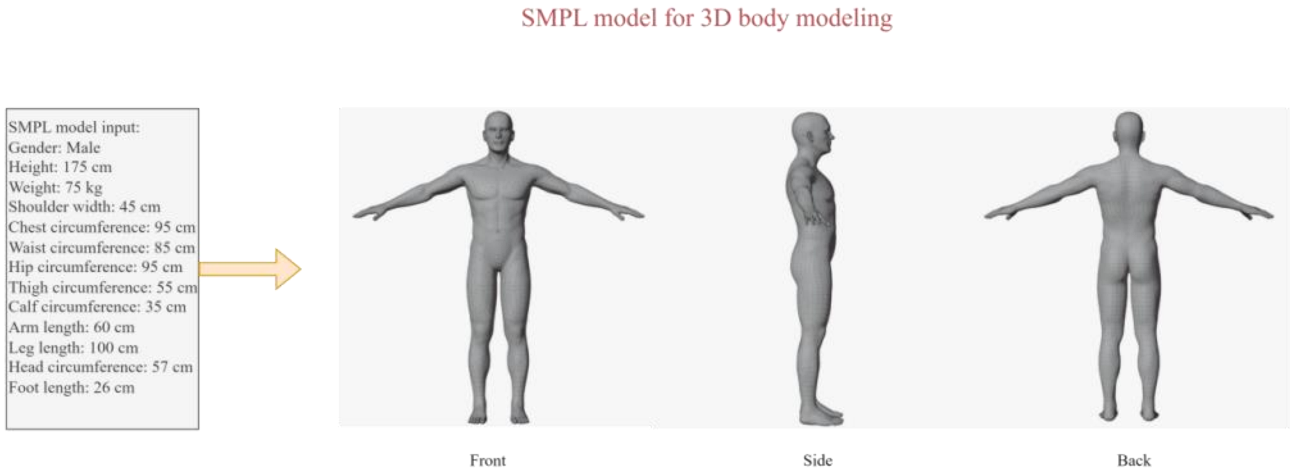

Figure 1. SMPL model for three-dimensional body modeling.

2.1.3. Dynamic optimization and personalized adjustment

This paper further introduces the human posture estimation algorithm PoseNet to optimize the accuracy and dynamic adaptability of user human body modeling. As an algorithm based on deep learning, it can capture the user's dynamic movements in real time through the camera and locate the user's bone joints. Compared with traditional two-dimensional image processing methods, PoseNet can accurately restore the user's movement details by calculating the user's three-dimensional bone position data in real time and feed it back to the virtual try-on platform.

According to **Figure 2**, PoseNet technology is not limited to static body capture, but can also track the user's dynamic posture in real time, ensuring that the virtual body model maintains a high degree of consistency in various movements. Combined with the SMPL model, the dynamic adaptability of the virtual body shape is significantly enhanced, further improving the realistic experience of virtual try-on. This study also implements personalized body shape adjustment strategies, customizing virtual body shape models for each user based on their body shape and sports preferences. At the same time, the adaptability of sports equipment can be flexibly adjusted according to the user's sports needs in different scenarios such as running, fitness, and outdoor activities. This personalized and precise adjustment not only optimizes the accuracy of the try-on, but also allows each user to enjoy a customized experience in the virtual try-on, significantly enhancing the immersion of the try-on.

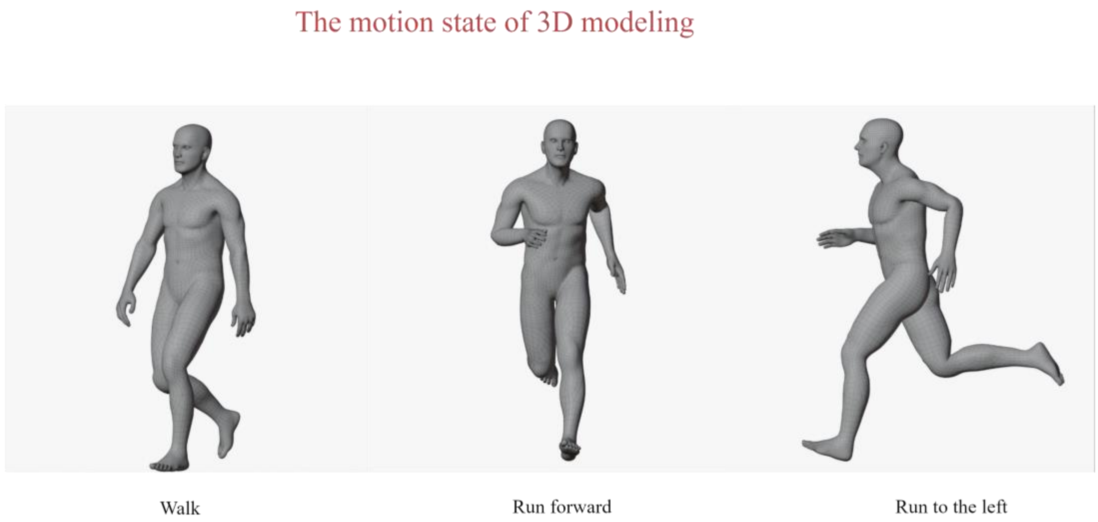

Figure 2. Dynamic poses of the model.

2.2. Dynamic simulation of sports equipment materials

During the virtual try-on process, the material performance and dynamic performance of sports equipment are crucial to the user experience. In order to achieve a more realistic sports equipment fitting experience, this paper provides a high-precision sports equipment material dynamic performance solution by combining physics engine, material rendering technology and dynamic performance simulation, aiming to truly reproduce the performance of sports equipment in dynamic scenes through the integration of physics and visual effects.

2.2.1. Material performance and texture generation

The material performance of sports equipment directly affects the user's perception of the product. In order to efficiently generate realistic material effects, this paper uses Substance Painter software to generate high-precision textures of sports equipment. Substance Painter supports detailed texture painting of materials, which can provide rich details on each equipment surface, such as the reflection of the upper, the texture of the clothing and the glossiness of the material. The material texture data generated by Substance Painter can precisely control the visual effects of sports equipment to ensure that its performance under different lighting conditions is consistent with the actual product.

In order to further improve the realism of materials, this study combines PBR technology. PBR technology can accurately reproduce the gloss, reflection, and roughness of objects in a virtual environment by considering the physical interaction between light and the surface of objects, providing a more realistic material perception. The leather surface of sports shoes can show natural reflective luster through PBR technology, while the fabric of sportswear can show breath-ability and elasticity. PBR technology is combined with the material texture generated by Substance Painter to ensure the natural presentation of equipment materials at different angles and lighting, greatly enhancing the visual realism in virtual try-on.

2.2.2. Dynamic performance simulation

Traditional virtual try-on often ignores the dynamic performance of sports equipment, while the dynamic characteristics of sports equipment, such as shock absorption and elasticity, have a particularly important impact on sports performance. In order to simulate the performance of sports equipment in actual sports, this paper uses the Finite Element Analysis (FEA) model to simulate the dynamic performance of sports equipment. The finite element analysis method decomposes the equipment into multiple small units and analyzes its deformation, stress distribution and motion response under the action of external forces. In sports shoe simulation, FEA can accurately simulate the cushioning function of the sole, thereby ensuring that the shoe provides perfect shock absorption and comfort performance when the gait changes; in sportswear simulation, FEA is used to analyze the elasticity, stretch-ability and comfort of fabrics, helping users experience the flexibility and adaptability of sports equipment during exercise.

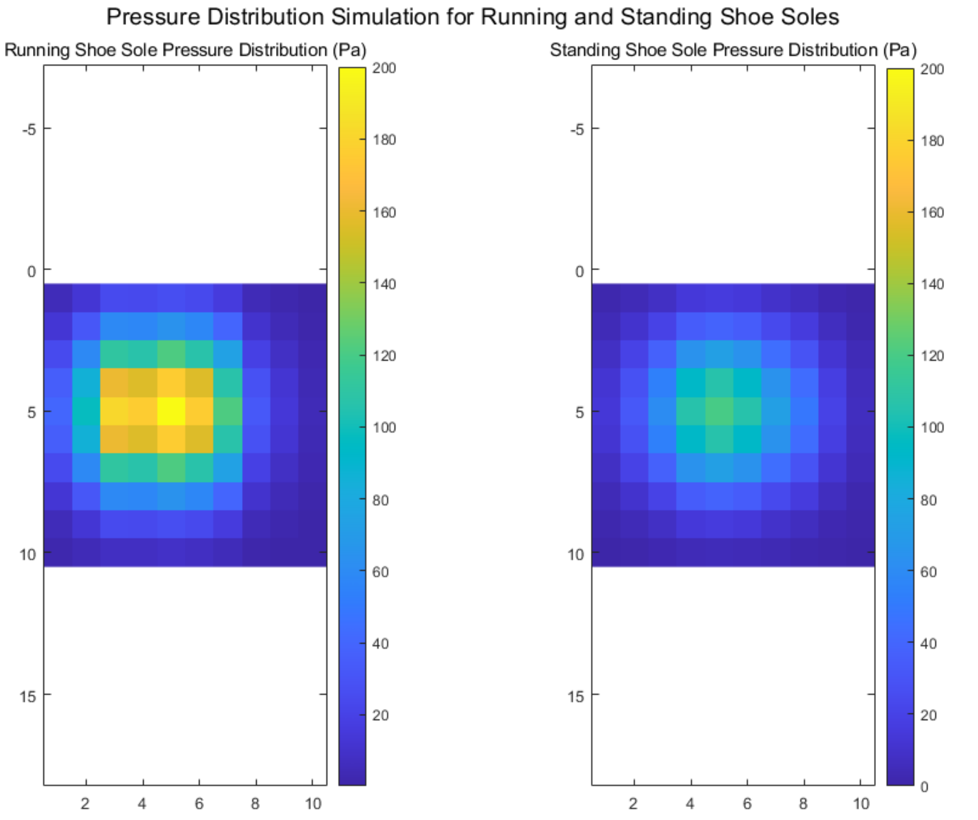

Figure 3. Pressure on the sole of the shoe during running and standing. **(a)** Pressure distribution on the sole of a running shoe; **(b)** Pressure distribution on the sole of a standing shoe.

To ensure the accuracy of the simulation, the input data of the FEA model includes the user's dynamic motion data and the actual material parameters of the equipment. The system simulates the performance of sports equipment in different sports scenarios by calculating the external pressure and the response of the equipment material. When running or jumping, the pressure distribution on the soles of sports shoes will directly affect the user's comfort and athletic performance, and the stretching and rebound effects of sportswear will affect the smoothness and comfort of movement. Through finite element analysis, a dynamic simulation environment based on a physics engine can be provided to users, so that the performance of sports equipment can be fully reproduced during the virtual try-on process.

Figure 3 shows the pressure distribution of the soles of the running and standing states. The left figure of **Figure 3** shows the pressure distribution of the soles of the running shoes. The pressure on the soles of the feet is relatively large when running, which is consistent with the force characteristics of the feet during exercise. The maximum pressure area on the sole when running reaches 200 Pa. The right figure in **Figure 3** shows the pressure distribution on the sole when standing. It can be seen that the pressure when standing is significantly reduced compared to running, and the maximum pressure area is around 100 Pa. Through the two images, it is clearly seen that there is a significant difference in the pressure distribution of the soles in the sports state and the static state, which is of great significance for the comfort and performance testing of sports equipment.

2.2.3. Real-time interaction and dynamic response

Dynamic interactivity in virtual try-on is the key to enhancing user immersion. In order to achieve real-time response of equipment to user actions, this paper uses the Inverse Kinematics (IK) algorithm to dynamically control the equipment. The IK algorithm can accurately adjust the relative position and posture of the equipment based on the user’s real-time motion data, ensuring dynamic adaptation of the equipment to the user’s movements.

Specifically, the IK algorithm analyzes the user’s skeletal joint data and the connection method between the virtual equipment, and calculates the optimal position and angle of the equipment in each frame in real time, thereby achieving synchronization between the equipment and the user’s movements. Taking sports shoes as an example, when the user runs, the IK algorithm will dynamically adjust the curvature of the shoes, the contact points between the soles and the ground, etc., so that the sports shoes show natural changes in dynamic scenes. For sportswear, the IK algorithm can simulate the wrinkles, stretching and other effects of clothing during exercise, thereby enhancing the authenticity of sports equipment under different sports movements.

In addition, the inverse kinematics algorithm can also be combined with the physics engine in dynamic scenes to further optimize the dynamic response of the equipment. During actions such as running and jumping, the reaction force generated when the shoes come into contact with the ground will affect the dynamic performance of the equipment. During running or jumping, the reaction force generated when the sole contacts the ground will affect the dynamic performance of the equipment. FEA simulates the elasticity and cushioning effect of sports shoes in different sports scenarios by calculating the external pressure and the response of the equipment material. The linkage between the IK algorithm and the physics engine makes this process smoother and more natural, enhancing the user’s immersive experience in virtual try-on. By combining Substance Painter with PBR technology to generate high-precision material textures, finite element analysis models to simulate dynamic performance, and inverse kinematics algorithms to control the dynamic response of equipment in real time, this paper constructs a comprehensive, multi-level dynamic simulation system for sports equipment. This system can truly reproduce the materials and performance of sports equipment in dynamic scenes, thereby providing users with a more immersive and accurate virtual try-on experience, making up for the shortcomings of insufficient try-on experience in traditional e-commerce.

2.3. Try-on experience in real scenarios

2.3.1. Scene construction and virtual environment construction

In virtual try-on, it is crucial to create a real virtual scene that matches user needs and sports equipment characteristics. In order to enhance the immersiveness of virtual try-on, this study used two advanced virtual engines, Unity and Unreal Engine, to build a real motion environment. Through these engines, various sports scenes such as running tracks, basketball courts, gyms, etc. can be accurately reproduced, providing users with a virtual experience similar to the actual sports environment.

During the scene construction process, the virtual environment is first set up according to the usage scenarios of the sports equipment and user needs. For example, when simulating running, the Unity engine is used to create a long-distance running track or an outdoor running track to ensure that the track's terrain, obstacles, etc. are consistent with the actual environment so that users can more realistically perceive the performance of sports equipment in the actual environment. To ensure the dynamics of sports scenes, real-time adjustment technology of lighting and weather effects is adopted, so that the light, shadow and weather conditions (sunny, cloudy or rainy) in the scene can change dynamically, thereby simulating the performance of sports equipment in different weather conditions in the sports environment.

In this way, the sports scenes in the virtual environment can match the sports venues in the real world, enhancing the user's immersion and experience. This highly restored environment setting not only enhances the authenticity of the virtual try-on, but also provides more realistic simulation conditions for the performance testing of sports equipment. Some users pointed out that scene lighting changes and weather effects have a significant impact on athletic performance during simulated running, and suggested enhancing the details of dynamic weather simulation. Based on this feedback, the system optimized the real-time adjustment of lighting and weather effects to ensure that the virtual scene is more realistic and natural.

2.3.2. Motion capture and real-time synchronization

In order to accurately map the user's movements to the virtual character in the virtual scene, this paper combines OpenPose technology to capture and analyze the user's real-time movements. OpenPose is a multi-person posture estimation algorithm based on deep learning, which can capture the user's skeletal key point data through the camera, including the dynamic changes of joints, limbs, and torso. This study configures multiple cameras, and the image data provided by each camera is processed by the OpenPose algorithm to extract the user's two-dimensional key point coordinates, and then convert these two-dimensional coordinates into positions in three-dimensional space through geometric reconstruction methods. It can capture the user's posture changes from multiple angles in real time and provide dynamic motion trajectories. These data are fine-tuned through the posture optimization algorithm to ensure that the movements of the virtual character are highly synchronized with the user's movements.

Once these key point data are captured, the system will map them to the virtual character in real time, allowing the virtual character to synchronize in real time according to the user's actions. For example, when a user starts running, OpenPose can accurately track the user's gait, leg bending angle, and range of motion, and feed this information back to the virtual character, so that the movement of the virtual character is completely consistent with the user's actual movements. At the same time, the sports shoes and sportswear on the virtual character will be dynamically adjusted as the movements change, showing the adaptability and performance of the equipment during exercise in real time.

Through OpenPose's real-time motion capture and mapping technology, this paper effectively solves the problem of asynchrony between user movements and virtual characters during virtual try-on. Accurate motion capture and real-time synchronization ensure that users can experience feedback consistent with actual movements when trying on sports equipment in a virtual scene, improving the interactivity and accuracy of the try-on.

Figure 4 shows the synchronization error and motion angle comparison between the user's motion and the virtual character's motion in the virtual try-on system. The bar graph on the left of **Figure 4** shows the motion synchronization errors of 15 key points in degrees. The error values range from 1° to 2.5°, and the overall error is small, indicating that the system can synchronize the movements of the user and the virtual character well at most key points. The line graph in **Figure 4** shows the angle change trend between the user and the virtual character at 15 key points. Overall, the movements of the user and the virtual character are highly consistent. Through these data analysis, it can be seen that the virtual try-on system can achieve good motion synchronization in most cases, but it still needs to be optimized at a few key points.

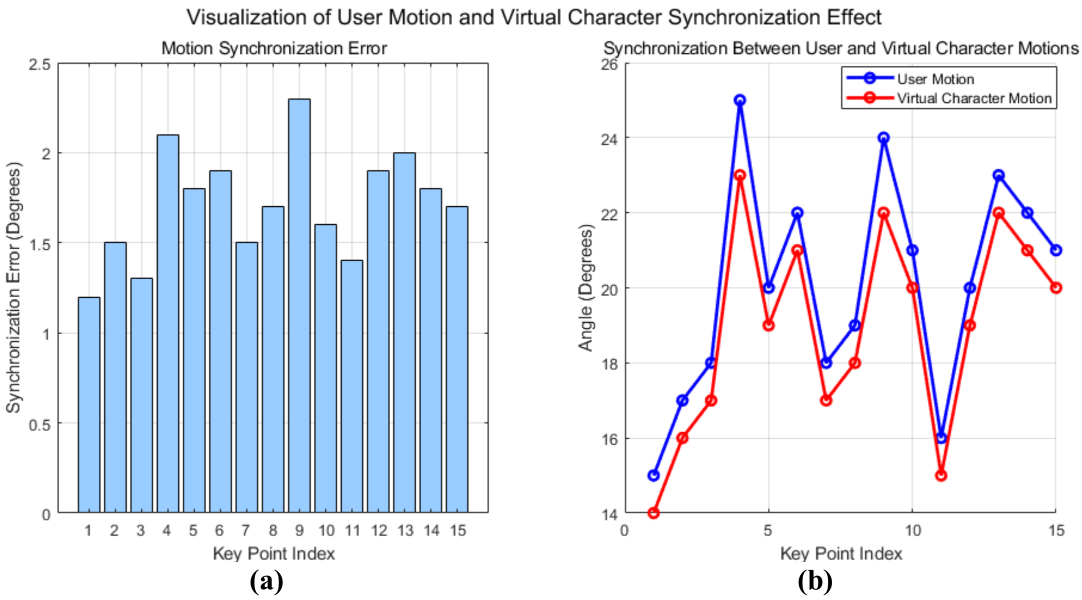

Figure 4. Comparison of synchronization error and motion angle between user motion and virtual character motion in the virtual try-on system. **(a)** Motion synchronization error at 15 key points; **(b)** Trend of angle changes between the user and the virtual character at 15 key points.

2.3.3. Equipment performance testing and virtual experience

Existing virtual fitting technology mostly relies on two-dimensional images or simple three-dimensional modeling, and lacks accurate dynamic performance simulation and personalized recommendations. In contrast, this research method significantly improves the fitting accuracy and dynamic adaptability.

Virtual try-on not only needs to focus on the appearance of the equipment, but also consider its performance in actual use. To achieve this goal, this study added equipment performance testing functions to the virtual scene, dynamically simulating the performance of sports equipment in various sports scenarios, such as the shock-absorbing effect of shoes when running and the ventilation and breath-ability of sportswear.

Specifically, the cushioning performance of sports shoes during the virtual try-on process is tested in real time through simulation of the physics engine. Every time the sneakers touch the ground, the physics engine calculates the reaction force between the sole and the ground, simulating the shock-absorbing ability and elasticity of the sole. Through this process, users can intuitively perceive the comfort and support of the shoes under different gaits. For sportswear, thermal flow simulation technology is used in a virtual environment to demonstrate the breath-ability and comfort of clothing during running or high-intensity exercise. By simulating air flow and clothing fabrics, the system can demonstrate the heat dissipation and drying effects of sportswear under different sports conditions.

In addition, the dynamic physical effects in the virtual scene combine motion capture data with equipment performance simulation to ensure that the performance of the sports equipment when the user is exercising is highly consistent with the actual motion state. For example, when the user is running quickly, the dynamic performance of the virtual shoes will provide real-time feedback based on the user's pace and landing force, presenting a more realistic cushioning effect and athletic performance. For sportswear, the ventilation effect of the clothing can be adjusted in real time according to the user's exercise intensity and ambient temperature, allowing the user to perceive the adaptability of the clothing under different conditions.

2.4. Personalized recommendation system

2.4.1. User data analysis and clustering classification

In the virtual fitting system, the core task of the personalized recommendation system is to provide each user with customized sports equipment recommendations based on the user's body shape data, exercise habits and personal preferences. In order to achieve this goal, first of all, the user's basic information and behavioral data need to be collected. These data include the user's body parameters (such as height, weight, shoulder width, etc.), exercise habits (such as the type of exercise they often participate in, exercise intensity, exercise frequency) as well as purchase history and browsing behavior.

During the data collection stage, this paper adopts the K-means clustering algorithm to conduct in-depth analysis and classification of user characteristics, aiming to classify users with similar exercise habits and body characteristics into the same group and build a diversified user cluster. For example, some users may be keen on running and cycling, while others may prefer fitness or basketball. By segmenting users, the system can gain a more accurate insight into user preferences and needs, and provide more appropriate sports equipment recommendations for each user group. The results of cluster analysis lay a solid foundation for the recommendation system. The system can provide more suitable recommendations by comparing the user's exercise type, intensity and equipment needs with similar user behaviors, effectively reducing the computational complexity and significantly improving improve the relevance and accuracy of recommendations.

In **Figure 5**, this paper uses the *K*-means clustering algorithm to group 100 users according to their body parameters (height) and exercise intensity, forming 4 user groups. Each group represents a group of users with similar body shapes and exercise habits. The *X*-axis represents the user's height, ranging from 150 to 200 cm, and the *Y*-axis represents the user's exercise intensity, ranging from 0 to 10. Through analysis, it was found that people with a height of around 180 cm usually have a higher exercise intensity, while people with taller heights do not exercise at a very high intensity. The analysis found that their greater weight causes them to consume energy faster. The cluster center identifies the average body shape and exercise intensity of each group as the representative characteristics of the group. This clustering method helps the virtual fitting system to more accurately understand the needs and exercise habits of different users, thereby achieving personalized sports equipment recommendations and improving the relevance of user experience and recommendations.

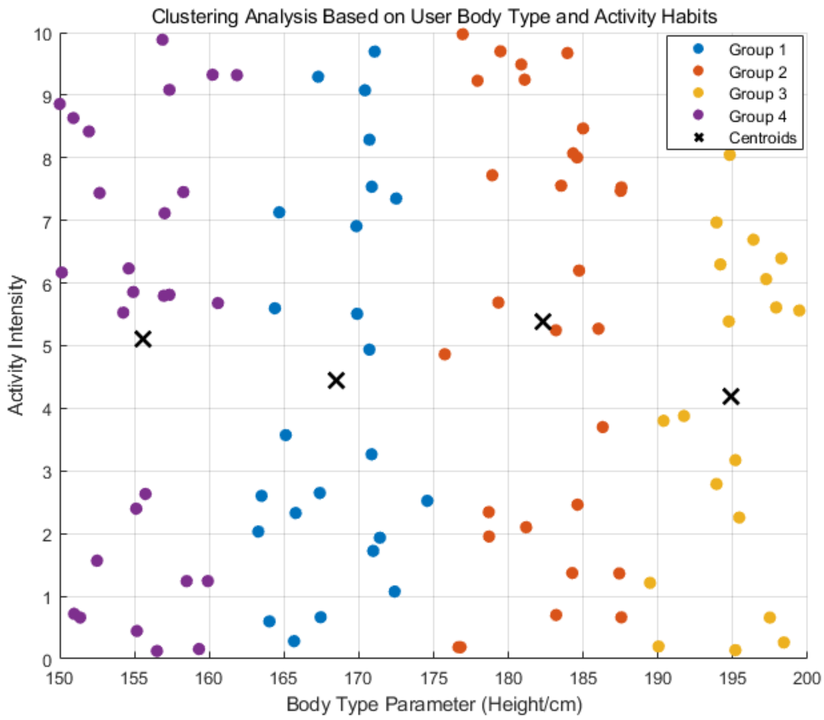

Figure 5. User body shape parameters and exercise intensity.

2.4.2. Recommendation algorithm and precise matching

Based on the user's feature analysis, this paper combines the collaborative filtering algorithm and the content-based recommendation method to build a personalized recommendation model. The collaborative filtering algorithm analyzes the similarities between users and recommends sports equipment that other similar users like. For example, if user A and user B are similar in body shape, sports type, etc., and user B purchases a pair of high-performance running shoes, the system may recommend the same running shoes to user A. Collaborative filtering can effectively capture the potential relationships between users and make recommendations based on these relationships, thereby improving the relevance of recommendation results and user satisfaction. On the other hand, content-based recommendation methods recommend sports equipment suitable for users based on the material, style, and function of the sports equipment. For example, if the system detects that the user prefers sportswear or running shoes with good breath-ability, the content-based recommendation method can recommend other equipment that meets the user's needs based on the product's breathable design, shock-absorbing function, etc. This recommendation method not only takes into account the user's personal preferences, but also combines the specific attributes of the equipment to ensure the accuracy and diversity of the recommendations.

2.4.3. Dynamic adjustment and real-time optimization

The core mechanism of Deep Q-Learning in personalized recommendation is to dynamically adjust the recommendation strategy based on the user's historical data, body size, sports preferences and other information through the reinforcement learning algorithm. The system continuously interacts with users to learn which sports equipment is most suitable for user needs in different scenarios, and evaluates the recommendation effect through the value function.

In order to further optimize the personalized recommendation strategy, in addition to relying on users' clicks, try-ons and purchase behaviors, the system also pays attention to users' "dissatisfaction" signals, such as skipping recommendations, not trying on or leaving quickly. These negative feedbacks can help the system identify users' true preferences and adjust the recommendation direction. At the same time, combined with sentiment analysis technology, by analyzing the emotional information in user comments or voice feedback, the system can better understand the user's emotional changes, further improve the personalization and accuracy of recommendations, and thus improve user experience and purchase conversion rate. When a user shows a high interest in a pair of sneakers, the system will recommend more sports equipment with similar characteristics to the user. In this way, the reinforcement learning algorithm can gradually optimize the recommendation strategy so that the recommended content is more in line with the user's needs and interests.

Deep Q-Learning, as a reinforcement learning algorithm based on deep neural networks, can gradually learn the optimal recommendation strategy in multiple rounds by simulating multiple interactions and feedback. By constantly adjusting its strategies, the system can ensure the relevance of recommendations while also adapting to changes in user needs in real time, thereby continuously improving the personalization of the recommendation system. In Deep Q-Learning, Q-value is used to estimate the expected reward of taking a certain action in a certain state. The Q-value is updated by the following Bellman equation, as shown in Equation (1):

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \left(r_t + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t) \right) \tag{1}$$

s_t is the current state (e.g., the user's current interests or browsing history). a_t

is the current action (e.g., recommended sports equipment). r_t is the immediate reward for the current action (e.g., feedback such as clicks, purchases, and tries on). γ is the discount factor, which is used to control the impact of future rewards. α is the learning rate, which is used to control the update amplitude of the Q value. $\max_{a'} Q(s_{t+1}, a')$ is the maximum Q value in the next state. Equation (1) is used to adjust the recommendation strategy based on the user's real-time feedback (reward) so that future recommendations are more in line with the user's interests. In Deep Q-Learning, the goal of the system is to learn a state-action value function $Q(s, a)$, which represents the maximum cumulative reward that can be obtained after performing action a in a certain state s. The Q function is the output of a deep neural network $Q(s, a; \theta)$, which represents the expected reward under the current parameters θ, and the formula is as follows:

$$Q(s_t, a_t; \theta) = \mathbb{E}\left[\sum_{t=0}^{T} \gamma^t r_t \mid s_0 = s_t, a_0 = a_t\right] \tag{2}$$

s_t is the state of the system at the time step. a_t is the action chosen by the system at the time step t (such as recommending a certain product). γ is the discount factor, which is used to weigh future rewards. r_t is the reward of the current time step (such as click, purchase, etc.). By optimizing the Q value, the system can learn how to choose the best recommended action under different user states, thereby improving the accuracy of recommendations. In Deep Q-Learning, the policy is optimized by selecting the action with the highest Q value, using Equation (3):

$$\pi^*(s_t) = \underset{a}{\operatorname{argmax}} Q(s_t, a; \theta) \tag{3}$$

$\pi^*(s_t)$ is the optimal strategy given state s_t, that is, the product recommended to the user. $\underset{a}{\operatorname{argmax}} Q(s_t, a; \theta)$ means that in state s_t, action a that maximizes the Q value is selected, that is, the recommended content that is most likely to receive the highest reward. By continuously updating the Q value, the strategy gradually tends to be optimal, so that the recommendation system can adaptively adjust the recommended content according to the user's real-time feedback, improving personalization and user experience.

By further enhancing the diversity of the system, more diverse sports scenes and equipment options can be provided to users in the future, or scene simulations of different sports and displays of various styles of equipment will be added to meet the needs of different users. In terms of intelligence, by combining deep learning and behavioral analysis, the system can more accurately predict user preferences and optimize recommendation algorithms. Improvements in interactive design, such as adding voice control, gesture recognition or augmented reality (AR) interaction, will enhance user immersion and ease of operation. At the same time, cross-device compatibility is enhanced, allowing users to seamlessly experience virtual try-ons on different platforms (mobile phones, PCs, VR devices, etc.). Combining harsh environments and user-specific behavioral data (heavy snow, stormy weather, morning jogging, etc.), the accuracy of recommendations can be further improved, making the try-on experience more in line with actual needs, thereby improving user satisfaction.

3. Evaluation indicators of virtual fitting experience

3.1. Accuracy of virtual body modeling

In virtual body modeling, in order to ensure that the accuracy of the model matches the real user's body shape, Chamfer Distance is used to evaluate the error between the virtual model and the real data. Chamfer Distance quantifies the difference between the two by calculating the average of the shortest distance and the reverse shortest distance from the surface points of the virtual body model to the real data point set. Specifically, first, the body data of the real user is compared with the generated virtual model to extract the key points of the surfaces of both. Then, the distance from each virtual model point to the nearest real data point is calculated, and the average of these distances is taken as the error indicator. By minimizing the Chamfer Distance, the details of the virtual model are precisely adjusted to ensure that it is highly consistent with the real body shape, thereby improving the accuracy of the virtual try-on experience.

By calculating the shortest distance from the virtual point cloud to the real point cloud (virtual to real Chamfer Distance), and the shortest distance from the real point cloud to the virtual point cloud (real to virtual Chamfer Distance), this paper can quantify the matching accuracy between the two. As can be seen from **Figure 6**, the virtual-to-real error distribution is relatively concentrated, indicating that the distance between most virtual points and real points is small, indicating that the model has a high similarity with the real body shape. Statistics show that the Chamfer Distance from virtual to real is concentrated at around 0.15 meters, and the Chamfer Distance from real to virtual is also concentrated at around 0.15 meters. The error between the virtual body model and the real body shape is within 0.5 meters, which is in line with the body shape difference range of most users and can effectively support high-precision virtual try-on experience. In general, by minimizing the Chamfer Distance, the accuracy of the virtual body model can be further improved, ensuring that the comfort and adaptability evaluation during the virtual try-on process is more accurate, thereby improving the quality of users' shopping decisions.

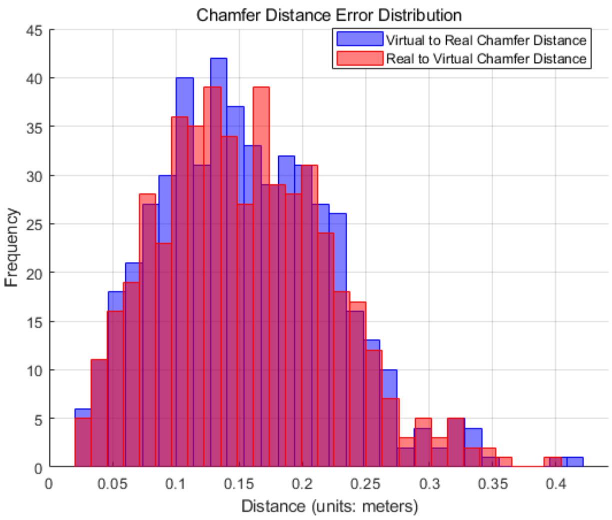

Figure 6. Chamfer distance error distribution between the virtual body model and the real data.

3.2. Material performance

In the material performance evaluation, Substance Painter is first used to generate high-precision material textures for the equipment, combined with PBR technology to simulate the gloss, texture, and surface details of the equipment. Next, a material performance scoring system is used to quantify the appearance and dynamic consistency of the virtual equipment, comparing the performance of the virtual equipment in the virtual environment with the experimental performance of the real equipment in actual sports (such as the cushioning effect of sports shoes and the breath-ability of clothing). By calculating the performance differences between virtual and real equipment in different sports scenarios, the realism and dynamic responsiveness of virtual materials are optimized.

According to the data in **Figure 7**, in the running scene, the gloss difference between the virtual equipment and the real equipment is small, only 1.5%, there is a lack of texture. In the cycling scene, the gloss error difference is 1%, the texture error difference is 1.1%, and the surface detail error is 0.7%, indicating that the virtual equipment's performance of details in cycling is closer to that of real equipment. In general, the errors between virtual equipment and real equipment in terms of surface details, texture and gloss are small, with an average error of only 1.35%, which reflects that virtual equipment performs well in different sports scenarios.

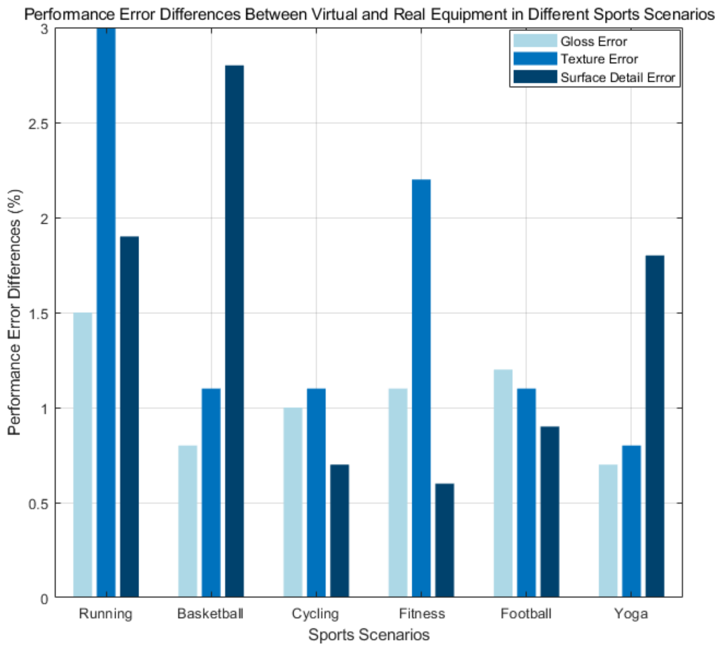

Figure 7. Performance errors of gloss, texture, and surface details between virtual equipment and real equipment in six motion scenes.

3.3. User experience and conversion rate and return rate

When evaluating the user experience, a questionnaire survey is first used to collect feedback from 100 users on the virtual fitting system, covering aspects such as fitting experience, fit and comfort of virtual equipment. Subsequently, data is collected and comprehensively analyzed based on the user' s conversion rate and return rate. By analyzing the purchase conversion rate after users try on clothes, the accuracy of system recommendations can be evaluated; the return rate reflects the user's satisfaction with the virtual try-on results and the actual matching degree of the equipment. Through this combination of quantitative and qualitative methods, the overall satisfaction of users with the virtual try-on system is comprehensively evaluated.

Table 2 presents the user experience evaluation results of the virtual try-on system in different sports equipment applications. Specifically, basketball shoes and cycling equipment receive the highest scores in the try-on experience, 4.5 and 4.4 respectively, highlighting their popularity in the virtual environment. Cycling equipment performs particularly well in terms of fit and comfort, with a fit score of 4.7 and a comfort score of 4.6, demonstrating its excellent body fit and comfort. In terms of purchase conversion rate, cycling equipment has the highest conversion rate, reaching 70%, indicating that its virtual try-on experience has a strong influence on purchase decisions. The overall return rate is below 10%, with cycling equipment having the lowest return rate (5%), indicating that the system has effectively reduced the risk of returns and improved user satisfaction.

Table 2. User experience, conversion rate and return rate.

Sports Equipment/Scene	Try-on Experience Rating (1–5)	Fit Rating (1–5)	Comfort Rating (1–5)	Purchase Conversion Rate (%)	Return Rate (%)
Running Shoes	4.2	4.5	4.3	60	8
Basketball Shoes	4.5	4.6	4.4	65	6
Gym Wear	4.3	4.4	4.2	58	9
Running Wear	4.1	4.3	4.1	55	7
Cycling Gear	4.4	4.7	4.6	70	5
Soccer Shoes	4	4.2	4	50	8

3.4. System response time

In the response time evaluation, the time delay from user gesture, voice command and click operation input to system response is first measured. By using high-precision timing tools, the time it takes for 100 users to initiate an operation and then provide feedback in the virtual environment is recorded, so as to optimize the system architecture and algorithms to reduce latency.

Table 3 shows the response time evaluation results of the virtual try-on system under different input methods. By measuring the response time in different sports equipment try-on scenarios, the average response time, maximum response time, minimum response time and pass rate under each input method (gesture, voice, click) are listed. The data shows that the click input method performs best in all scenarios, with the shortest average response time. For example, the response time when trying on cycling equipment is 78 ms, and the pass rate reaches 99%. In contrast, the maximum response time of gesture input when trying on fitness equipment is higher, reaching 110 ms, which is slightly worse. Overall, the average response time of all input methods is 88.7 ms, which is less than 100 ms. Its fast response speed also shows that the system performs well in terms of interactive fluency. The pass rate in most scenarios is over 90%, which reflects the efficient responsiveness of the virtual try-on system under different input methods.

Table 3. Response time of the virtual try-on system under different input modes.

Test Scenario	Input Method	Average Response Time (ms)	Maximum Response Time (ms)	Minimum Response Time (ms)	Pass Rate (< 100 ms)
Running Gear Try-On	Gesture Input	85	95	75	98%
Basketball Gear Try-On	Voice Input	92	105	80	96%
Cycling Gear Try-On	Click Input	78	88	70	99%
Fitness Gear Try-On	Gesture Input	100	110	90	94%
Football Gear Try-On	Voice Input	95	105	85	97%
Yoga Gear Try-On	Click Input	82	90	74	99%

4. Conclusion

This paper proposes a sports equipment fitting solution based on virtual reality technology, aiming to solve the problem that users cannot truly experience products on traditional e-commerce platforms. Through 3D scanning technology, SMPL model and posture optimization algorithm, the user body model was successfully generated, and it was adapted to various motion scenarios through dynamic posture adjustment and PoseNet optimization. Combining Unity Physics and high-definition texture mapping technology, the system achieves dynamic performance and realistic appearance of sports equipment materials, reproducing the effect of the equipment in actual use. In addition, the Deep Q-Learning algorithm is used to recommend the most suitable sports equipment based on the user's body shape and sports preferences. Experimental results show that the performance error between virtual equipment and real equipment is only 1.35%, the virtual try-on pass rate exceeds 90%, and the return rate is less than 10%, which verifies the feasibility of the system in e-commerce and effectively improves users' online shopping experience. Although the method proposed in this paper has achieved certain results, there are still some shortcomings, such as the diversity of user scenarios and the personalized recommendation of virtual try-on experience may need to be further optimized. Future research can combine more data sources to improve the accuracy of personalized recommendation algorithms, and explore the combination of augmented reality technology and virtual try-on systems to further enhance user immersion and purchase decision efficiency.

Ethical approval: Not applicable.

Funding: Key Project of Humanities in Universities of Anhui Province: Research on the Development Model and Path of Rural E-commerce in Western Anhui under the Background of New Quality Productivity (2024AH052316).

Conflict of interest: The author declares no conflict of interest.

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