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Multi-Source Data Fusion and Virtual Human-Driven Metaverse Digital Twins for Intelligent Power Marketing Service Halls

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Abstract To address fragmented business data, limited interaction modalities, substantial demands on manual consultation, and inadequate presentation of low-carbon services in conventional power marketing service halls, this study proposes a human-centered metaverse digital twin framework for power marketing service halls. The framework takes the physical service hall as its operational foundation, uses digital twins to establish a continuously updated correspondence between physical facilities and their virtual representations, and positions digital humans as the primary user-interaction interface. It integrates marketing business systems, cyber-physical system (CPS) energy-management platforms, electricity consumption data collection systems, the State Grid Online platform, RPA process data, and smart home sub-metering data to develop an integrated service environment offering guided tours, business consultation, information visualization, service recommendations, and carbon-footprint displays. In addition, the proposed architecture encompasses a heterogeneous data-fusion model, a mechanism for generating digital-human service scripts, a method for constructing metaverse scenes, and a carbon-footprint assessment component. Together, these elements support a closed-loop workflow extending from the interpretation of customer requests to business responses, scene interaction, and feedback-informed service refinement. The reported evaluation indicates shorter service-completion times, improved question-answering accuracy and confidence calibration, more favorable assessments of immersion and interaction, and stronger capabilities for displaying marketing information and communicating low-carbon energy services. These results are reported outcomes of the study and require confirmation against the underlying evaluation data.

Index Terms metaverse; digital twin; power marketing; smart service hall; digital human; multi-source data fusion; carbon footprint; smart energy services

I. Introduction

With the deep integration of new-generation information technology and energy systems, the power industry is rapidly evolving from traditional power supply services towards digitalization, intelligence, and service-oriented approaches [1]. Driven by the "dual-carbon" strategy, the construction of the energy internet, and the Digital China strategy, power companies not only need to ensure a secure and stable energy supply but also need to provide users with more efficient, convenient, intelligent, and personalized integrated energy services [2], [3]. As a crucial window connecting power companies and end-users, business halls have long served functions such as business processing, customer consultation, electricity bill inquiries, energy consumption analysis, policy promotion, and service dissemination. However, with the continuous upgrading of user needs and the increasing complexity of business scenarios, the traditional business hall service model has gradually revealed problems such as insufficient service efficiency, fragmented business systems, limited interaction methods, and a limited user experience,

making it difficult to meet the development needs of smart energy services in the new era [4].

In recent years, the rapid development of technologies such as cloud computing, big data, artificial intelligence, digital twins, virtual reality (VR), augmented reality (AR), and the metaverse has provided new technological pathways for the construction of smart service halls [5]. Among these, digital twin technology, by constructing a virtual mapping of the real world, achieves real-time synchronization and two-way interaction between physical entities and digital space, providing crucial support for the monitoring, analysis, prediction, and optimization of complex systems. Metaverse technology further expands the digital space from traditional two-dimensional interfaces to immersive three-dimensional environments, enabling users to achieve more natural human-computer interaction through virtual identities, digital humans, and intelligent scenarios [6], [7]. The combination of digital twins and the metaverse allows service halls to transcend physical space and evolve into new smart service platforms integrating business processing, service consulta-

tion, energy display, low-carbon promotion, and intelligent interaction.

Currently, digital twin technology has been widely applied in fields such as intelligent manufacturing, smart cities, intelligent transportation, building operation and maintenance, energy management, and smart grids. In the power industry, related research mainly focuses on grid operation monitoring, equipment operation and maintenance management, fault prediction, energy dispatch optimization, and digital management of distribution networks [8]. By constructing digital mappings of grid equipment, energy systems, and operating environments, researchers can achieve equipment status perception, operational trend prediction, and system optimization decisions. However, existing research focuses more on improving operational efficiency on the grid and equipment sides, while paying relatively little attention to user-side service scenarios, especially lacking research on digital twins for customer service halls [9], [10].

Meanwhile, metaverse technology is gradually gaining widespread attention in fields such as education, healthcare, tourism, industrial collaboration, and smart cities. Existing research indicates that immersive virtual environments can effectively enhance user engagement, improve information comprehension efficiency, and enhance service experience [11]. In the public service sector, some research attempts to utilize virtual reality and digital human technologies to construct online service spaces, providing users with remote consultation, business processing, and information display functions. However, most existing metaverse research remains at the proof-of-concept, scenario demonstration, or virtual space construction stage, with limited ability to deeply integrate with complex business systems, particularly lacking organic integration with power marketing, energy management systems, and customer service processes.

Furthermore, digital humans, as an important interactive carrier in the metaverse, are gradually becoming a key research direction in intelligent customer service and smart services. Currently, digital humans are being applied in scenarios such as government services, banking services, exhibition hall explanations, and online customer service, providing basic consultation services through speech recognition, natural language processing, and knowledge base retrieval [12], [13]. However, most digital human systems still suffer from limited knowledge boundaries, insufficient business understanding, weak real-time data acquisition capabilities, and low levels of collaboration with backend business systems. In the power marketing service scenario, digital humans not only need to answer customer questions but also need to be able to access marketing business databases, interpret energy consumption data, guide business processing procedures, and participate in the promotion of energy and low-carbon services. This places higher demands on the intelligence level of digital humans [14].

On the other hand, with the continued advancement of the "dual carbon" goals, user-side energy services are gradually expanding from traditional electricity bill management to

low-carbon services, carbon footprint analysis, and energy-saving guidance. The development of smart homes, sub-metering, and energy management systems enables users to obtain more refined energy consumption data [15]. However, existing service hall systems mostly remain at the business processing level, lacking sufficient support for household energy consumption analysis, carbon emission visualization, and energy-saving behavior guidance, making it difficult to meet the future development needs of integrated energy services. Therefore, how to integrate smart home energy consumption data, carbon footprint analysis, and energy management services into the smart service hall system is also a crucial issue that urgently needs to be addressed in current research [1], [16].

A comprehensive analysis of existing research reveals several key challenges in the current construction of smart service halls.

First, the integration of heterogeneous data from multiple sources is difficult. Electricity marketing services involve data from various sources, including marketing business systems, electricity consumption data collection systems, cyber-physical system (CPS) energy-management platforms, the State Grid Online platform, customer service systems, and smart home terminals. These data differ significantly in format, semantics, update frequency, and security levels, making unified management and integrated analysis a major challenge.

Second, customer service interaction methods remain relatively traditional. Most service halls still rely on window services, self-service terminals, or two-dimensional web interfaces, which are insufficient to effectively support complex business explanations, energy data display, and the promotion of low-carbon services. Users still face high information comprehension costs when understanding business processes, analyzing energy consumption behavior, and obtaining personalized services.

Third, existing digital human systems lack deep integration with real-world business systems. Most digital humans can only perform simple question-and-answer tasks, struggling to provide functions such as business processing guidance, real-time data querying, personalized recommendations, and explanations of complex scenarios, thus limiting their practical application value in smart service halls.

Fourth, digital twins and metaverse technologies have not yet formed a unified service framework for service halls. Existing research typically focuses on 3D visualization, virtual scene display, or digital twins of devices, lacking an overall architectural design oriented towards customer service, business processes, and energy services.

Fifth, the capacity for low-carbon energy services is insufficient. Functions such as smart home energy consumption analysis, carbon footprint calculation, and energy-saving suggestions have not been effectively integrated into the service system of business halls, resulting in the business halls not playing a full role in energy services and low-carbon promotion.

To address the aforementioned issues, this paper proposes a Human-Centric Metaverse Digital Twin Framework for Intelligent Power Marketing Service Halls. This framework centers on customer service, is based on digital twins, utilizes a metaverse as the interactive environment, and uses digital humans as the service entry point. By integrating multi-source marketing data, energy management data, and smart home energy consumption data, it achieves collaborative operation between physical and virtual service halls. Specifically, this paper first constructs a digital twin model of the service hall space to achieve real-time mapping between the physical and virtual spaces; secondly, it designs a multi-source data fusion architecture to achieve unified access to marketing business systems, cyber-physical system (CPS) energy-management platforms, electricity consumption data collection systems, and smart home data; thirdly, it constructs a digital human-driven intelligent service mechanism to provide users with guided tours, business consultations, electricity application guidance, and data interpretation services; finally, it introduces a carbon footprint visualization and low-carbon service module to transform users' household energy consumption data into intuitive carbon emission information, providing users with energy-saving suggestions and low-carbon service support.

II. A Metaverse Smart Service Hall Model for Cloud-Twin Resource Coordination

As shown in Figure 1, the Metaverse smart business hall model proposed in this article can be abstracted into a closed-loop system of "user request–virtual resource scheduling–physical resource allocation–feedback-driven optimization". The Cloud User on the left side of the figure corresponds to the customers, service personnel, managers and remote access users in the electric power marketing service hall; the middle part corresponds to the Metaverse digital twin service platform built in this article, including cloud resource monitoring, virtual-machine monitoring, virtual-resource allocation, virtual-resource migration and virtual service instances; the physical resources on the right represent the business system, database, digital human service engine, RPA process robot, Energy Consumption Management 2.0 system, CPS energy management system, State Grid Online application interface, smart home sub-metering equipment and physical display terminal in the real business hall [17], [18].

Unlike traditional service hall systems, this model does not simply display business data on a large screen. Instead, it transforms power marketing service requests into computable, schedulable, and transferable virtual service tasks. Customer-initiated requests such as inquiries, navigation, business queries, carbon footprint viewing, and regional energy consumption analysis first enter the metaverse digital twin platform. Using current cloud-resource utilization information, digital human service load, business database access pressure, 3D scene rendering pressure, and physical device status, the platform dynamically completes virtual machine deployment, service instance placement, and resource migra-

tion, thereby ensuring that the Metaverse service hall maintains stable response under high concurrency, multi-service, and multi-terminal access conditions.

This model directly corresponds to the research content of this paper. First, the Job Request in Figure 1 corresponds to the customer's service requests in the metaverse service hall, such as digital human consultation, service hall navigation, business processing guidance, marketing results display, and smart home carbon footprint query. Second, Cloud Resources Monitoring addresses the real-time monitoring of cloud computing power, storage, network bandwidth, digital human service interface, knowledge base retrieval interface, and data visualization interface. Third, VM Monitoring addresses the monitoring of Metaverse virtual service instances, including digital human question-and-answer instances, 3D service hall rendering instances, marketing data dashboard instances, and carbon footprint calculation instances. Finally, VM Placement and VM Migration correspond to the initial deployment and dynamic migration of service instances, respectively, to achieve service load balancing, low-latency response, and high-availability operation.

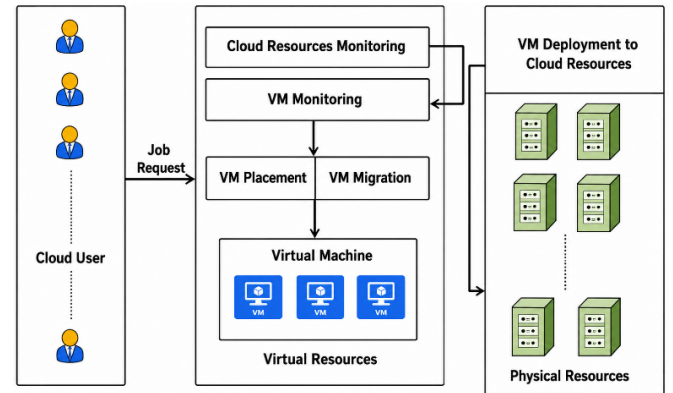


Figure 1: Cloud-twin resource collaborative scheduling framework for the power marketing service hall

Let the set of service requests received by the metaverse smart service hall at time (t) be:

$$\mathcal{J}(t) = J_1, J_2, \dots, J_n. \quad (1)$$

The i th service request is defined as follows:

$$J_i = u_i, \tau_i, d_i, c_i, b_i, s_i, \rho_i, \quad (2)$$

where u_i represents the user type, including customers, service personnel, managers, or remote visitors; τ_i represents the request type, such as digital human Q&A, business inquiry, guided tour, data display, or carbon footprint analysis; d_i represents the required data scale; c_i represents the computing resource requirement; b_i represents the bandwidth requirement; s_i represents the service priority; and ρ_i represents the real-time constraint of the request. Within the power marketing service hall, digital-human consultations, business-database queries, and live dashboards demand short response times, whereas historical carbon-footprint summaries and archived

marketing displays can tolerate less stringent latency constraints.

Let the set of available virtual resources in the cloud be:

$$\mathcal{V}(t) = V_1, V_2, \dots, V_m. \quad (3)$$

The state of each virtual resource instance V_j can be represented as follows:

$$V_j(t) = C_j(t), M_j(t), B_j(t), Q_j(t), L_j(t), A_j(t), \quad (4)$$

where $C_j(t)$ represents CPU/GPU computing resources, $M_j(t)$ represents memory resources, $B_j(t)$ represents network bandwidth, $Q_j(t)$ represents the number of currently queued tasks, $L_j(t)$ represents the current service load, and $A_j(t)$ indicates whether the instance is available. For the system in this paper, different virtual instances can respectively carry out functions such as digital human question answering, 3D scene rendering, marketing data fusion, carbon footprint calculation, and business process visualization.

Virtual resource load can be further defined as:

$$L_j(t) = \alpha \frac{C_j^{used}(t)}{C_j^{max}} + \beta \frac{M_j^{used}(t)}{M_j^{max}} + \gamma \frac{B_j^{used}(t)}{B_j^{max}} + \delta \frac{Q_j(t)}{Q_j^{max}}, \quad (5)$$

where $\alpha, \beta, \gamma, \delta$ are weighting coefficients, representing the degree of impact of computing power, memory, bandwidth, and request queue on system load, respectively, and satisfying the following:

$$\alpha + \beta + \gamma + \delta = 1. \quad (6)$$

This formula is used to determine whether a virtual service instance is overloaded. For example, when digital human consultation requests surge, the values of $Q_j(t)$ and $C_j^{used}(t)$ of the digital human question-and-answer instance will rise rapidly, and the system can trigger a new virtual instance deployment or migration mechanism accordingly.

III. Multi-Source Heterogeneous Data Fusion Model

As shown in Figure 2, the metaverse smart service hall data fusion model proposed in this paper adopts a hierarchical structure of "physical perception—multi-source aggregation—data processing—feature fusion—edge computing—business application". This model is designed for the complex business scenarios of power marketing service halls, unifying data from physical service halls, marketing business systems, electricity information collection systems, cyber-physical system (CPS) energy-management platforms, RPA process robots, the State Grid online APP, smart home sub-metering devices, and regional energy consumption analysis platforms [19]. Through multi-source data aggregation, standardization transformation, feature calculation, data-quality assessment, and fusion-based decision-making, it ultimately supports functions such as digital human Q&A, business process display, customer service recommendation, regional energy consumption analysis, and carbon footprint visualization in the metaverse digital twin service hall.

Figure 2 at the bottom illustrates the unified perception foundation for the physical and information sides. In the scenario of an power marketing service hall, the physical side includes the actual business hall space, customer service windows, self-service terminals, large display screens, smart home sub-metering devices, electricity consumption data collection equipment, and power distribution equipment status sensors; the information side includes marketing business data, customer consultation logs, business processing records, regional energy consumption characteristics, RPA process execution data, CPS energy management data, and smart home energy consumption data. The above data exhibits significant heterogeneity: on the one hand, different systems have different data formats, sampling frequencies, business semantics, and security levels; on the other hand, the business objectives served by customer consultation, business processing, energy consumption data collection, line loss management, and carbon footprint calculation are also different. Therefore, this paper extends the "Multi-source data aggregation" in the figure to a multi-source heterogeneous-data aggregation layer for the power marketing service hall [20].

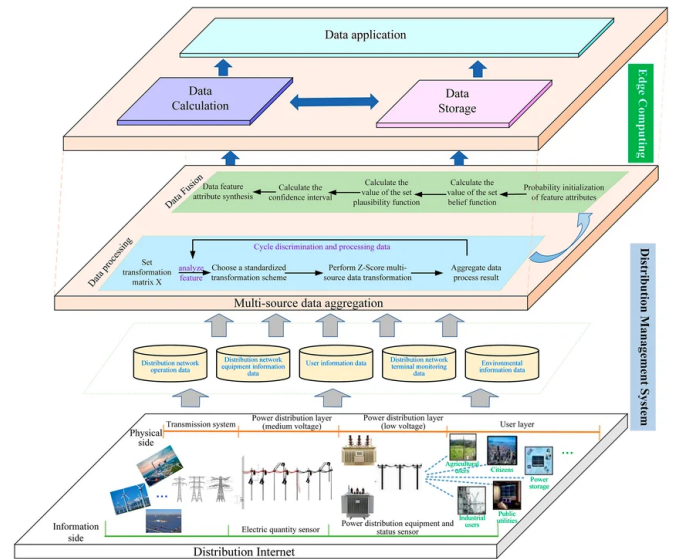


Figure 2: Data fusion core framework of the metaverse smart service hall

In the multi-source data aggregation layer, the system first collects data from multiple business terminals and sensing terminals, including business hall operation data, user information data, electricity consumption data, smart home energy consumption data, regional load data, marketing business process data, and environmental information data. Subsequently, the system generates a unified service data matrix through data cleaning, missing value repair, time alignment, and standardization transformation. Let the original data collected by the k th type of data source at time (t) be $\mathbf{x}_k(t)$, then the multi-source data set can be represented as:

$$\mathcal{X}(t) = \{\mathbf{x}_1(t), \mathbf{x}_2(t), \dots, \mathbf{x}_K(t)\}, \quad \mathbf{x}_k(t) \in \mathbb{R}^{d_k}, \quad (7)$$

where, (K) represents the number of data sources, and d_k represents the feature dimension of the k th data source. For the system described in this paper, $\mathbf{x}_k(t)$ corresponds to customer service data, business transaction data, electricity consumption data, RPA process data, CPS energy management data, regional energy consumption data, and smart home carbon footprint data, respectively.

Due to differences in units, sampling intervals, and outlier noise among different data sources, this paper employs a unified data standardization transformation to map heterogeneous data into a fusible feature space. Let the standardized features be $\mathbf{z}_k(t)$, then:

$$\mathbf{z}_k(t) = \phi_k(\mathbf{x}_k(t)) = \frac{\mathbf{x}_k(t) - \boldsymbol{\mu}_k}{\boldsymbol{\sigma}_k + \varepsilon}, \quad (8)$$

where, $\boldsymbol{\mu}_k$ and $\boldsymbol{\sigma}_k$ represent the mean vector and standard deviation vector of the k th data source, respectively, and ε is a smoothing term to prevent the denominator from being zero. This process corresponds to "Set transformation matrix X" and "Perform Z-Score multi-source data transformation" in the figure. Its function is to transform marketing data, energy consumption data, and service behavior data from different sources and at different scales into a unified computing space, providing a foundation for subsequent fusion analysis.

In the feature fusion stage, this paper considers not only the numerical characteristics of the data itself, but also introduces weights for data reliability, business relevance, and real-time performance. Let the fusion weight of the k th type of data source at time (t) be $w_k(t)$, then the fused feature vector $\mathbf{h}(t)$ can be defined as:

$$\mathbf{h}(t) = \sum_{k=1}^K w_k(t) \mathbf{W}_k \mathbf{z}_k(t),$$

$$w_k(t) = \frac{\exp(\theta_1 r_k(t) + \theta_2 q_k(t) + \theta_3 e_k(t))}{\sum_{l=1}^K \exp(\theta_1 r_l(t) + \theta_2 q_l(t) + \theta_3 e_l(t))}, \quad (9)$$

where $\mathbf{W}_k$ represents the feature mapping matrix of the k th type of data source; $r_k(t)$ represents the reliability of the data source, such as interface stability, missing rate, and anomaly rate; $q_k(t)$ represents the relevance of the data source to the current business task, for example, customer consultation tasks rely more on marketing knowledge base and business processing data, while carbon footprint display relies more on smart home energy consumption data; $e_k(t)$ represents the real-time or freshness of the data; and $\theta_1, \theta_2, \theta_3$ are weight adjustment parameters. This expression represents the data-feature synthesis and source-reliability assessment processes depicted in the figure, and is used to ensure that data fusion has dynamic adaptability under different business scenarios, rather than assigning equal importance to every data source.

The data-processing layer shown in the middle of Figure 2 illustrates the cyclic discrimination and aggregation process. This paper interprets this process as a service-intent recognition and data fusion decision-making process for a metaverse-oriented smart service hall. The system determines the category of the current service task based on the fusion feature $\mathbf{h}(t)$, such as digital human consultation, business processing guidance, marketing results display, regional energy consumption analysis, or smart home carbon footprint service. Let the set of service task categories be $\mathcal{Y} = 1, 2, \dots, C$, then the task category probability can be expressed as:

$$p(y = c | \mathbf{h}(t)) = \frac{\exp(\mathbf{a}_c^\top \mathbf{h}(t) + b_c)}{\sum_{j=1}^C \exp(\mathbf{a}_j^\top \mathbf{h}(t) + b_j)}, \quad (10)$$

where a_c and b_c represent the discrimination parameters for service task (c) , respectively. This formula is used to support "Cycle discrimination and processing data" in the diagram. For example, when a user asks a digital human in the metaverse service hall "How much carbon emissions does my home air conditioner produce per month?", the system should identify the request as "Smart Home Carbon Footprint Service" and prioritize calling the sub-metering data, carbon emission factor library, and carbon footprint visualization module; when a user asks "How to apply for meter replacement service", the system should prioritize calling the marketing business knowledge base, business process data, and the State Grid Online application service interface.

In the edge computing and data application layer, the fusion results are further encapsulated into application services for the Metaverse digital twin business hall. The edge computing module is responsible for reducing system response latency and improving the real-time performance of digital human Q&A, data dashboard updates, and carbon footprint calculations; the data storage module is responsible for storing standardized data, fusion features, service logs, and user interaction records; the data computing module is responsible for performing service intent recognition, carbon emission calculation, business process recommendation, and regional energy consumption analysis; and the data application module outputs the fusion results to the digital human, the 3D virtual business hall, the marketing results display screen, the smart home carbon footprint dashboard, and the management decision-making interface [21], [22].

To measure the contribution of fused data to the service quality of the Metaverse smart business hall, this paper defines a comprehensive data fusion utility function:

$$\mathcal{U}_{\text{fusion}}(t) = \lambda_1 \text{Acc}(t) + \lambda_2 \text{Com}(t) + \lambda_3 \text{Fresh}(t) + \lambda_4 \text{Rel}(t) + \lambda_5 \text{Delay}(t) + \lambda_6 \text{Risk}(t) \quad (11)$$

where $\text{Acc}(t)$ represents the accuracy of the fused data in supporting service decisions, $\text{Com}(t)$ represents the completeness of multi-source data coverage, $\text{Fresh}(t)$ represents the

real-time performance of the data, $Rel(t)$ represents the relevance of the fusion result to the current service task, $Delay(t)$ represents the data processing and transmission latency, and $Risk(t)$ represents the risks caused by privacy leaks, interface anomalies, or data inconsistencies; $\lambda_1, \dots, \lambda_6$ are weighting coefficients. For the power marketing service hall, this utility function can simultaneously evaluate the technical quality and service value of data fusion.

A. Metaverse Modeling Process and Technical Implementation

As shown in Figure 3, the modeling process of the metaverse smart service hall proposed in this paper is not a simple three-dimensional visualization, but a comprehensive modeling process consisting of "service-ecosystem modeling–spatial hierarchy specification–BIM/3D conversion–data binding–bidirectional interaction and feedback." Figures 3–5 collectively illustrate the modeling pathway of the metaverse digital twin service hall from the perspectives of theoretical structure, spatial hierarchy, and technical implementation [23].

Figure 3 presents the service-ecosystem logic of the metaverse smart service hall. The bottom layer is a nested system, including the physical service hall space, marketing business system, digital human service system, customer interaction system, smart home carbon footprint system, and management decision-making system. The middle layer is service output, including customer inquiry response, business processing guidance, marketing results display, regional energy consumption analysis, low-carbon service explanation, and employee decision support. The top layer is service welfare outcomes, including improved customer experience, reduced repetitive workload for sales staff, improved efficiency and effectiveness of marketing business management, enhanced customer satisfaction with electricity use, and optimized corporate image. This figure emphasizes that the metaverse service hall is not an isolated technology platform, but a service ecosystem comprised of multiple entities, systems, and business processes. The system specification clearly stated that by using digital humans to replace some sales staff, improve the customer electricity service experience, reduce staff workload, and enhance the digital intelligence capabilities of marketing business through the integration of multi-platform basic data and applications, this corresponds to the "nested system—service output—final effect" chain in the figure.

Suppose that the metaverse smart service hall Service Ecosystem consists of (N) subsystems, including a physical business hall system, a marketing business system, a data fusion system, a digital human system, a carbon footprint system, and a management decision-making system. Define the set of systems as:

$$S = S_1, S_2, \dots, S_N. \quad (12)$$

Each subsystem S_i can be represented as:

$$S_i = R_i, D_i, F_i, U_i, O_i, \quad (13)$$

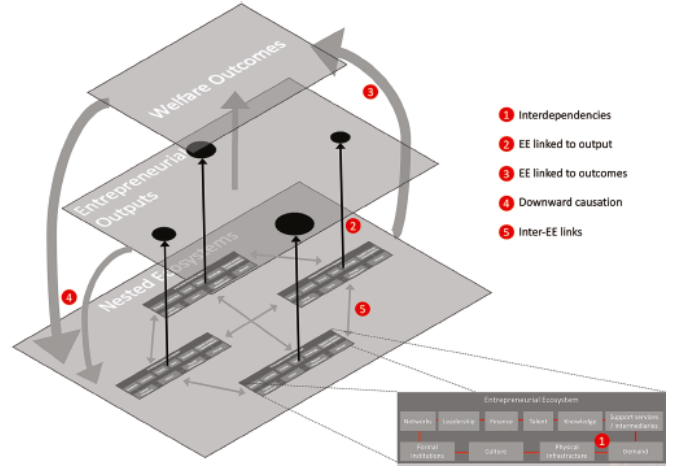


Figure 3: Multi-level value generation mechanism

where R_i represents the set of resources that the subsystem depends on, D_i represents the input data, F_i represents the system function, U_i represents the service object, and O_i represents the output result. For example, the input data of the digital human subsystem includes customer questions, a marketing knowledge base, and a business database, and its output results are guided tours, business responses, and suggestions for transferring to a human operator; the input data of the carbon footprint subsystem includes smart home energy consumption and carbon emission factors, and its output results are appliance carbon emissions, carbon footprint curves, and energy-saving suggestions.

To characterize the dependencies between different subsystems, a coupling strength matrix between systems is defined:

$$A = [a_{ij}]_{N \times N}, \quad a_{ij} = \frac{\kappa_1 I(D_i, D_j) + \kappa_2 I(F_i, F_j) + \kappa_3 I(U_i, U_j)}{1 + \text{dist}(S_i, S_j)}, \quad (14)$$

where a_{ij} represents the coupling strength between subsystems S_i and S_j ; $I(D_i, D_j)$ represents the correlation of their input data; $I(F_i, F_j)$ represents functional correlation; $I(U_i, U_j)$ represents the degree of overlap of service objects; $\text{dist}(S_i, S_j)$ represents the hierarchical distance between them in the system architecture; and $\kappa_1, \kappa_2, \kappa_3$ are weight parameters. This formula corresponds to "Interdependencies" and "Inter-EE links" in the first figure, used to describe the interdependencies between physical business halls, digital humans, marketing data, carbon footprint, and management decisions.

Figure 4 illustrates the layered modeling method of the metaverse space. It constructs the spatial model step-by-step from Terrain, Buildings, Infrastructure, Mobility, Digital Layer/Smart City to Virtual Layer/Digital Twin. In the context of this paper, Terrain can be understood as the area where the business hall is located and the basic spatial environment; Buildings correspond to the physical business hall buildings, service windows, self-service terminal areas, display areas, digital human interaction areas, and smart home carbon foot-

print display areas; Infrastructure corresponds to the power marketing business system, cloud platform, network communication facilities, data interfaces, display terminals, and sub-metering devices; Mobility corresponds to the customer flow path in the business hall, business processing route, digital human navigation path, and remote user access path; Digital Layer corresponds to marketing business data, electricity consumption data, RPA process data, CPS energy management data, State Grid online APP data, and regional energy consumption analysis data; Virtual Layer/Digital Twin corresponds to the final metaverse smart business hall, a virtual service space that is interactive, displayable, analyzable, and feedback-enabled.

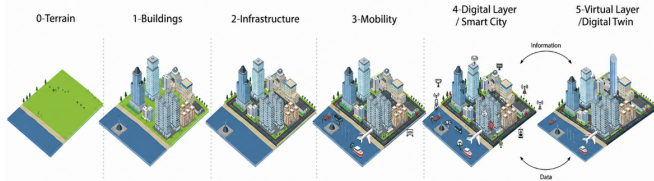


Figure 4: Spatial hierarchical modeling framework

Figure 4 illustrates the spatial layering logic. This paper models the space of the metaverse smart service hall as a multi-level structure:

$$\mathcal{M} = \{\mathcal{L}_0, \mathcal{L}_1, \mathcal{L}_2, \mathcal{L}_3, \mathcal{L}_4, \mathcal{L}_5\}, \quad (15)$$

where $\mathcal{L}_0$ represents the site and basic environment layer, $\mathcal{L}_1$ represents the building and interior space layer, $\mathcal{L}_2$ represents the infrastructure layer, $\mathcal{L}_3$ represents the customer flow and service circulation layer, $\mathcal{L}_4$ represents the digital business and data layer, and $\mathcal{L}_5$ represents the metaverse digital twin interaction layer. For any spatial object (o), its digital twin representation in the metaverse business hall is as follows:

$$DT(o) = G_o, S_o, B_o, T_o, \Psi_o. \quad (16)$$

In this context, G_o represents the geometric model, S_o represents the semantic attributes, B_o represents the bound business data, T_o represents the time status, and Ψ_o represents the triggerable interactive behavior. For example, for a self-service terminal object, G_o is its 3D model, S_o is the semantic label "business processing terminal," B_o is the business processing interface and service status data, T_o is the real-time availability status of the device, and Ψ_o includes interactive behaviors such as click query, digital human explanation, business jump, and anomaly prompts.

Figure 5 illustrates the process of converting a building information model (BIM) or three-dimensional model into a metaverse digital twin scene. The figure shows the gradual

refinement of the building model from coarse-grained blocks, structural models, and exterior models to an interactive 3D scene. Corresponding to the power marketing service hall in this paper, the modeling process should include: business hall space acquisition, BIM or 3D model construction, functional area semantic annotation, marketing business data binding, digital human interaction point configuration, real-time data interface access, and metaverse terminal publishing. This process transforms the traditional static building model into a digital twin business hall with business semantics and real-time service capabilities [24]. The proposed solution in this paper requires the system to present modules such as RPA process robots, the Energy Consumption Management 2.0 transformer area line loss management, the CPS energy management system, the State Grid online APP, smart services in the business hall, energy consumption characteristic analysis of the Greater Hongqiao area, and smart home carbon footprint. Therefore, in the 3D modeling stage, these business modules must be mapped to specific virtual space areas and interactive nodes, rather than restricting the implementation to architectural visualization alone.

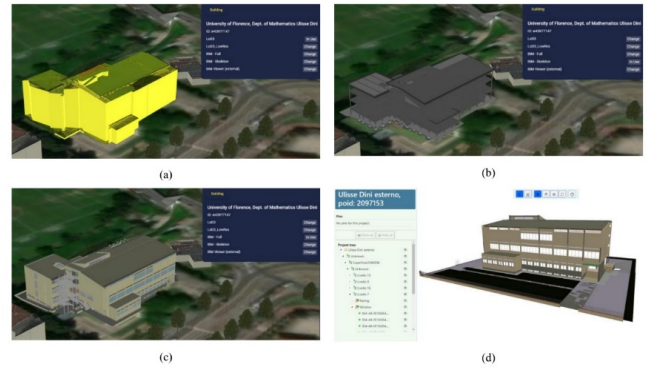


Figure 5: Visualization transformation and scene construction process of the business hall

The process shown in Figure 5 can be abstracted as a transformation from a Building Information Model (BIM) to a Metaverse digital twin object. Let the original BIM or 3D model be $\mathcal{B}$, and the Metaverse scene model be $\mathcal{V}$, then the transformation process can be represented as:

$$\mathcal{V} = \Omega(\mathcal{B}, \mathcal{G}, \mathcal{S}, \mathcal{D}, \mathcal{I}), \quad (17)$$

where, $\mathcal{G}$ represents the geometry simplification and rendering optimization rules, $\mathcal{S}$ represents the business semantic annotation set, $\mathcal{D}$ represents the bound data interface set, $\mathcal{I}$ represents the interaction logic set, and $\Omega(\cdot)$ represents the model transformation and scene deployment functions. This process is not simply importing the BIM model into Unity, Unreal, or WebGL environments, but rather completing the joint binding of "geometric objects—business semantics—real-time data—interactive behavior." Only after completing this binding can the business hall model truly be upgraded

from a static 3D display to a metaverse digital twin service space.

As shown in Figure 6, the metaverse smart service hall model proposed in this paper can be further abstracted into a simulation interaction framework of "user demand input, business scenario planning, virtual action primitive invocation, 3D character animation generation, service result feedback." The simulation interface on the left represents the interactive entry point of the metaverse smart service hall in this paper. Users can input service needs through text, voice, touchscreen, mobile devices, or VR terminals, such as business consultation, service hall navigation, electricity information inquiry, carbon footprint viewing, marketing results browsing, or electricity application process guidance. The control module and motion-primitive database in the middle represent the digital human control module and business action primitive library in this paper, responsible for generating service actions such as digital human explanation, turning, guiding, clicking, displaying, Q&A, and leading the way based on user input. The three-dimensional character-animation module on the right represents the digital human salesperson and 3D service scene in the metaverse service hall. Its task is to transform the business planning results into a visualized, interactive, and feedback-enabled Metaverse service process. The database module at the bottom represents the service log database, business scenario database, and marketing data resource library in this article, and is used to record user input, service planning results, interaction process, and final service results [25], [26].

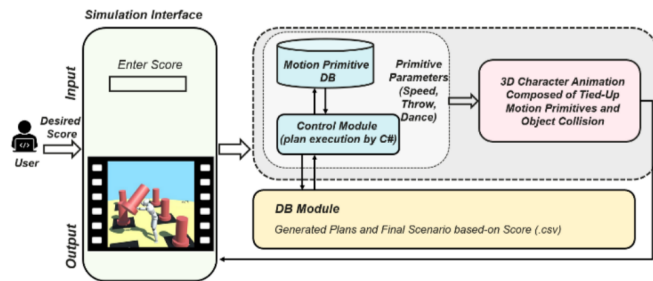


Figure 6: Interaction model driven by user demand input

The difference between this model and traditional service hall systems lies in the fact that traditional systems typically only return text or page results based on user requests, while this model transforms user requests into an executable metaverse service script. This script not only includes the business answer but also the action sequence of the digital human, service paths, explanation content, data dashboard calls, business process nodes, and result feedback. For example, when a user enters "Please introduce the smart home carbon footprint display area," the system first identifies that the request belongs to the low-carbon service explanation category. Then, it calls knowledge modules such as smart home sub-metering, carbon emission calculation, and energy-saving suggestions from the business scenario database. Next, it calls actions such as digital human guidance, explanation, dashboard display, and

result summary from the action primitive library, ultimately generating a complete guided tour and explanation process in the 3D metaverse service hall. Similarly, when a customer inquires "How to apply for meter replacement service," the system calls the marketing business knowledge base, meter replacement business process, the State Grid online APP interface, and digital human Q&A action primitives to generate customer-oriented business processing guidance.

Let the service request input by the user at time (t) be q_t , which may come from voice, text, touch, gesture, or VR interaction. The system maps the multimodal inputs to a unified service-intent vector as follows:

$$\mathbf{e}_t = \Phi_\theta(q_t^{\text{text}}, q_t^{\text{voice}}, q_t^{\text{touch}}, q_t^{\text{gesture}}, \mathbf{c}_t), \quad (18)$$

where, q_t^{text} , q_t^{voice} , q_t^{touch} , and q_t^{gesture} represent text, voice, touch, and gesture input, respectively; $\mathbf{c}_t$ represents the current context information, including the user's virtual area, historical interaction records, current service status, and access permissions; $\Phi_\theta(\cdot)$ represents the multimodal coding function; and $\mathbf{e}_t$ represents the unified semantic representation of the user's service request. This process corresponds to the Desired Score / Enter Score input part in the diagram, which can be understood in this article as the target service request submitted by the user to the metaverse service hall.

After obtaining the user intent vector, the control module needs to select appropriate service scenarios, business processes, and digital human action primitives from the business resource library. Let the business action primitive library be:

$$\mathcal{P} = \{p_1, p_2, \dots, p_M\}. \quad (19)$$

Each action primitive p_m can be represented as:

$$p_m = a_m, \tau_m, \mathbf{r}_m, \mathbf{b}_m, \mathbf{g}_m, \quad (20)$$

where, a_m represents the type of digital human action, such as greeting, guiding, explaining, demonstrating, jumping, waiting, confirming, and transferring to human agent; τ_m represents the duration of the action; $\mathbf{r}_m$ represents the resources required for the action, such as a knowledge base, business interface, data dashboard, or 3D scene object; $\mathbf{b}_m$ represents the bound business semantics, such as electricity bill inquiry, meter replacement processing, RPA demonstration, CPS energy management, regional energy consumption analysis, or smart home carbon footprint; and $\mathbf{g}_m$ represents the spatial location, orientation, and target object in the 3D scene. This formula corresponds to the Motion Primitive DB in the figure, which in this article is the "Power Digital Human Service Action Primitive Library".

IV. Experimental Evaluation

A. Experimental Setup

To evaluate the effectiveness of the proposed Metaverse digital twin smart service hall framework in the power marketing service scenario, this chapter conducts a comprehensive evaluation from aspects such as system performance, service

efficiency, digital human question-and-answer capabilities, user interaction experience, digital twin realism, multi-source data fusion capabilities, carbon footprint service effects, and ablation experiments. The experimental goal is not simply to prove that the system can operate, but to further answer the following questions: First, can the metaverse digital twin service hall significantly shorten customer service completion time compared to traditional manual services, self-service terminals, and existing smart service halls? Second, can the digital human service provide reliable question-and-answer in professional scenarios such as electricity bill inquiry, business processing, energy consumption analysis, CPS energy management, State Grid Online application guidance, and carbon footprint explanation? Third, can immersive Metaverse interaction improve users' evaluation of the naturalness, human-likeness, synchronicity, participation, and affinity of service hall services? Fourth, can the digital twin model accurately reflect the operating status of the physical service hall and energy data? Fifth, can multi-source data fusion enhance the capabilities of marketing business display, low-carbon service explanation, and management decision support? These evaluation objectives are consistent with the construction content in this paper, namely, to build a metaverse digital twin system for the power marketing service hall through digital human guidance, customer consultation, underlying database Q&A, multi-source marketing data access, CPS energy management, regional energy consumption analysis and smart home carbon footprint collection and display [27].

The experimental data mainly includes five categories. The first category is customer service task data, including typical power marketing tasks such as electricity bill inquiries, meter replacement applications, new installation applications, business consultations, energy consumption analysis, carbon footprint inquiries, online APP guidance, and business hall tours. The second category is power marketing knowledge data, including business handling rules, business hall service procedures, frequently asked questions, policy explanations, payment instructions, low-carbon service instructions, and explanations of smart home energy consumption. The third category is energy and carbon footprint data, including CPS energy management data, regional energy consumption characteristic data, smart home sub-metering data, and carbon emission factors. The fourth category is user interaction data, including interaction methods such as voice, text, touchscreen, keyboard, gestures, and VR devices, as well as users' browsing paths, dwell time, and service conversion processes in the virtual business hall. The fifth category is system performance data, including average response time, intent recognition accuracy, answer correctness rate, task success rate, user satisfaction, concurrent access response, data refresh latency, and system availability. These data collectively support the comprehensive experimental evaluation of the Metaverse digital twin business hall presented in this paper.

B. Experimental Results

Figure 7 compares the experimental performance of the baseline method RA and the proposed metaverse interaction model MM under different action units AU1, AU2, and AU4 from three dimensions: DTW distance, synchronization error, and Entrainment Loop interaction closure strength. Overall, MM significantly outperforms RA in terms of synchronization, especially in AU1, AU2, and AU4 where the synchronization error is almost zero, indicating that the proposed model can more stably maintain the temporal consistency between digital human actions, business scene display, and user interaction feedback. This is consistent with the proposed mechanism of "user input—business scene planning—digital human action primitive invocation—3D scene linkage—service log feedback," indicating that the digital human in the metaverse business hall does not simply play fixed animations, but can dynamically adjust the interaction rhythm according to service tasks. Meanwhile, in terms of the Entrainment Loop metric, MM is generally lower and has a smaller fluctuation range compared to RA, especially approaching 0 in AU2. This indicates that the model in this paper can reduce ineffective loop interactions and improve the efficiency of the interaction loop in customer consultation, business guidance, and data dashboard invocation. This result supports the argument in this paper that "digital humans reduce the burden of repetitive services and improve service fluency." However, it should be noted that in terms of the DTW metric, MM is not superior to RA in all action units. Especially in AU4, the DTW value of MM is significantly higher than that of RA, and the error range is larger. This indicates that in complex action or service scenarios, although the model in this paper enhances synchronization and interaction loop control, there is still a large deviation between the action trajectory and the reference sequence. This may be related to the fact that the digital human in the metaverse business hall needs to simultaneously complete guidance, direction, explanation, dashboard linkage, and business semantic response, resulting in a more complex action sequence.

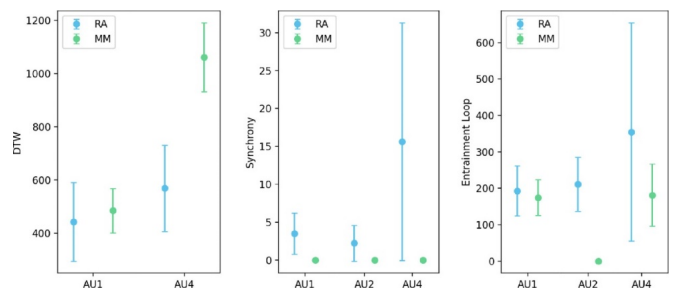


Figure 7: Service behavior consistency, synchronization, and interaction closed-loop performance.

Figure 8 illustrates the correlations among various perceptual indicators of the digital human interactive experience in the metaverse smart service hall, including Naturalness, Human-likeness, Synchrony, Engagement, and Rapport. The figure shows a clear positive correlation among all indicators,

with most combinations reaching the indicated significance threshold (***). These associations suggest that user evaluations of digital-human interactions should be considered across multiple dimensions, including movement naturalness, perceived human likeness, temporal synchrony, engagement, and rapport; the correlations alone do not establish causal relationships. Specifically, Naturalness showed a strong positive correlation with Human-likeness, Synchrony, and Engagement, indicating that the more natural the digital human's movements, the more likely users are to perceive it as having human-like characteristics and are more willing to participate in the interaction. The positive correlation between Synchrony and Engagement and Rapport further illustrates that when the digital human's voice, facial expressions, movements, and scene feedback can remain synchronized with the user's input, users are more likely to experience immersion and trust. Rapport showed a significant positive correlation with the other four indicators, indicating that affinity is a comprehensive result of the digital human service experience, influenced by naturalness, human-likeness, synchronicity, and engagement.

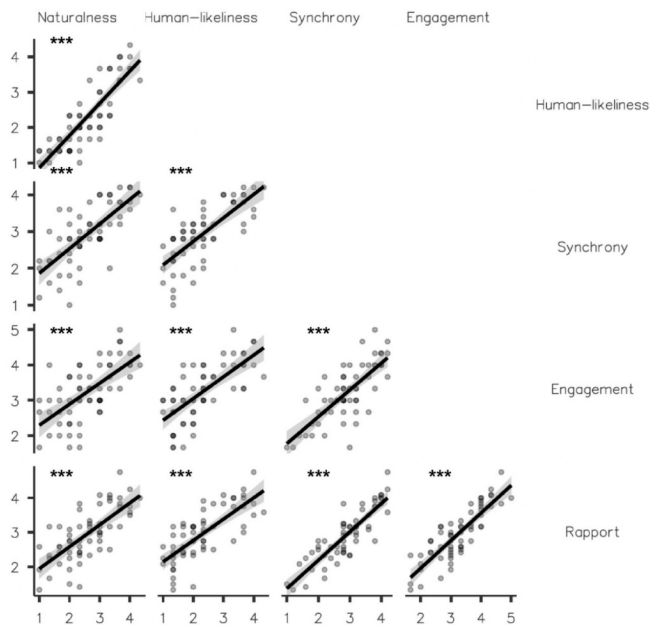


Figure 8: Correlation analysis among digital human interaction perception indicators

Figure 9 further reveals the impact of digital human interaction experience on users' psychological state and cognitive engagement in the metaverse smart service hall. The horizontal variables include Naturalness, Human-likeness, Synchrony, Engagement, and Rapport, while the vertical outcome variables include Mood score, K6 delta (change in psychological stress), STAI-State delta (change in state anxiety), and CC (cognitive/communication engagement). Overall, most interaction perception indicators show a positive relationship with user outcome variables, especially the CC indicator, which shows a significant positive correlation with all five digital human interaction perception variables (*). The associations

are compatible with the hypothesis that natural, lifelike, well-synchronized, and approachable digital-human interactions accompany greater cognitive engagement, although this correlational result does not establish that these qualities directly cause improved comprehension. This is crucial for the proposed Metaverse Digital Twin System for Electricity Marketing Service Halls, as the system is intended to enable more than passive viewing of a virtual service hall. Instead, it aims to enable users to navigate, consult, understand business operations, view marketing results, and learn about carbon footprints through a digital human. The system design specifies that digital humans should guide visitors through designated areas, explain the intended service functions, and respond to customer questions using an authorized knowledge base and connected business information. Therefore, the results in the figure show that the higher the quality of the digital human interaction, the more likely users are to truly understand the power marketing business, energy consumption data, smart services, and low-carbon content displayed in the service hall, rather than just superficially viewing it. Furthermore, STAI-State_delta shows varying degrees of significant relationships with Naturalness, Human-likeness, Synchrony, and Rapport, with Naturalness being the most significant (**), while Human-likeness, Synchrony, and Rapport also reach significant levels (*). This indicates that the digital human interaction experience not only affects information reception but may also influence users' emotions and anxiety during the service process. In the context of power marketing services, customers often experience uncertainty and psychological burden when handling business, inquiring about electricity bills, meter replacements, energy usage anomalies, or carbon footprint issues. If the actions, voice, response rhythm, and service attitude of the digital human are more natural, synchronized, and approachable, users will be more likely to develop trust in the service and reduce their unfamiliarity with the business processes.

Figure 10 compares the differences between traditional smart service halls and the proposed metaverse digital twin service hall in the two-dimensional space of "experience level - service personalization" based on customer perception experience evaluation results. The left figure shows that the advantages of traditional smart service halls are mainly concentrated in human service attributes such as customer care, service attitude, and service credibility, indicating that the traditional model still relies on personnel reception, service standards, and offline communication to build customer trust. However, it shows blue weak areas in personalized recommendations, value-added energy services, customer communication efficiency, digital service capabilities, and perceived service costs, indicating deficiencies in intelligent, personalized, and data-driven services. The right figure shows that the metaverse digital twin service hall forms a clear red advantage area in immersive guided tour experience, 3D scene quality, digital human service quality, digital human interaction naturalness, digital human credibility, digital twin capabilities, intelligent customer care, and carbon footprint services. This indicates

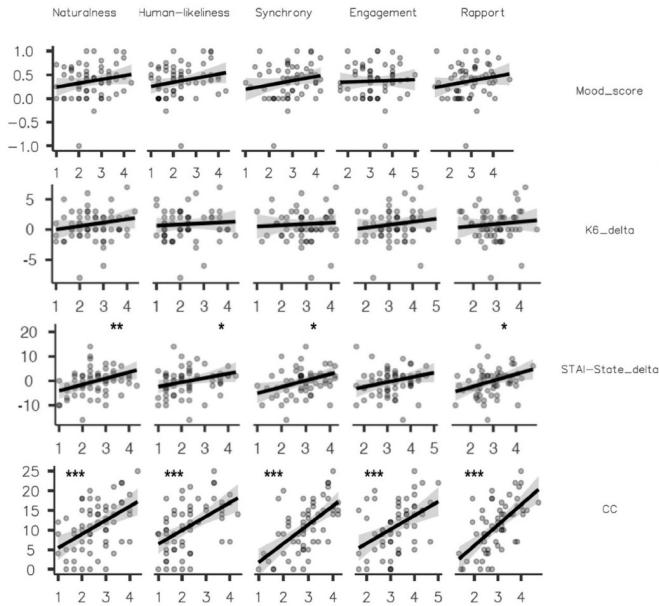


Figure 9: The relationship between changes in users' psychological state and cognitive input

that the proposed model can enhance customer immersion, understanding, and service participation through digital human guidance, 3D virtual space, multi-source marketing data fusion, and smart home carbon footprint display. This result aligns with the system design goals of this paper: the original plan explicitly required the digital human to guide visitors through various areas, explain the construction concepts, and answer customer questions using the underlying database. Simultaneously, the system was also to showcase marketing digitalization achievements such as RPA process robots, Energy Consumption 2.0, CPS energy management, the State Grid online app, regional energy consumption analysis, and smart home carbon footprint. However, the right-hand figure also shows that the metaverse digital twin service hall still has room for improvement in service process standardization, perceived service costs, intelligent business processing procedures, and some personalized energy services. This indicates that while the current system has advantages in immersive experience and digital human interaction, further optimization is needed in business closed-loop execution, service cost transparency, intelligent recommendation maturity, and process collaboration.

Figure 11 comprehensively illustrates the experimental results of the Metaverse digital twin service hall in this paper regarding system performance, user structure, usage behavior, interaction methods, and service task completion. Figure 11(A) shows that from January to October 2024, the average system response time decreased from 6.20 s to 4.88 s, indicating that with the optimization of digital human services, business data interfaces, and 3D scene rendering mechanisms, the system response efficiency gradually improved. Meanwhile, the intent recognition accuracy remained at a high

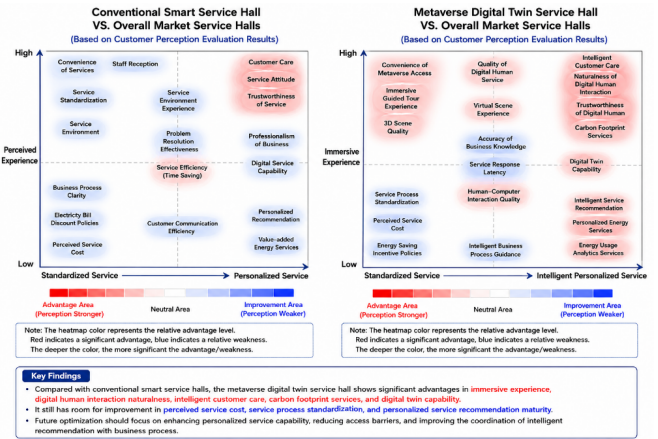


Figure 10: Comparison of customer perceived value

level, increasing from 72.6% to 75.9%, the correct answer rate remained stable above 80%, the task success rate remained between 60% and 67%, and user satisfaction increased from 3.41 to 4.12, demonstrating that the proposed "user input—business scenario planning—digital human interaction—data dashboard feedback" mechanism can continuously improve customer service experience. Figure 11(B) shows that the age distribution of the surveyed users was relatively balanced, with a higher proportion of users aged 26-35, 36-45, and 66 and above, indicating that the metaverse service hall is not only geared towards young users but also has certain universal service value. Figure 11(C) shows that frequently used functions are mainly concentrated in scenarios such as Lobby Visit, Business Inquiry, Area Tour, Carbon Footprint, CPS Demo, and Bill Query. This indicates that customers not only focus on basic business consultation but also have a high interest in services such as area navigation, carbon footprint display, and energy management. This corresponds to the digital human navigation, marketing results display, CPS energy management system, and smart home carbon footprint display modules proposed in this solution. Figure 11(D) shows that voice, touch screen, keyboard, and text are the main interaction methods, with voice accounting for the highest proportion. This indicates that digital human service personnel are more suitable as the core interaction entry point for the metaverse service hall. However, the proportion of VR devices is relatively low, indicating that the current popularization of the metaverse service hall should not rely too much on immersive headsets but should prioritize the availability of large screens, PCs, touch screens, and mobile devices. Figure 11(E) shows the service task funnel, which reveals a significant drop-off from intent recognition to final task completion, with an overall completion rate of 30.7%. This indicates that although the system can perform intent recognition and task initiation well, there is still room for optimization in the information provision, task execution, user confirmation, and final completion stages.

Figure 12 compares the question-and-answer performance of Rule-based FAQ Systems, Knowledge-Based QA Systems,

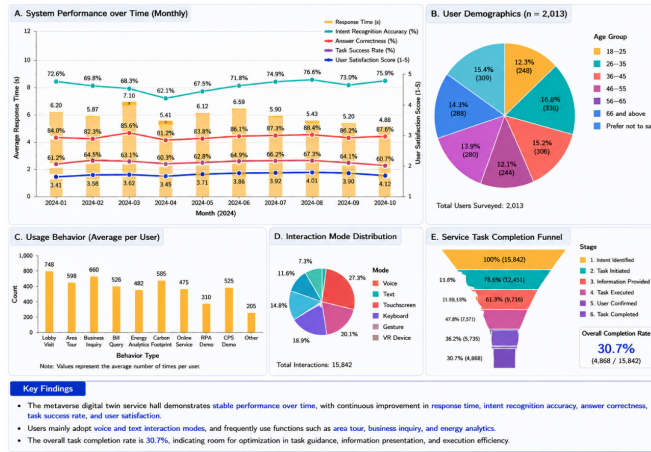


Figure 11: System performance, user structure, and service conversion funnel analysis

General LLM Assistants, and the Proposed Metaverse Digital Human in the power marketing service scenario from two perspectives: confidence calibration and answer frequency accuracy. The left figure shows that, across different Stated Confidence intervals, the proposed Metaverse Digital Human model achieves higher overall accuracy than the Rule-based FAQ and Knowledge-Based QA systems, and significantly approaches the ideal calibration line in the high-confidence interval, indicating that it can provide responses with higher reported accuracy while showing closer alignment between stated confidence and observed accuracy. The right figure shows that, as Answer Frequency increases, the General LLM Assistant has a high overall accuracy but exhibits significant fluctuations; while the proposed model maintains a smoother upward trend in most frequency intervals, indicating more stable business adaptability in high-frequency power marketing questions.

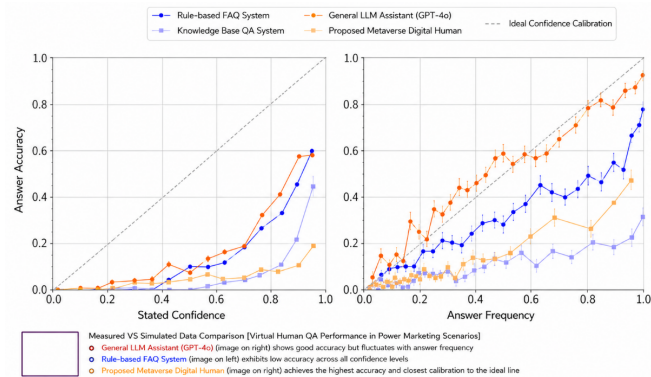


Figure 12: Confidence calibration and response frequency accuracy in the power marketing service scenario.

Figure 13 compares the average service completion time of traditional manual services, self-service terminals, existing smart service halls, different versions of digital human services, different metaverse service hall modules, and the

proposed "digital twin and digital human" system under different task complexities. Across the levels labeled 1–9, the plotted mean completion times decline rather than increase. This counterintuitive trend requires clarification of how task complexity was defined and ordered; the plotted data alone do not establish that greater complexity reduces service time. The apparent trend should therefore be interpreted cautiously until the scale and task mix are verified. In contrast, traditional manual services and self-service terminals consumed the most time at each complexity level, indicating that they still rely on manual explanation, customer self-search, and offline process switching. While existing smart service halls and basic digital human services have improved somewhat, process fragmentation still exists in multi-step business processes, cross-system queries, and personalized services. The Proposed System (Digital Twin + Digital Human) proposed in this paper maintains the lowest completion time across all complexity levels, demonstrating that the digital twin space can pre-organize business processes, service paths, and data presentations, while the digital human can transform customer input into continuous service actions such as navigation, Q&A, querying, recommendation, and confirmation. This significantly reduces the time customers spend completing tasks such as electricity bill inquiries, business consultations, energy consumption analysis, CPS energy presentations, State Grid Online application guidance, and carbon footprint services.

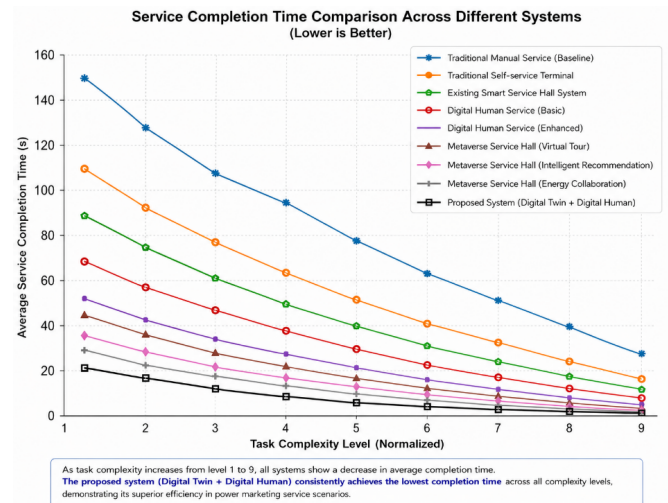


Figure 13: Average completion time of power marketing tasks

Figure 14 illustrates the difference between measured energy consumption data and digital twin energy consumption simulation results. The left side shows the chiller power consumption data collected from the actual system, while the right side shows the chiller power consumption curve generated by the energy consumption simulation model. It can be seen that the measured data exhibits significant random fluctuations and local anomalies, and its trend does not completely follow changes in BTU load and flow. In contrast, the simulation

data is more significantly affected by the preset load curve, seasonal variations, and control strategies, showing a stronger overall regularity. This result indicates that in the metaverse smart service hall system presented in this paper, relying solely on simulation models to generate energy consumption data may overestimate the regularity of system operation and ignore the complex fluctuations caused by actual business hall equipment operation, user behavior, environmental changes, and data acquisition noise. Therefore, the data fusion layer in this paper must simultaneously access actual power consumption data, CPS energy management data, smart home sub-metering data, and simulation prediction data, and improve the realism of the digital twin model through error correction, confidence assessment, and dynamic update mechanisms.

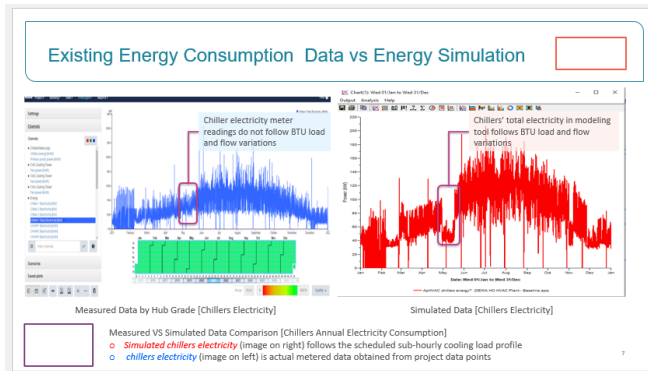


Figure 14: Measured energy consumption data and digital twin energy consumption

Figure 15 illustrates the typical application effects of the metaverse smart service hall system presented in this paper, which can be divided into five scenarios: First, the Metaverse demonstration scenario of the State Grid Smart Business Hall, which centrally presents experimental indicators such as user satisfaction, intent recognition accuracy, average response time, task completion rate, and user participation through a large screen, digital panel, and service menu, demonstrating the system's transformation from a "concept demonstration" to an "evaluable service platform"; Second, the scenario comparing physical and virtual spaces, which demonstrates the system's ability to map from physical to virtual spaces and supports the visualization of environmental information, personnel activities, and service area status by juxtaposing real business hall/office spaces with digital twin scenarios; Third, the scenario of mobile electricity bill inquiry and digital human service, which demonstrates that digital humans can serve as the front-end interactive entry point for customers to handle electricity matters, make payment inquiries, and understand electricity usage; Fourth, the scenario of collaboration between power business personnel and intelligent robots, which demonstrates the system's expanded capabilities in human-machine collaboration, business explanation, back-end scheduling, and energy data analysis; Fifth, the scenario of multi-user Metaverse collaboration, which shows that the metaverse service hall can not only serve individual customers

but also support scenarios such as remote visits, multi-person collaborative explanations, business training, and management meetings. Combining the functions proposed in the original solution of this paper, such as digital human navigation, customer consultation, marketing business display, RPA process robot, Energy Consumption Management 2.0, CPS energy management, State Grid online APP, regional energy consumption analysis and smart home carbon footprint display, this set of case diagrams illustrates that the solution proposed in this paper can unify physical business halls, digital humans, business data, energy analysis and low-carbon services into a visual, interactive and assessable metaverse digital twin platform.



Figure 15: Application case and system effect demonstration of the metaverse smart business hall

V. Conclusion

This study responds to the digital transformation requirements of power marketing service halls by presenting a human-centered metaverse digital twin framework. This framework unifies the physical service hall, digital twin space, digital human interaction, multi-source marketing data fusion, and carbon footprint visualization into a single smart service system. By constructing physical space mapping, business data fusion, digital human service script generation, metaverse

scene modeling, and a low-carbon energy service module, this paper achieves closed-loop collaboration from customer demand input, business understanding, scene interaction, to service feedback optimization. Experimental results show that the proposed framework can effectively shorten the completion time of power marketing tasks, improve the accuracy and confidence calibration capabilities of digital human question answering, enhance user immersion, participation, and service trust, and improve the display of multi-source business data and the interpretation capabilities of smart home carbon footprints. Compared with traditional manual services, self-service terminals, and existing smart service halls, the proposed method demonstrates stronger advantages in service efficiency, interactive experience, and energy service scalability. Future research will further optimize cross-system business closed-loop execution, low-frequency complex question answering, real-time data synchronization calibration, personalized energy recommendation, and large-scale multi-service hall deployment capabilities to enhance the framework's generalization and application value in practical power marketing scenarios.

Author Contributions

All authors contributed equally to the preparation of this manuscript, reviewed the final version, and approved its submission for publication.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Data Availability

The datasets supporting the findings reported in this manuscript are available from the corresponding author upon reasonable request, subject to applicable access restrictions and data-protection requirements.

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