Design of Digital Protection and Immersive Experience System for Red Sports Resources— Taking the History of Basketball Development as an Example

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ABSTRACT The digital preservation and intelligent utilization of large-scale cultural and historical resources require efficient multimodal information acquisition, semantic fusion, and real-time visualization technologies. This study proposes an integrated framework combining multimodal sensing, knowledge graph modeling, and digital twin technology for immersive information presentation and interactive exploration. High-resolution three-dimensional laser scanning, UAV photogrammetry, optical character recognition, and multimodal data fusion are employed to construct structured digital assets from heterogeneous sources. A domain-oriented semantic knowledge graph is developed to organize entities, events, and spatiotemporal relationships, while an event-driven reasoning engine dynamically generates interactive content and scene transitions. A lightweight digital twin framework enables real-time rendering and behavioral simulation in immersive environments. Experimental results demonstrate that the proposed framework achieves entity recognition accuracy exceeding 97.8%, maintains an average rendering performance above 110 FPS under most operating conditions, and supports low-latency dynamic content generation. The proposed approach provides an effective solution for multimodal information processing, semantic knowledge representation, digital twin construction, and interactive visualization, offering potential applications in intelligent sensing, virtual environments, and digital information systems.

INDEX TERMS multimodal sensing, knowledge graph, digital twin, semantic information fusion, immersive visualization, real-time rendering

I. INTRODUCTION

RED sports represent culturally significant assets that embody a revolutionary past and contain spiritual value. Protecting the digital heritage of these assets, including the intricate craftsmanship of historical artifacts, and creating innovative methods to pass on their legacies is critical to the continuation of historical memory and the promotion of sports as a source of inspiration. By digitizing the unique weaving techniques and material textures associated with this heritage, we ensure that the artisanal wisdom of the industry remains a tangible part of the cultural narrative for future generations. The fast growth of immersive technologies, including virtual reality (VR) and augmented reality (AR), has opened up completely new technological opportunities for revitalizing and using the resources associated with these assets; it has enabled the development of experiences that blend the authenticity of historical records with the emotions created by those records, while at the same time calling for a transformation of the paradigm that governs the preservation and protection of cultural heritage from static preservation, to a dynamic storytelling approach [1-2].

Recent studies indicate that there are some very specific challenges that researchers are facing today. Firstly, digital protection of red sports resources includes multiple types of resources such as physical cultural artefacts or relics, historical documents, video material and oral history. The current technical solutions are unable to efficiently integrate different types of multimodal data, which results in fragmented digital archives/profiles and siloed information [3-4]. Experience design for most immersive systems is focused primarily on the visual reconstruction of scenes and interacting with them in a basic way. In addition, they generally do not encode and present the unique dynamic processes that occur within a sport (e.g. the evolution of basketball tactics/ rules) or the underlying narrative upon which the red spirit is based, resulting in an experience that lacks depth and educational value [5-6]. The most significant issue is that there has been a complete breakdown in the relationship between the static data created through the use of digital protection technologies and the dynamic and programmable content needed to create an immersive experience. This means that there is no cohesive pathway for converting "data" into "narrative" into "experience" that has currently been established [7-8].

Current research has been conducted on potential strategies to tackle the issues at hand, including the use of very accurate 3D scans and database systems to create digital repositories for permanent storage and easy retrieval of resources within a digital archive. Unfortunately, the data that is produced by these means does not contain the understandable semantic relationships for computing systems nor can this data drive the expressive attributes required for producing complex narrative logic [9-10]. With respect to immersive tech applications, gaming engines have been utilized in an array of studies (e.g., virtual exhibit halls and recreated historical scenes) to improve the visceral experience and enjoyment drawn from using the immersive tech display system associated with the archival material. However, their content is mostly pre-scripted and fixed processes, with weak dynamic generation capabilities, making it difficult to adapt to personalized narratives and deep interactions [11-12]. Some cutting-edge work has attempted to introduce knowledge graph technology to organize cultural content, but its construction is largely geared towards general domains, failing to perform ontological modeling of the unique historical event chains, character networks, and spiritual connotations of Red Sports, resulting in limited domain explanatory power and narrative support for the graphs [13-14]. While these studies have achieved some success in digital preservation or immersive technology, they have failed to systematically bridge the structural gap between data protection and experience generation. To address the disconnect and semantic gap between digital preservation and immersive experience, this paper proposes an end-to-end construction method driven by the fusion of narrative knowledge graph and digital twin. This method defines a dedicated ontology for the field of red basketball, performs semantic annotation and relation extraction on multi-source heterogeneous data, and constructs a narrative knowledge graph with historical events as nodes. Furthermore, a narrative logic engine based on rule and event triggering mechanisms is designed. This engine parses user interaction intent, traverses and reasons through the knowledge graph in real time, and dynamically generates historically accurate narrative clues and scene scheduling instructions. Finally, relying on a lightweight digital twin framework, instructions are rendered and physically simulated in real time within an immersive environment, achieving mechanistic-level reproduction and interactive feedback of historical scenes. The main contribution of this research is that, through the design of the domain ontology and narrative engine, it endows digital assets with machine-executable narrative potential at the data layer, thereby enabling a seamless integration of preservation and interactive experience through a unified architectural framework. This research contributes a domain-specific event-driven narrative framework for red sports heritage, which goes beyond generic knowledge graph applications. The key novelty lies in three aspects: (1) a red basketball-specific ontology that models the unique causal and temporal relationships among historical events, figures, and artifacts; (2) an event-triggered narrative engine that dynamically generates coherent storylines based on user interactions and historical logic; and (3) a seamless integration of static preservation data with interactive experience generation, transforming the knowledge graph from a passive repository into an active narrative driver. This framework is specifically tailored to convey the revolutionary spirit and historical evolution embedded in red sports resources. By mapping the intricate relationships between artisanal craftsmanship and cultural events, it provides a computable and scalable solution for the digital narrative of red sports resources within the broader context of heritage preservation.

II. NARRATIVE MODELING AND IMMERSIVE SYSTEM CONSTRUCTION OF RED BASKETBALL RESOURCES

The integrated system for digital protection and immersive experience of red basketball resources follows the systems engineering logic from data collection to final experience generation. Its overall design architecture is shown in Figure 1.

Figure 1 illustrates the system's three-layer progressive architecture. The data layer transforms raw resources into structured digital assets through multimodal acquisition and processing. The logic layer, centered on a narrative knowledge graph, dynamically generates narrative instructions through an event-driven engine, achieving semantic organization and narrative arrangement from data to knowledge. The presentation layer, based on lightweight digital twins and real-time rendering technology, transforms instructions into a cross-platform immersive experience and forms a closed loop through interactive feedback. The core innovation of this architecture lies in using a knowledge graph as a hub to systematically connect the entire process from digital protection to immersive generation.

A. DIGITAL ACQUISITION AND PROCESSING OF RED BASKETBALL RESOURCES BASED ON MULTIMODAL FUSION

The digital protection of red basketball resources begins with the high-precision, structured acquisition of multi-source heterogeneous raw data. The core task of this stage is to establish a standardized technical process to transform physical objects, documents, and image materials into standardized digital assets that can be directly processed and associated by the computing system. For three-dimensional physical artifacts such as historical basketballs, trophies, and

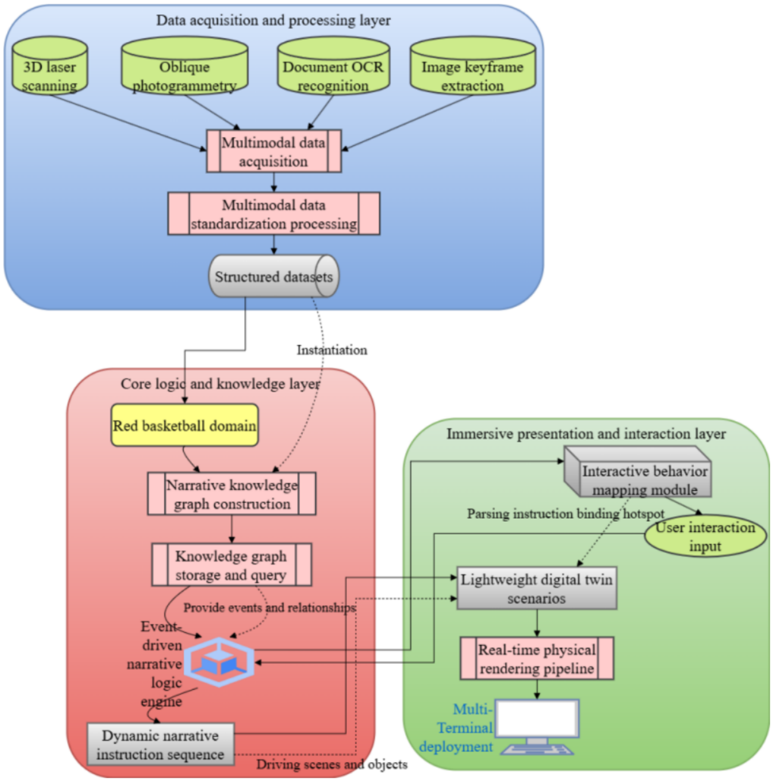

FIGURE 1. System architecture for digital protection and immersive experience of red basketball resources

simple basketball hoops, as well as historical site ruins, a combination of terrestrial three-dimensional laser scanning and UAV (unmanned aerial vehicle) oblique photogrammetry is used for data acquisition [15-16]. Laser scanning acquires high-precision geometric point cloud data. The three-dimensional coordinates $P_i(x_i, y_i, z_i)$ of each point in the point cloud record the spatial position of the object's surface, and their set constitutes the object's geometric skeleton. Simultaneously acquired texture images are applied to the surface of the geometric model using multi-view matching and mapping techniques to create a realistic appearance. This process must meet a preset accuracy threshold; the geometric error of the model is typically controlled using root mean squared error:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} d_i^2}. \tag{1}$$

Here, d_i represents the shortest distance between sampling point i and the model surface, and this metric ensures a high degree of fidelity in form between the digital model and the original physical object. The morphology of two-dimensional materials (e.g., paper documents, newspapers and manuscripts) is constructed using very high-resolution planar scanned digital images. In addition, the use of deep learning-based optical character recognition (OCR) technology performs text recognition and layout analyses [17-18]. The recognition process can be formalized as a sequence labeling problem, where the model converts the sequence of images (i.e., $X = \{x_1, x_2, \ldots, x_T\}$) to the character sequence (i.e., $Y = \{y_1, y_2, \ldots, y_L\}$) by maximizing the conditional probability $P(Y \mid X; \theta)$, where θ is the model parameter. This step not only extracts the text content but also uses layout analysis to identify the logical structure of titles, body text and illustrations, thereby producing a structured representation of the text with semantic tag. For dynamic images and oral history audio materials, computer vision methods are used to extract keyframes and perform speech recognition [19-20]. Keyframe extraction is achieved by calculating the difference between video frames, such as the difference based on the color histogram:

$$D_t = \|H_t - H_{t-1}\|. \tag{2}$$

When D_t exceeds the threshold, it is determined to be a keyframe, thus condensing the video content. Audio data is converted into text by a speech recognition engine and aligned with timestamps to form a searchable transcript. All the multimodal data output from the above processing steps, including 3D meshes and texture files, structured text, keyframe images, and timestamp text, are given a unified metadata description framework. This framework defines the core attributes of the resource, such as identifier, source, type, acquisition time, and spatial reference system, providing a standardized data foundation that is consistent and ready for association for the next stage of semantic fusion and knowledge construction.

B. CONSTRUCTION OF DOMAIN ONTOLOGY AND KNOWLEDGE GRAPH FOR NARRATIVE GENERATION IN THE RED BASKETBALL ERA

To transform standardized multimodal data into machine-understandable and reasonable narrative knowledge, a dedicated domain ontology needs to be constructed as the skeleton for semantic modeling. This ontology inherits the basic framework of the event ontology at its top level. Its core is the formal definition of key concept categories (Class), properties, and their constraints in the historical narrative of red basketball. Concept categories include "Historical Period," "Person," "Organization," "Sports Event," "Rule," "Venue," "Cultural Relic," and "Historical Activity," which serves as the core narrative unit. Properties are used to describe entity characteristics or define rich semantic relationships between entities, especially relationships that connect narratives, such as participatesIn (a person participates in an event), occursAt (an event occurs at a venue), leadsTo (event A leads to event B), and evolvesFrom (rule B evolves from rule A). The design of the ontology follows narrative logic, ensuring that instances of "historical activities" can form a coherent dynamic event network through spatiotemporal and causal attribute chains.

Based on this ontology, the construction of the knowledge graph is a semantic mapping and filling process from multimodal data to graph instances. For the generated structured text, named entity recognition and relation extraction are performed using a pre-trained language model [21-22]. The entity recognition task can be formalized as sequence labeling, while relation extraction determines the relation r defined in the

ontology for entity pairs (e_i, e_j). The model learns a classification function $f : (e_i, e_j, \text{context}) \to r$, and infers relations such as (participatesIn) from the context. For non-textual data such as 3D models, spatiotemporal and classification information already labeled in their metadata is used to directly instantiate them into (Venue) or (CulturalRelic) class nodes, and link them with related event nodes through attributes such as (occursAt). Finally, all extracted and mapped entities and relations are imported into the graph database to form a narrative knowledge graph with (HistoricalActivity) as the hub, entities as nodes, and semantic relations as edges. The structured query of this graph supports complex narrative path discovery, providing a computable knowledge base for subsequent immersive narrative generation.

Historical accounts of red sports events sometimes contain inconsistencies or gaps. To manage this, the knowledge graph incorporates a confidence scoring mechanism for each relation triple (e.g., leads to, evolves from). Conflicting statements are stored as parallel edges with different confidence weights derived from source authority and cross-validation. During narrative generation, the engine prioritizes higher-confidence paths; when data is sparse, the system gracefully degrades to simpler narrative templates rather than fabricating details. This approach ensures historical fidelity while maintaining narrative coherence.

C. DESIGN OF EVENT-TRIGGERED DYNAMIC NARRATIVE LOGIC ENGINE

The core function of the narrative logic engine is to dynamically generate coherent, immersive narrative content based on a knowledge graph and real-time interaction states. This engine transforms the "Historical Activity" nodes in the knowledge graph and their relationships such as "leadsTo" and "occursAt" into an event state network. Internally, the engine maintains a current narrative state vector:

$$S_t = (e_c, c_c, u_i). \tag{3}$$

e_c represents the currently active core historical event node; c_c represents the user's spatial coordinates and viewpoint in the virtual environment; and u_i represents the most recently captured user interaction. The engine operates according to an event triggering and state transition rule. Each time the user interacts with u_i or reaches a specific spatiotemporal coordinate c_c, the engine takes it and the current state S_t as input and performs a query in the knowledge graph. The goal of this query is to find all potential subsequent event sets E_{next} that are directly relat ed to e_c through relationships such as (leadsTo) and whose occurrence conditions match S_t. The decision function $f(S_t, E_{\text{next}}) \to e_{\text{next}}$ selects the most suitable event e_{next} from E_{next} as the next narrative unit based on preset narrative weights. The state is then updated to S_{t+1}. The engine immediately outputs the 3D scene instructions, character behavior scripts, audio narration, and a new set of interactive objects bound to e_{next} to the rendering system, driving the seamless evolution of the experience content and forming a dynamic narrative flow determined by the user's interaction intent and historical causal logic.

D. REAL-TIME RENDERING AND INTERACTION IMPLEMENTATION OF LIGHTWEIGHT DIGITAL TWIN SCENES

This section transforms the instructions output by the narrative logic engine into an interactive, immersive experience through two complementary technical mechanisms: physics-based visual rendering and event-driven behavioral simulation. The virtual reality system encourages exploration within a physical and ordered space; both venue and cultural relic entities are used to drive the scene from the knowledge graph and instantiate them into the engine. A simplified implementation of Quadric Error Metric (QEM) allows for a consistent representation across platforms while minimizing the cost of the error matrix Q through iterative approaches to shrinkage, achieving a balance between visual quality and rendering speed [23-24]. Lighting is driven by a hybrid of pre-computed global illumination and screen space reflections. The final pixel color L_{final} is produced from pre-computed irradiance L_{baked} and real-time specular $L_{\text{real-time}}$, in order to physically represent the historical properties of materials. A single unified agent is use to implement an integrated interactive system utilizin the agentto parse all interactive objects and their correspon-ding behavioral scripts in the narrative instructions. Upon intersecting with the object's 3D thermal detection system , and if the current narrative state S_t triggers an event, the agent triggers feedback visually or audibly; in addition , the agent can also send events back into the engine in order to create a closed-loop interactive system.

III. EXPERIMENTS

A. EXPERIMENTAL ENVIRONMENT AND DATASET

To validate complete effectiveness for digital preservation quality, system operational performance, user experience, and culture dissemination effect, tests are simulated in a controlled lab. The primary hardware is a high end work-station equipped with an NVIDIA GeForce for executing the Digital Twin rendering engine and logical reasoning services; the immersive experience terminal is a Meta Quest 3 all-in-one Virtual Reality (VR) machine that has display resolutions of 2064 horizontally x 2208 vertically pixels per eye and refresh rates of 120hz generating an adequate level of fidelity and smoothness benchmark parameters for completing tests. The software development environment is based on the Unity LTS engine and integrates the HDRP (High Definition Render Pipeline) high-definition rendering pipeline to achieve physically based rendering effects [25-26]. The construction, storage, and querying of the knowl-edge graph rely on the Neo4j graph database system [27-28]. The reported frame rates (FPS) are achieved via PC VR streaming mode: the high-end workstation performs all rendering and computation, while the Meta Quest 3 functions as a display terminal connected via USB link (bandwidth 2.5 Gbps) or Wi-Fi 6. This configuration enables high-fidelity graphics that exceed the standalone rendering capability of the Quest 3. The system's "lightweight" claim refers to the optimized asset pipeline and efficient rendering algorithms (Section 2.4) that reduce computational load, not to standalone mobile execution. To support this experiment, a domain dataset specifically for the history of red basketball is constructed, the specific composition and scale of which are shown in Table 1.

As shown in Table 1, this dataset covers 3D geometry, text, imagery, and structured knowledge in terms of modal-ity, providing a sufficient data foundation for subsequent analysis in terms of scale. 3D models and documentary text constitute the direct objects of digital preservation and the entity basis for quality assessment; historical imagery provides visual materials for the atmosphere restoration and narrative details of immersive scenes; and large-scale structured knowledge triples are key inputs for verifying the quality of narrative knowledge graph construction and the reasoning ability of the logic engine. The multimodal and structured characteristics of this dataset provide complete empirical materials for systematically evaluating the full-link effectiveness from "data acquisition" to "knowledge construction" to "experience generation."

B. EVALUATION INDICATORS AND EXPERIMENTAL PROCEDURE

To comprehensively verify the overall effectiveness of the system, this paper defines multi-dimensional quantitative evaluation indicators and designs a controlled experimental procedure. The evaluation system covers four levels:

At the digital preservation level, the geometric mean square error and structural similarity index (SSIM) are used to measure the geometric accuracy and texture fidelity of 3D reconstruction, respectively [29-30]; the quality of the knowledge graph is evaluated through entity recognition performance (F1-Score).

At the system performance level, the average frame rate (Frames Per Second, FPS) and narrative generation latency (NGL) of the application in the VR environment are recorded.

At the user experience level, the internationally rec-ognized Presence Questionnaire (PQ) is used to measure immersion.

The cultural transmission effect is quantified by com-paring the difference in historical knowledge test scores (ΔScore) and cultural identity scores between the experi-mental group and the control group before and after the experience.

The 60 recruited participants are then randomly dis-tributed into an experimental and a control group. No significant differences exist between these two groups' de-mographics (gender and age) or their backgrounds (bas-ketball knowledge). The experimental procedure uses the traditional methodology of "pre-test, experi ence/viewing, post-test, questionnaire survey." This study was approved by the Ethics Committee of Lvliang University, and was performed in accordance with the principles of the Declara-tion of Helsinki. All eligible participants signed an informed consent form.

The specific operational components used to collect data from both groups are shown in Table 2.

The design of the experiment demonstrates meticulous attention to controlling all variables of the experiment. Both groups are given similar assessments of their knowledge pre-and post-test, ensuring an equitable comparison between learning outcomes for each group. In the core intervention phase, the experimental group participates in immersive interactive learning, while the control group participates in passive audiovisual learning. This design meets the criteria of controlling the independent variable of "immersive in-teraction" with respect to dependent variables (knowledge acquisition and sense of presence, etc). The collection of real world automatic performance data along with standard-ized questionnaires provides both objective and subjective performance measures for the assessment; these measures serve as the basis for statistical analysis after the completion of data collection (analysis of variance (ANOVA)).

TABLE 1. Statistics of the digital resource dataset for the history of red basketball

Data Type	Collection Method	Scale/Quantity	Primary Description and Purpose
3D Entity Models	High-precision laser scanning, photogrammetric reconstruction	87 models	High-fidelity geometric and texture data of historical artifacts and scenes, including basketballs, trophies, hoops, and typical courts.
Historical Document Texts	High-resolution flatbed scanning, OCR recognition	1,542 pages	Structured texts primarily from relevant newspaper reports, internal archives, and training manuals dated 1930–1970.
Historical Image/Video Materials	Digital restoration, keyframe extraction	127 minutes, 412 keyframes	Historical game footage, documentary clips, photographs, etc., with timestamp and content description metadata.
Structured Knowledge Triples	Manual annotation and model extraction	5,843 triples (Entities: 2,156; Relations: 3,687)	Semantic relationships between persons, organizations, events, and locations extracted from the above data based on the domain ontology, forming the core of the knowledge graph.

TABLE 2. Comparison of experimental and control group evaluation procedures

Stage	Experimental Group Operations and Data Collection	Control Group Operations and Data Collection
Pre-test Phase	Complete a multiple-choice test on red basketball history knowledge (baseline score test).	Complete the same multiple-choice test on red basketball history knowledge.
Experience Phase	Use the VR system freely for 15 minutes; system backend records FPS, NGL.	Watch a 15-minute traditional documentary closely matched in theme and content to the system.
Post-test Phase	Complete a historical knowledge test of comparable difficulty but with different questions; fill out the PQ and system usability scales.	Complete the same post-test knowledge test; fill out a questionnaire regarding the documentary viewing experience.
Data Analysis	Calculate ΔScore, analyze PQ scores and system performance logs for comprehensive evaluation.	Calculate ΔScore for comparative analysis with the experimental group data.

To further validate the advantage of the narrative knowledge graph, we introduced an additional control condition: a linear-scripted VR system built using the same 3D assets but with a fixed, pre-authored narrative path (no dynamic adaptation). Twenty new participants were recruited and followed the same procedure as the experimental group, experiencing this linear VR version.

IV. RESULTS

A. MULTIMODAL DATA RECONSTRUCTION QUALITY AND SEMANTIC ORGANIZATION EFFICIENCY IN DIGITAL PRESERVATION

In order to systematically assess the efficiency of the digital preservation process, this section presents the quantitative analyses of the multimodal data acquisition and processing results. These verify the geometric accuracy, texture fidelity, and accuracy of structured semantic information extracted from the original data in the 3D reconstruction process, through a thorough evaluation process. By comparing the performance of high-precision and conventional methods on different data types, this section objectively presents the quality baseline of the constructed red basketball historical dataset, and its core evaluation results are shown in Figure 2.

Figure 2 compares the data distribution of six technical solutions across three core metrics. In the geometric accuracy (negative RMSE (Root Mean Squared Error), unit: mm) results, the error values of the high-precision laser scanning group are concentrated in the range of -0.09 to -0.15 mm, lower than the -1.35 to -2.01 mm of the consumer-grade photogrammetry group. This difference stems from the inherent advantage of laser scanning in directly acquiring surface point cloud data, avoiding the cumulative errors introduced by feature matching and dense reconstruction in photogrammetry. Figure 2b shows that the SSIM value corresponding to laser scanning reaches 0.978 to 0.985, while that of the photogrammetry method is 0.865 to 0.892. The decrease is mainly affected by uneven ambient lighting and distortion of model texture mapping. In Figure 2c, the entity recognition F1-Score of professional scanning combined with commercial OCR reaches 97.8% to 99.1%, far exceeding the 85.9% to 90.2% of ordinary scanning and open-source OCR solutions. This is because the professional process preprocesses and optimizes document images and uses a recognition model trained on a large-scale corpus. For historical images, keyframes that have undergone digital restoration and manual annotation achieve a recognition performance close to 99%, while directly cropped frames, due to image degradation and limitations of automatic annotation, have an F1 value that drops to 71.2% to 76.4%. Analysis shows that adopting a professional-grade acquisition and processing workflow is a key prerequisite for constructing high-quality, semantically rich digital cultural heritage assets.

B. RUNTIME PERFORMANCE AND REAL-TIME NARRATIVE GENERATION OF THE IMMERSIVE SYSTEM

To evaluate the smoothness, stability, and response efficiency of the core intelligent modules in actual operation of the immersive system, this section conducts time-series monitoring and analysis of key performance indicators of the system during the coherent narrative experience. The experiment simulates the complete user experience flow from scene initialization to the triggering of the climax event and then to the ending. The system frame rate and the response latency data of the narrative logic engine under different complexity scenarios are continuously collected to reveal the correlation between system performance and dynamic load.

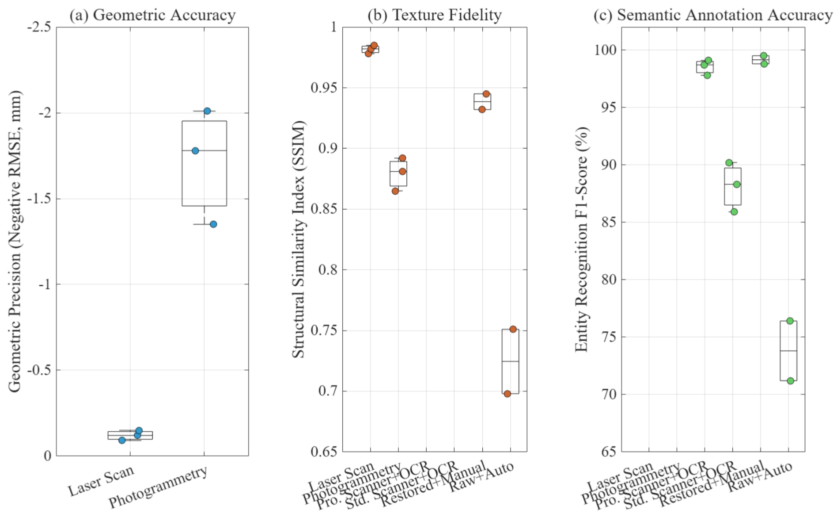

FIGURE 2. Multimodal digital conservation quality assessment: (a) Geometric accuracy, (b) Texture fidelity, (c) Semantic annotation performace

Its core performance characteristics are shown in Figure 3.

Figure 3 presents the system performance over a 150-second experience timeline. The left Y-axis represents the frame rate (FPS), with its line and error bars showing the average frame rate and fluctuation range; the right Y-axis represents the narrative generation latency (milliseconds); the background color blocks indicate low, medium, and high scene complexity periods; the data labels on the bars show the number of user interaction events triggered. At low-complexity levels, the average frame rate (119.5 FPS) and narrative latency (less than 20 milliseconds) both indicate that the system is able to perform efficiently under a low basic level of load. However, at high-complexity levels, average frame rate (89.3 FPS), frame rate standard deviation (8.9 FPS), and narrative latency (45.1 milliseconds) all drop dramatically during the core period (60 to 90 seconds) of narrative function where complexity increases. The major cause for this degraded performance is most likely due to the increased total processing load of the vertices, the frame buffer and pixel buffers being used for scene rendering, and the increased complexity of real-time reasoning in the knowledge graph, both during the same time. At this time, a maximum of eight user interactions are triggered, thus confirming that this period has high density of interaction. Once scene complexity has reduced, performance levels quickly recover. Overall analysis demonstrates that the system can provide smooth and low-latency response what is greater than or equal to 110 FPS across the majority of loads. The only point of performance degradation occurs during a very specific time period with multiple dynamic and complex narratives and rendering occurring, thereby providing quantitative evidence for future targeted optimizations.

C. USER EXPERIENCE'S PRESENCE AND INTERACTION FLUENCY

In order to assess how users perceive the quality of their experience and how effectively they are able to interact with the virtual historical environment, this chapter quantitatively evaluates users' experiences while using the immersive system through a standardized questionnaire survey. This experiment evaluates users' subjective ratings of the immersive system along three core dimensions: spatial presence; sense of participation; and natural interaction. The collected experimental results are used to evaluate the usability and emotional immersion of the immersive system. By collecting and analyzing experimental data from the 30 participants in the experimental group, a general profile of the user's experience of the immersive system has been established, and the core subjective perception evaluation result is presented in Figure 4.

The distribution of participant ratings for three presence dimensions, the spatial dimension (PQ-SP; PQ-Spatial Presence), the participatory dimension (PQ-INV; PQ-Involvement), and the natural interaction dimension (PQ-REAL; PQ-Realism), are shown in Figure 4. The semi-transparent lines show the profiles of each individual score, highlighting the variation in individual scores for the dimension of Realism, which has scores that ranged from 4.0 to 6.8 and has the most variances among participants. The blue outline represents the overall group means of scores for each dimension: 6.10 for Spatial Presence, 5.76 for Involvement, and 5.66 for Realism. The relatively low score for Realism is due to some participants experiencing unexpected feedback when they interact with the virtual objects, as well as slight delays in their actions when interacting with virtual objects that relate to historical contexts but do not correspond with modern interactions. Consequently, the way in which they evaluate fluency and naturalness is impacted by their experiences during interaction. The reason for the high score on the spatial immersion dimension is attributable to the quality of the 3D scene and historical accuracy of the visual detail, thereby making spatially engaged experiences much more realistic. Analysis shows that the system excels in creating a sense of historical spatial immersion, and also

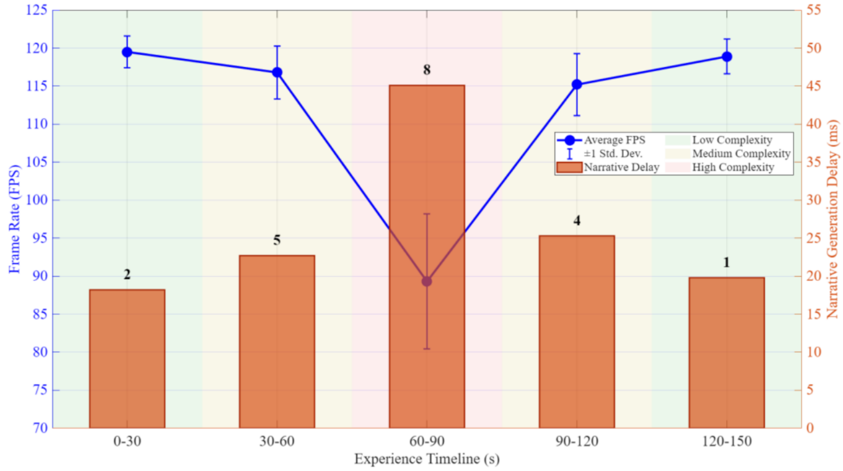

FIGURE 3. Runtime performance and narrative generation latency analysis

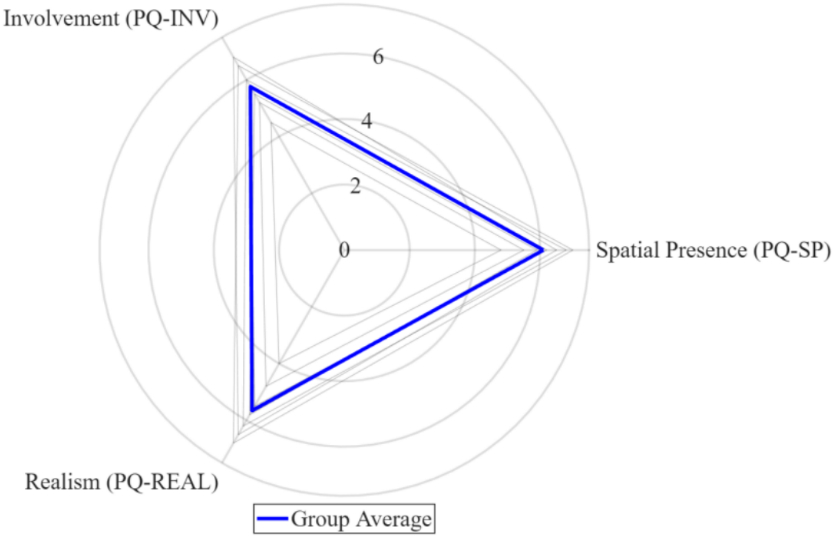

FIGURE 4. Subjective experience profile analysis

demonstrates excellent performance in the intuitiveness and fluency of its interactive design.

D. KNOWLEDGE TRANSFER AND CULTURAL IDENTITY EFFECTS BASED ON THE HISTORY OF RED BASKETBALL

To quantitatively evaluate the actual effectiveness of the immersive system in the dissemination of the history and culture of red basketball, this section designs a controlled experiment to examine the system's comprehensive impact on promoting cognitive learning and stimulating emotional identification. Participants are randomly divided into an experimental group and a control group. The experimental group experiences the immersive system developed in this paper, while the control group watches traditional red sports documentaries with matching themes and durations. Data on cognitive gain and changes in emotional attitudes is collected by administering historical knowledge tests and cultural identity questionnaires to both groups before and after the experience, comparing the differences in the depth of knowledge transfer and the intensity of cultural value shaping between the two media modes. The core inter-group comparison results are shown in Figure 5.

Figure 5 compares the performance of the experimental group and the control group on three core indicators: "Knowledge Gain (ΔScore)," "Mean Score of Cultural Identity," and "Post-Test Score of Historical Knowledge." In the knowledge gain dimension, the experimental group's mean score reaches 35.4, significantly higher than the control group's 16.4. Furthermore, the experimental group's individual data distribution is more dispersed and at a higher level. The immersive aspect of the system creates historical knowledge with embedded historical elements (historical knowledge points) within the context of action (i.e., within a

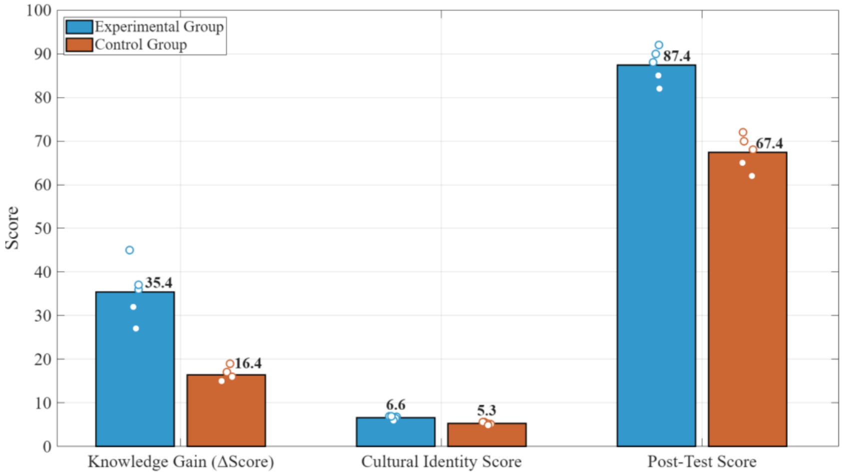

FIGURE 5. Comparison of knowledge transfer and cultural identity effects

narrative interaction), thus strengthening both the organization of memory encoding and the retrieval cues associated with those memories. The results for the cultural identity dimension show that the experimental group has a mean score of 6.6 (out of 7) compared to the control group's mean score of 5.3. This result reflects the use of role-playing and an emotional narrative designed for the system that provides users with an empathetic connection to both the historical character and their "spirit" and surpasses the efficiency of traditional media when transmitting emotionally (one-way) from creator to audience (e.g., documentary). The mean score for the experimental group post-testing (i.e., after completing the study) is 87.4, which is 20 points greater than the control group's mean score. This provides clear evidence of the impact/context-based learning can have on "internalizing" knowledge through repeated experience, like role-playing. The detailed findings of the analysis of the data collected demonstrate that there are statistically significant positive differences between the use of this medium (the system) and traditional mediums regarding their ability to increase the correct understanding (accuracy) of history and to increase the awareness of the value of red culture. Comparison with linear-scripted VR. Table 3 presents the performance of the three conditions: the proposed dynamic narrative VR, the linear-scripted VR, and the traditional documentary. The linear VR outperforms the documentary but lags behind our system in all metrics, with particularly notable gaps in knowledge gain (ΔScore: 26.8 vs. 35.4) and cultural identity (6.2 vs. 6.6). This confirms that the narrative knowledge graph's dynamic adaptation contributes significantly to deeper engagement and learning, beyond the mere use of VR.

TABLE 3. Performance comparison across different media conditions

Condition	ΔScore	Cultural Identity (out of 7)	Post-Test Score
Proposed Dynamic VR	35.4 ± 4.2	6.6 ± 0.4	87.4 ± 5.1
Linear-Scripted VR	26.8 ± 3.9	6.2 ± 0.5	78.3 ± 4.8
Traditional Documentary	16.4 ± 3.1	5.3 ± 0.6	67.1 ± 4.2

V. CONCLUSIONS

This paper addresses the fragmented technical processes and superficial narrative experiences in the protection and inheritance of red sports resources by integrating the systematic digitization of historical craftsmanship and material textures into the cultural preservation framework. By unifying the structural logic of traditional weaving with modern narrative techniques, the research ensures that the artisanal heritage of the industry is deeply embedded within a coherent and immersive digital storytelling system. It proposes an end-to-end system construction method driven by the fusion of narrative knowledge graphs and digital twins. This method defines an ontology for the red basketball domain, semantically links multimodal digital resources into a machine-understandable knowledge network, and dynamically generates immersive narrative content using an event-driven engine. Ultimately, interactive presentation is achieved in a lightweight digital twin scenario, thus constructing a cohesive pathway from static digital assets to dynamic, interactive historical narratives within a unified technical framework. Experimental verification shows that this method effectively ensures the quality of digital protection. The constructed knowledge graph, professionally scanned and combined with commercial OCR, achieves an entity recognition F1-Score exceeding 97.8%. The system maintains an average frame rate above 110 FPS under most load conditions, and the narrative generation latency is below 26ms in medium-complexity scenarios. The average spatial presence score for user experience reaches 6.1 points (out of 7), with the system performing most outstandingly in creating a sense of historical immersion. This study confirms the feasibility of the method in the digital revitalization of revolutionary sports cultural heritage, particularly the history of basketball. Its technological paradigm uses knowledge graphs as an intelligent hub to connect the entire process of protection and experience. This framework provides a valuable solution for the innovative digital transmission of narrative cultural heritage by ensuring that the intricate craftsmanship and material wisdom of the industry are preserved as computable, interactive knowledge assets.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

This study was approved by the Ethics Committee of Lvliang University, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form.

AUTHOR CONTRIBUTIONS

Conceptualization –Li Xin and Xueyong Sheng; methodology – Li Xin and Xueyong Sheng; investigation – Li Xin and Xueyong Sheng; writing-original draft preparation – Li Xin and Xueyong Sheng. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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