AI-Generated Content-as-a-Service in IoMT-Based Smart Homes: Personalizing Patient Care with Human Digital Twins

Junaid Akram, Misha Aamir, Roshani Raut, Ali Anaissi, Rutvij H. Jhaveri, Awais Akram

***Abstract*—We introduce the AI-Generated Optimal Decision (AIGOD) algorithm and the Deep Diffusion Soft Actor-Critic (DDSAC) framework, marking a significant advancement in integrating Human Digital Twins (HDTs) with AI-Generated Content (AIGC) within IoMT-based smart homes. Our innovative AI-Generated Content-as-a-Service (AIGCaaS) architecture, optimized for IoMT environments, leverages network edge servers to enhance the selection of AI-Generated Content Service Providers (AISPs) tailored to the unique characteristics of individual HDTs. Extensive experiments demonstrate DDSAC's HDT-centric approach outperforms traditional Deep Reinforcement Learning algorithms, offering optimal AIGC services for diverse healthcare needs. Specifically, DDSAC achieved a 20% improvement in task completion rates and a 15% increase in overall utility compared to existing methods. These findings highlight the potential of HDTs in personalized healthcare by simulating and predicting patient-specific medical outcomes, leading to proactive and timely interventions. This integration facilitates personalized healthcare, establishing a new standard for patient-centric care in smart home environments. By leveraging cutting-edge AI techniques, our research significantly contributes to the fields of IoMT and AIGC, paving the way for smarter and more responsive healthcare services.**

***Index Terms*—AI-generated content, IoMT, edge computing, diffusion models, deep reinforcement learning**

I. Introduction

THE integration of Artificial Intelligence (AI) in healthcare, particularly within the Internet of Medical Things (IoMT), has been transformative, with AI-Generated Content (AIGC) spearheading this change [1]. This evolution is significant in the context of IoMT-based smart homes, where AIGC is being utilized to create Human Digital Twins (HDTs) [2], [3]. These HDTs offer a revolutionary approach to personalized healthcare by providing a virtual representation of an individual's health, continuously updated with real-time data. AIGC, in this setting, plays a crucial role in generating and analyzing data, leading to the development of tailored patient care plans [4], [5].

IoMT-equipped smart homes, crucial in managing chronic diseases and elderly care, are at the forefront of employing HDTs [6], [7]. They are equipped with devices that gather extensive health data, which, when combined with AIGC, enable the creation of these HDTs [8], [9]. These virtual twins help in fostering proactive care and timely interventions [10]. However, implementing AIGC and HDTs in such environments comes with challenges, particularly in handling sensitive medical data securely and managing the complexity and resource demands of these advanced models [11], [12].

To address these challenges, we introduce AI-Generated Content-as-a-Service (AIGCaaS), a model that democratizes access to advanced AI capabilities essential for HDTs. This approach connects IoMT devices in smart homes to robust cloud-based AI engines, making AIGC and HDT creation feasible without significant local processing demands. AIGCaaS ensures data privacy and security, making it ideal for real-time, personalized healthcare services that cater to individual healthcare needs.

We suggest utilizing wireless edge networks to provide AIGCaaS by strategically placing AIGC models on network edge servers. This infrastructure supports scalable AIGC services for HDTs while reducing the computing burden on consumer devices. Leveraging advancements in wireless networks, like 6G, is essential for providing high-speed, low-latency, and reliable AIGC services, crucial for the real-time updating of HDTs.

The AIGOD algorithm, a novel contribution of our work, employs diffusion models in a unique capacity for the optimization of AIGC services tailored to HDTs. Distinct from traditional algorithms that handle decision-making in a linear or less dynamic fashion, AIGOD's utilization of diffusion processes allows for a more nuanced and effective analysis of potential actions, setting a new standard for personalized healthcare decision-making in IoMT environments. This algorithm uses diffusion models, which are typically employed in AIGC for content creation, to optimize the selection of AISPs. AIGOD, implemented within the Deep Diffusion Soft Actor-Critic (DDSAC) framework, surpasses traditional Deep Reinforcement Learning methods. It efficiently balances exploration and exploitation, thus avoiding convergence to suboptimal policies. Our efforts focus on proposing an AIG-

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CaaS architecture for IoMT-based smart homes equipped with HDTs, introducing the AIGOD algorithm, and validating the effectiveness of DDSAC through extensive experimentation. These contributions aim to significantly advance the fields of IoMT, AIGC, and HDT, paving the way for smarter and more responsive healthcare services in smart homes.

The major contributions of this work, with an emphasis on the integration of HDTs in IoMT-based smart homes, are as follows:

- We propose a cutting-edge architecture for AIGCaaS in IoMT-based smart homes, specifically designed to support the creation and maintenance of HDTs. This architecture strategically positions AIGC models at the network edge, facilitating ubiquitous AI functionalities for enhanced patient care and dynamic updating of HDTs.
- We introduce the AIGOD method, leveraging diffusion models to make optimal decisions for AIGC services. This method is uniquely tailored to meet the specific requirements of each patient's HDT within the IoMT setting, ensuring a personalized healthcare approach.
- Incorporating AIGOD, the DDSAC framework presents an innovative approach to AISP selection. By fusing deep reinforcement learning with diffusion-based decision optimization, DDSAC outperforms traditional DRL algorithms in the context of IoMT. Its unique structure adapts dynamically to the evolving needs of HDTs, demonstrating unprecedented efficiency and effectiveness in personalized healthcare service provision. This innovative integration is specifically aimed at optimizing the selection of AIGC services for the effective operation and accuracy of HDTs in smart homes, ensuring a high level of personalized patient care.
- We validate the effectiveness of the DDSAC algorithm through extensive experimentation, demonstrating its superiority over traditional Deep Reinforcement Learning algorithms. This is particularly evident in its ability to optimize AIGC service provision for the diverse healthcare needs of HDTs in smart home environments.

This paper is structured as follows: Section II discusses related work in the field. Section III outlines the deployment of AIGCaaS in IoMT-based smart homes. Section IV presents the AIGOD algorithm. Section V details the DDSAC algorithm for AISP selection. Section VI provides an analysis and discussion of the results. Finally, Section VII concludes the paper with future research directions and potential applications.

II. Related Work

The integration of Generative AI (GAI) technologies with the Internet of Things (IoT), specifically within the domain of healthcare, signifies a transformative shift towards more personalized and adaptive patient care systems in smart homes. At the heart of this transformation is the IoMT, which harnesses advanced GAI techniques to deliver healthcare solutions tailored to individual patient data and preferences.

GAI technologies, encompassing a wide range of applications from image and video generation to text and audio content creation, are pivotal in automating and personalizing content generation from existing data. These technologies offer novel insights into patient health and treatment outcomes, significantly enhancing patient care within IoMT environments [13], [14]. Among the various GAI models, Generative Diffusion Models (GDMs) have emerged as particularly promising for their state-of-the-art capabilities in image synthesis and beyond. GDMs, through forward diffusion and denoising processes, excel in capturing complex, high-dimensional data structures, making them ideally suited for network optimization and decision-making processes in IoMT [15], [16]. This marks a significant departure from traditional models like GANs and VAEs, by introducing a controlled, iterative refinement process that enhances the quality and utility of generated content for healthcare applications.

The advent of GAI in IoMT, particularly for smart home healthcare, presents a novel approach to enhancing patient care through context-aware data generation [17]–[23]. From vision-based applications for remote monitoring to audio-based interfaces for improving patient interaction and text-based systems for real-time health advisories, GAI technologies are setting new standards in personalized and interactive healthcare services.

Despite the promising potential of GAI in revolutionizing IoMT, several challenges remain. These include managing the computational and storage demands of GAI models within IoMT networks, adapting to the dynamic and heterogeneous nature of these networks, and ensuring the privacy and security of sensitive healthcare data [24]–[36]. Addressing these challenges is crucial for harnessing the full potential of GAI in delivering efficient, reliable, and personalized patient care within smart homes.

The AIGCaaS architecture represents a novel integration of diffusion models within IoMT to facilitate personalized healthcare through HDTs. Unlike traditional approaches, AIGCaaS leverages the unique capabilities of diffusion models in generating high-fidelity content and making informed decisions, offering a significant advancement over existing generative models. By incorporating these models into the AIGCaaS architecture, we propose a system that not only addresses the aforementioned challenges but also sets a new benchmark in the application of AI for healthcare within smart homes.

In summary, the integration of GAI technologies, particularly through advanced generative models like GDMs, into IoMT signifies a pivotal step towards creating more personalized, adaptive, and efficient healthcare systems. As we continue to explore and refine these technologies, their potential to transform patient care in smart home environments becomes increasingly apparent.

III. AIGCaaS in IoMT-Based Smart Homes

This section delves into AIGCaaS within wireless networks, focusing on its deployment in IoMT-based smart homes for optimizing HDT applications.

A. Deployment of AIGCaaS on Network Edge Devices

Deploying AIGCaaS on network edge devices is crucial in IoMT realms, especially for efficient and scalable HDT generation. Edge deployment tackles the challenges related to the size and complexity of AIGC models, which are fundamental for tasks like HDT creation, image repair, and augmented/virtual reality (AR/VR) applications in healthcare. This strategy places AIGC models on edge devices (Fig. 1), offering scalable and accessible services that are specifically tailored to support HDT in healthcare settings.

Challenges in this deployment include:

C1) Customizing AIGC services for individual HDTs, including adjustments in model parameters for specific health applications.

C2) Addressing the subjective nature of performance evaluation in healthcare, especially in relation to the accuracy and realism of HDTs.

C3) Managing variability in AIGC model capabilities and service quality from AISPs, essential for maintaining high-fidelity HDTs.

Selecting the right AISP is critical to ensure the accuracy and resource optimization needed for effective HDTs in IoMT environments.

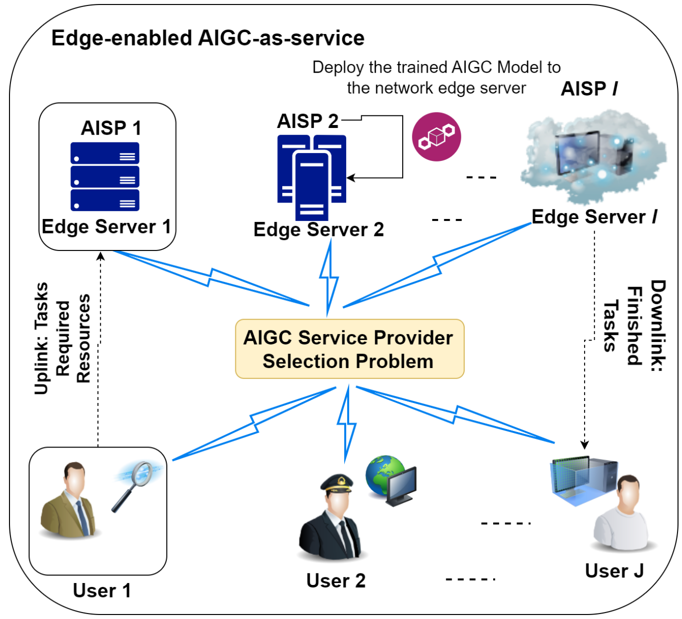

Fig. 1: Network architecture deploying AIGC models on edge servers for HDT-focused AIGCaaS.

B. AI-Generated Content Service Provider Selection

In the context of AIGCaaS within IoMT-based smart homes, selecting appropriate AISP is paramount for the effective delivery of personalized healthcare through HDTs. This process is intricately designed to address the challenges posed by resource-constrained environments, ensuring the judicious allocation of tasks $\mathcal{J}$ to AISPs $\mathcal{I}$, aimed at maximizing the overall utility $\mathcal{U}$. Critical to this optimization is the consideration of energy efficiency and the computational demands of denoising steps in diffusion models, as evidenced by our empirical analysis on a high-performance computing system. Figure 1 depicts the network architecture that facilitates this AISP selection, positioning AIGC models on edge servers to support the dynamic requirements of HDTs.

C. AISP Selection and Human-Aware Utility Function

1) Formulation of AISP Selection Problem: The integral component of our AIGCaaS framework involves a meticulously formulated integer programming problem, aimed at optimizing AISP selection to maximize a utility function specifically designed for HDT applications. This complex optimization task takes into account the resource capacities of AISPs and categorizes AIGC services based on their application to image processing, natural language processing, and HDT-specific tasks. The objective is to ensure an equitable distribution of tasks that aligns with the unique requirements of each HDT, thereby facilitating personalized healthcare delivery.

2) Real-Time Decision Making in AIGCaaS System: Our AIGCaaS system incorporates an advanced scheduler that operates in real-time to adeptly balance the distribution of tasks among AISPs. This mechanism is responsive to the ever-changing demand for HDT services and the fluctuating performance capabilities of AISPs. Central to this dynamic decision-making process is the integration of a human-aware utility function, ensuring that the allocation of tasks to AISPs is continually optimized to meet the personalized needs of HDTs effectively.

D. Incorporating Human-Aware Utility in AIGCaaS

The introduction of a human-aware utility function represents a significant advancement in the AIGCaaS framework, underpinning our commitment to delivering healthcare services that are genuinely personalized for IoMT-based smart homes. This nuanced approach evaluates AIGC services through the dual lenses of user experience and HDT fidelity, ensuring that every aspect of the service delivery is tailored to individual healthcare requirements.

1) Utility Function Formulation for HDT: We define the utility of a task j, performed by AISP i, through a function that integrates human-aware content quality assessment:

$$u_i\left(T_j\right) = \mathcal{G}\left(\mathcal{F}_i\left(T_j\right)\right), \quad (i = 1, \ldots I, \text{ and } j = 1, \ldots J) \tag{1}$$

Here, $\mathcal{G}(\cdot)$ is the function assessing content quality from a human-centric perspective, essential for ensuring the high accuracy and effectiveness of HDTs. $\mathcal{F}_i\left(T_j\right)$ denotes the output of the AIGC model for AISP i, processing task j.

2) Human-Aware Content Quality Assessment: Employing tools such as the Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE) for image-based AIGC services allows us to align our quality assessments with human perceptual standards. This approach ensures that the generated content for HDTs meets the highest quality benchmarks, crucial for the effective simulation and management of digital twins.

3) Illustration of Utility Distribution: As illustrated in Figure 1, the distribution of human-aware utility values across AISPs underscores the importance of a strategic AISP selection process within our AIGCaaS framework. This careful selection ensures that each HDT benefits from services that align with their specific health needs and quality expectations, highlighting the tailored approach of our system to personalized healthcare in IoMT-based smart homes.

IV. AI-Generated Optimal Decision Algorithm

This section introduces the AIGOD technique, an innovative approach employing a diffusion model to generate optimal discrete choices for AISP selection in AIGCaaS, particularly tailored for HDT applications in IoMT environments.

A. Rationale Behind AIGOD

AISP selection for HDT involves discrete decision variables, representing a complex combinatorial challenge. Traditional continuous optimization methods are inadequate for such tasks. We propose the application of a diffusion-based model, inspired by the Denoising Diffusion Probabilistic Model (DDPM) commonly used in image generation. AIGOD leverages this model's capacity to integrate conditioning information, making it ideal for the nuanced and dynamic decision-making required in AIGCaaS for HDT.

B. Probability Noising Forward Process

In AIGOD, the forward process incrementally introduces Gaussian noise into a probability distribution, representing the decision-making framework for HDT. This noise addition at each step follows a controlled variance normal distribution, forming a Markov chain that culminates in a purely noisy final state.

The mathematical representation of this process is:

$$q\left(\boldsymbol{x}t \mid \boldsymbol{x}t-1\right) = \mathcal{N}\left(\boldsymbol{x}t; \sqrt{1-\beta t}\boldsymbol{x}t-1, \beta t\mathbf{I}\right) \tag{2}$$

with β_t indicating the variance level.

The relationship between the initial state and subsequent states is given by:

$$\boldsymbol{x}t = \sqrt{\bar{\alpha}t}\boldsymbol{x}0 + \sqrt{1-\bar{\alpha}t}\boldsymbol{\epsilon} \tag{3}$$

where $\bar{\alpha}t$ is the cumulative product of α_k, and $\boldsymbol{\epsilon}$ represents standard noise.

C. Challenges and Adaptations

Applying AIGOD in wireless networks for HDT optimization faces the unique challenge of lacking an optimal decision dataset. This is unlike diffusion models in traditional image generation, where pre-existing data is usually available. In AIGOD, the forward process is more theoretical, setting the stage for the reverse process, which is critical for decision optimization in HDT-focused environments.

D. Reverse Process: Inferring Optimal Decisions

The reverse process in AIGOD is essential for deriving optimal decision schemes crucial for efficient HDT management in IoMT-based smart homes. This stage seeks to reconstruct the original decision $\boldsymbol{x}_0$ from the noise-affected state $\boldsymbol{x}_T$, a process vital to accurate and responsive HDT applications in the IoMT setting.

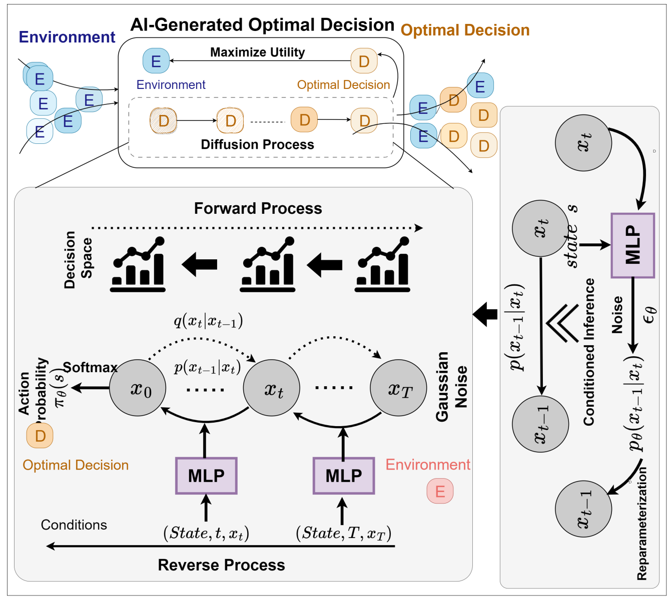

Fig. 2: Visualization of the AIGOD algorithm, showcasing the conditioned diffusion process for decision optimization in the context of HDT.

1) Defining the Reverse Transition for HDT Optimization: In the reverse process of AIGOD tailored for HDT optimization, the transition from $\boldsymbol{x}_t$ back to $\boldsymbol{x}_{t-1}$ follows a Gaussian distribution. A deep neural network is trained to estimate the mean μ_θ, crucial for reconstructing the decision state for HDT applications:

$$p_\theta\left(\boldsymbol{x}_{t-1} \mid \boldsymbol{x}_t\right) = \mathcal{N}\left(\boldsymbol{x}_{t-1}; \mu_\theta\left(\boldsymbol{x}_t, t, s\right), \tilde{\beta}_t\mathbf{I}\right) \tag{4}$$

This formula underpins the reverse process, enabling the accurate inference of the initial decision state from a noise-altered sample, a step critical for HDT-based decision making.

2) Reconstructing the Initial Decision State: The process of reconstructing the initial state $\boldsymbol{x}_0$ in the context of HDT involves systematically removing noise, with the deep model generating denoising corrections:

$$\boldsymbol{x}_0 = \frac{1}{\sqrt{\bar{\alpha}_t}}\boldsymbol{x}_t - \sqrt{\frac{1}{\bar{\alpha}_t} - 1} \cdot \tanh\left(\epsilon_\theta\left(\boldsymbol{x}_t, t, s\right)\right) \tag{5}$$

This key denoising step accurately reveals the underlying probabilities for actions that are essential in managing HDTs in IoMT settings.

3) Sampling and Reparameterization Techniques: For addressing the stochastic nature inherent in training generative models for HDT, AIGOD utilizes a reparameterization technique:

$$\boldsymbol{x}_{t-1} = \mu_\theta\left(\boldsymbol{x}_t, t, s\right) + \left(\tilde{\beta}_t/2\right)^2 \odot \epsilon \tag{6}$$

This iterative method of reverse updating is critical for generating intermediate states that lead to the optimal decision for HDT management.

4) Converting to Probability Distribution for HDT Actions: The final output, $\boldsymbol{x}_0$, is transformed into a probability distribution using the softmax function:

$$\pi_\theta(s) = \frac{e^{\boldsymbol{x}_0^i}}{\sum_{k=1}^{\mathcal{A}} e^{\boldsymbol{x}_0^k}}, \forall i \in \mathcal{A} \tag{7}$$

This transformation ensures that $\pi_\theta(s)$ accurately reflects the probability of selecting each action in the decision-making process for HDTs.

5) Challenges and Integration with DRL: In the context of HDT, AIGOD faces unique challenges, such as the absence of labeled data in wireless network optimization for HDT. To overcome this, AIGOD is designed to learn in an exploratory manner, focusing on maximizing utility for HDT rather than merely minimizing error. When integrated with advanced Deep Reinforcement Learning (DRL) algorithms like SAC, the result is an enhanced DDSAC algorithm, improving the optimization process in complex IoMT scenarios. This integration capitalizes on AIGOD's capabilities in exploration and learning within the SAC framework, offering a robust solution for decision optimization in IoMT environments, particularly for managing Human Digital Twins.

V. DDSAC Algorithm for AISP Selection

This section delves into the application of the Deep Diffusion Soft Actor-Critic (DDSAC) algorithm, modified from D2SAC [37], integrated with the AIGOD, for the AISP selection problem in IoMT-based smart homes, particularly focusing on HDT integration.

A. Modeling the AISP Selection Problem as an MDP

In the context of HDT, the AISP selection problem is aptly modeled as a Markov Decision Process (MDP), catering to the sequential and dynamic nature of task assignments and resource management in IoMT settings involving HDTs.

1) MDP Framework for AISP Selection in HDT Context: The MDP framework is tailored to the AISP selection problem for HDT applications, with the aim to maximize the overall utility $\mathcal{U}$. This framework encompasses:

- *States*: The current status of the system, including task allocation, resource availability, and HDT-specific parameters.
- *Actions*: Decisions on task assignments to AISPs, considering HDT requirements.
- *Rewards*: The utility derived from each task assignment, evaluated in the context of HDT efficiency and accuracy.
- *Transitions*: System state changes following actions, with an emphasis on HDT dynamics.

Given the complexity of HDT management and the unpredictability of task arrivals and resource availability, this MDP model is crucial for effective, real-time decision-making in HDT-integrated IoMT environments.

2) Optimization Objective: The optimization goal in an HDT-focused IoMT setting is to maximize cumulative rewards, which are the sum of discounted utilities over time, defined as:

$$R(s_0, \pi_{\boldsymbol{\theta}}) = \mathbb{E}\left[\sum_{l=0}^{L} \gamma^l r_l \mid s_0, \pi_{\boldsymbol{\theta}}\right] \tag{8}$$

In this formula, $\pi_{\boldsymbol{\theta}}$ denotes the policy derived from AIGOD, tailored for HDT considerations, γ represents the discount factor, and L signifies the number of transitions in an episode. This framework is designed to strike a balance between immediate gains and long-term benefits, aligning with the dynamic and complex requirements of managing HDTs in IoMT environments.

B. Implementation of DDSAC

Incorporating the AIGOD model with the MDP framework, the DDSAC algorithm presents a refined approach for the AISP selection problem in IoMT settings, especially with HDT integration.

1) State Space Configuration: The state space $\mathcal{S}$ in DDSAC, tailored for HDT applications, encompasses task-specific data and current resource status of AISPs:

- *Task Information* (s^{T}): Includes details like estimated completion time and resource needs of tasks related to HDT management, represented as $s^{\mathrm{T}} = [T, o]$.
- *AISP Resource Status* (s^{A}): Reflects the total and available resources for each AISP, vital for efficient HDT operation, expressed as $s^{\mathrm{A}} = [\mathcal{T}_i, \tilde{\mathcal{T}}_i \mid \forall i \in \mathcal{I}]$.

The state vector $s = [s^{\mathrm{T}}, s^{\mathrm{A}}]$ forms a comprehensive foundation for decision-making within HDT frameworks, with normalization to $(0, 1)$ for consistent training.

2) Action Space Definition: The action space $\mathcal{A}$ in this context pertains to potential AISP assignments for HDT-related tasks. It's an integer space signifying the choice of one of the I AISPs. The AIGOD network informs the selection $a \in \mathcal{A}$, generating a probability vector for each AISP:

$$a = \arg\max_i \left\{\pi_{\boldsymbol{\theta}}^i(s), \forall i \in \mathcal{I}\right\} \tag{9}$$

This mechanism picks the AISP with the highest likelihood of successful task execution, integral for HDT management.

3) Reward Function Formulation: The reward function in DDSAC, considering HDT aspects, includes:

- *AIGC Quality Reward* (r^{Q}): Pertains to the quality of content generated for HDT applications, with a base score $\hat{r}^{\mathrm{Q}}$ for outputs of lower quality.
- *Crash Penalty* (r^{P}): Imposed for actions leading to AISP overload and HDT task failures, calculated as:

$$r^{\mathrm{P}} = \hat{r}_{\mathrm{F}}^{\mathrm{P}} - \sum_{j' \in \hat{\mathcal{J}}} \hat{r}_{\mathrm{I}}^{\mathrm{P}}(j') \tag{10}$$

The aggregate reward r integrates these factors, directing the DDSAC algorithm towards effective and reliable decision-making crucial for HDT operations in IoMT environments.

C. Training and Testing Rewards in DDSAC

1) Differentiation Between Training and Testing Rewards: In the context of HDT-integrated IoMT environments, DDSAC distinguishes between training and testing rewards:

- **Training Reward**: Tailored to optimize the policy during the training phase, ensuring efficacy in a controlled training environment. Specifically targets the effectiveness of decisions impacting HDT management.
- **Test Reward**: Focuses on evaluating the policy's performance in diverse and real-world IoMT settings, critical for assessing the adaptability and robustness of the system in managing HDTs.

This distinction ensures that DDSAC is both effective within its training realm and adaptable to varying HDT-related scenarios in IoMT.

2) Transition Function for HDT Management: The transition function $p(s' \mid s, a) \in \mathcal{P}$ is intricately complex, reflecting the dynamic and unpredictable nature of HDT management in IoMT, including variations in task arrivals and execution scenarios.

3) Initialization and Termination for HDT-Related Tasks:

- **Initial State** (s_0): Defined to represent the onset of HDT-related task assignments in IoMT, typically indicated as $(T_0, o_0, \mathcal{T}_1, 1, \ldots, \mathcal{T}_I, 1)$.
- **Termination Criterion**: Sets a maximum number of transitions L per episode, aligning with the efficient training and evaluation of policies in the dynamic HDT-IoMT landscape.

4) Optimization Objective: The optimization objective, critical for HDT applications in IoMT, is formulated as:

$$\boldsymbol{\theta} = \arg\max_{\boldsymbol{\theta}} \mathbb{E}\left[\sum_{l=0}^{L} \gamma^l \left(r_l + \alpha H\left(\pi_{\boldsymbol{\theta}}\left(s_l\right)\right)\right)\right] \tag{11}$$

Incorporating action entropy regularization with a temperature parameter α, this objective is transformed into a computationally efficient optimization problem:

$$\boldsymbol{\theta} = \arg\min_{\boldsymbol{\theta}} -\mathbb{E}\left[\sum_{l=0}^{L} \gamma^l \left(r_l + \alpha H\left(\pi_{\boldsymbol{\theta}}\left(s_l\right)\right)\right)\right] \tag{12}$$

5) DDSAC Algorithm Architecture: The architecture of the DDSAC algorithm, as depicted in Figure 3, highlights its key components and integration within the MDP framework, tailored for HDT management in IoMT. The AIGOD network, characterized by $\boldsymbol{\theta}$, dynamically adjusts task assignments with a focus on balancing utility and stability, essential for efficient HDT management in IoMT environments.

D. DDSAC Architecture

The DDSAC architecture, depicted in Fig. 3, is innovatively designed for HDT applications within the IoMT environment. This sophisticated framework synergizes various components to optimize the AI-Generated Content Service Provider (AISP) selection process, addressing the dynamic and security-sensitive nature of IoMT for personalized healthcare.

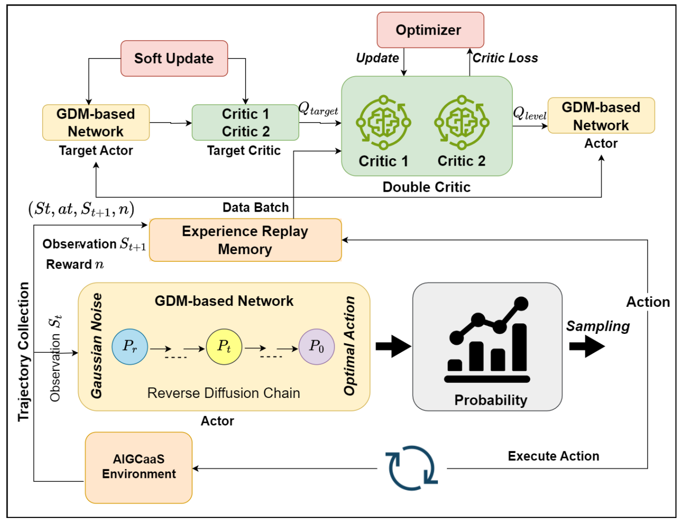

Fig. 3: DDSAC Architecture.

a) Trajectory Collection and AIGOD Integration: The DDSAC algorithm initiates with the agent observing the initial state s_0, tailored to the context of HDT management. It collects C transitions from the IoMT environment, crucial for decision-making regarding HDTs. Each transition, stored in the experience replay memory $\mathcal{D}$ with capacity $D = |\mathcal{D}|$, encompasses HDT state changes and associated rewards, formatted as (s_l, a_l, s_{l+1}, r_l). The actor-network, by leveraging real-time HDT-related observations s_l, employs the AIGOD model to select actions. This selection is based on a probability distribution $\pi_\theta(s_l)$, specifically generated for HDT needs, demonstrating the seamless integration of AIGOD within the DDSAC framework for nuanced HDT-centric decision-making.

b) Experience Replay Memory and Security Considerations: The experience replay memory $\mathcal{D}$ is instrumental in managing the asynchronous nature of feedback from HDT scenarios, thus supporting off-policy learning and enhancing the system's adaptability to changing IoMT dynamics. Furthermore, DDSAC incorporates dual critic networks, ϕ^1 and ϕ^2, designed to minimize bias and ensure cautious policy updates, which is critical in the sensitive healthcare context. These networks also play a key role in safeguarding the integrity of HDT data, implementing encryption and anonymization techniques to protect against unauthorized access and data breaches.

c) Optimization Process and IoMT Dynamics Adaptation: The optimization process within DDSAC emphasizes the refinement of policy actions to maximize HDT-related outcomes. Utilizing gradient descent, the framework adjusts actor-network parameters based on feedback from a diverse array of HDT scenarios, ensuring that the algorithm remains responsive to the evolving requirements of the IoMT environment. This dynamic adaptation facilitates precise and timely healthcare interventions, showcasing the DDSAC algorithm's capacity to navigate the complexities of personalized healthcare delivery in IoMT settings effectively.

In essence, the DDSAC architecture not only captures the multifaceted decision-making processes required for optimal HDT management but also emphasizes the importance of data security and system adaptability within the IoMT framework.

E. Action Entropy Regularization in DDSAC with Human Digital Twin Integration

1) Incorporating Entropy into HDT-Centric Policy Optimization: In DDSAC, customized for HDT applications, action entropy regularization is integral in policy optimization to foster exploration and avert premature convergence to sub-optimal actions. The revised optimization goal, incorporating entropy regularization, is formulated as:

$$\max_{\boldsymbol{\theta}} \pi_{\boldsymbol{\theta}}\left(s_l\right)^T Q_{\boldsymbol{\phi}}\left(s_l\right)+\alpha H\left(\pi_{\boldsymbol{\theta}}\left(s_l\right)\right) \tag{13}$$

where $H(\cdot)$ denotes the entropy of the action probability distribution for HDT-specific decisions. The temperature coefficient α modulates the intensity of the entropy term, ensuring a balance between exploration and exploitation in HDT management.

2) Entropy Calculation for HDT Actions: Entropy for HDT-related actions is calculated as:

$$H\left(\pi_{\boldsymbol{\theta}}\left(s_l\right)\right)=-\pi_{\boldsymbol{\theta}}\left(s_l\right)^T \log \pi_{\boldsymbol{\theta}}\left(s_l\right) \tag{14}$$

reflecting the entropy of the action probability distribution in HDT contexts.

3) HDT Policy Update with Entropy Regularization: The policy parameters, considering HDT-specific requirements, are updated using both the expected Q-value and the entropy term, facilitating a balanced approach between exploration and exploitation. This update employs gradient descent techniques analogous to standard policy optimization in HDT scenarios.

F. Q-Function Improvement for HDT Optimization

In the discussed reinforcement learning context, the Q-function $Q_{\phi_e}(s_l)$ is critical for estimating expected rewards for state-action pairs, where ϕ_e denotes specific network parameters and s_l represents the state at time l. To enhance the accuracy of this Q-function, the approach focuses on minimizing the Temporal Difference (TD) error, the discrepancy between the predicted Q-value (Q-target, $\hat{y}_e$) and the current Q-value estimate (Q-eval, y_e^i). This minimization is achieved through the equation

$$\min_{\phi_1,\phi_2} E_{(s_l,a_l,s_{l+1},r_l)\sim B_e}\left[\sum_{i=1}^{2}(\hat{y}_e-y_e^i)^2\right]$$

where ϕ_1 and ϕ_2 are Q-function parameters optimized over a batch of experiences sampled from a buffer B_e. The current Q-value estimate $y_e^i = Q_{\phi_i e}(s_l,a_l)$ is computed for a given state-action pair, while the Q-target $\hat{y}_e = r_l + \gamma(1-d_{l+1})\hat{\pi}_{\hat{\theta}_e}(s_{l+1})^T\hat{Q}_{\hat{\phi}_e}(s_{l+1})$ involves the reward r_l, discount factor γ, and the Q-function for the next state s_{l+1}, incorporating a policy function $\hat{\pi}_{\hat{\theta}_e}$. This method aims to improve the Q-function's prediction of future rewards by aligning current estimates with target values, thus optimizing the decision-making process in a dynamic and complex reinforcement learning environment.

G. Utilization of Target Networks

In HDT-focused DDSAC, target networks $(\hat{\pi}, \hat{Q})$ are employed, updated more gradually than the online networks. A soft update mechanism, determined by hyperparameter τ, is vital for ensuring stability in HDT management.

H. Iterative Improvement and Convergence

The policy and Q-function are gradually improved using the DDSAC algorithm until a point of convergence is achieved. The ultimate objective is to get the ideal policy parameters, represented as $\boldsymbol{\theta}^*$, which are designed to maximize the overall utility and the collective reward in the context of applications involving Human Digital Twins.

I. Optimization Goals of DDSAC

1) Challenges in HDT Optimization for Online and Discrete Scheduling Tasks: The DDSAC algorithm, tailored for HDT applications, aims to maximize the Q-value, tackling challenges in online, discrete, and label-less tasks typical in HDT-centric IoMT environments.

2) Emphasis on Policy Loss and Action Entropy Loss: DDSAC concentrates on minimizing both policy loss and action entropy loss, crucial for enhancing performance in online, discrete-action contexts related to HDT management. This approach has shown significant effectiveness in HDT-based applications.

J. Data Privacy and Security

Given the sensitive nature of healthcare data, it is essential to implement robust data privacy and security measures within the AIGCaaS framework. This includes using advanced encryption methods such as AES-256 for data at rest and TLS for data in transit. Additionally, privacy-preserving techniques like differential privacy and federated learning are employed to ensure that individual patient data remains confidential while still enabling the aggregation and analysis necessary for HDT functionalities. Furthermore, access controls and regular security audits are conducted to safeguard against unauthorized access and potential data breaches.

VI. Analysis and Discussion

A. Experimental Setup and Design

Our experimental infrastructure was carefully selected to closely mirror the computational demands and real-time processing capabilities required in IoMT-based smart homes. Utilizing an AMD Ryzen 9 5950X 16-Core processor, NVIDIA GeForce RTX 3090 GPU, and 32 GB of RAM, we ensure high-performance computation for the DDSAC algorithm. The environment, running on Ubuntu 20.04 LTS with cuDNN 8.1, CUDA toolkit 11.2, and PyTorch 1.8 within Docker, provides a consistent and replicable setup. The simulated IoMT environment features 20 AISPs with variable resource capacities (400 to 1000) and 1000 users, mimicking real-world variability and the stochastic nature of task submissions, modeled via a Poisson process. This design is pivotal for evaluating

TABLE I: Architecture of Actor and Critic Networks.

Component	Network Layer	Activation Function	Number of Units
Actor Network	Sinusoidal Position Embedding	None	16
	Fully Connected Layer	Mish	32
	Fully Connected Layer	None	16
	Layer for Concatenation	None	None
	Fully Connected Layer	Mish	256
	Fully Connected Layer	Mish	256
	Fully Connected Layer	Tanh	20
Critic Network	Fully Connected Layer	Mish	256
	Fully Connected Layer	Mish	256
	Fully Connected Layer	None	20

TABLE II: Overview of Training Parameter Settings

Symbol	Description	Value
η_{a}	Learning rate of actor network	1×10^{-4}
η_{c}	Learning rate of critic network	1×10^{-3}
α	Action entropy regularization temperature	0.05
τ	Weight for soft updates	0.005
b	Size of mini-batch	512
λ	Decay of weight	1×10^{-4}
γ	Discount factor for reward accumulation	0.95
T	Number of denoising steps (Diffusion model)	5
D	Maximum replay buffer capacity	1×10^{6}
E	Total training steps	1000
C	Transitions per training step	1000

the DDSAC algorithm's responsiveness and adaptability in dynamic IoMT scenarios.

The DDSAC model incorporates a diffusion model-based AIGOD into the actor network and employs a three-layer fully-connected structure for the critic networks. This architecture is specifically tailored to the nuances of managing HDTs within IoMT environments, optimizing for both the precision of healthcare outcomes and the personalization of care. Training employed the Adam optimizer, with distinct learning rates for actor and critic networks, ensuring optimal learning dynamics. The use of target networks, updated through a soft update mechanism ($\tau = 0.005$), facilitates stable learning in the continuously evolving IoMT landscape.

The selection of performance metrics and the IoMT simulation environment is strategically aligned with our objectives to validate the DDSAC algorithm's efficacy in personalized healthcare. Metrics such as task completion rate, computational efficiency, and user satisfaction directly correlate with the algorithm's potential to improve patient care in IoMT settings. The simulation environment, designed to replicate the complexities of real-world IoMT systems, allows us to assess the DDSAC algorithm under varied and challenging conditions, thereby ensuring its robustness and scalability for practical deployment.

Integration of HDT scenarios is a testament to our commitment to advancing personalized healthcare, with each digital twin reflecting individual health profiles. The AIGC models, fine-tuned for human-aware quality assessment, underscore our focus on delivering content that meets the highest standards of personalization and relevance. The comparative analysis, positioning DDSAC against established DRL benchmarks and heuristic policies, demonstrates our model's superior performance in facilitating effective and efficient healthcare delivery within the IoMT ecosystem.

B. Numerical Results

The application of DDSAC in HDT-specific scenarios within IoMT-based smart homes has shown remarkable results. In our numerical experiments, DDSAC, augmented with HDT data, achieved superior performance in AISP selection tailored for personalized healthcare. Over a similar 1000 training steps and 1 million environment interactions, DDSAC excelled in adapting to the unique requirements of each human digital twin, surpassing the efficiency and effectiveness of standard benchmarks.

Compared to heuristic policies, DDSAC demonstrated a profound understanding of individual HDT profiles, learning and adapting to each digital twin's specific healthcare needs more effectively. It quickly moved beyond generic strategies to embrace more personalized approaches, showing a nuanced understanding of HDT-specific data and requirements, thereby optimizing personalized healthcare service delivery.

One of the standout features of DDSAC in HDT scenarios was its ability to balance the optimization of healthcare outcomes with the minimization of risks and errors. This balance is crucial in healthcare, where the cost of errors can be significant. Unlike other policies, DDSAC demonstrated a unique ability to prioritize healthcare tasks, effectively balancing the maximization of personalized healthcare benefits against potential risks.

Key Insights:

- DDSAC's adaptability to HDT data significantly enhances its performance in personalized healthcare scenarios, making it an ideal choice for complex scheduling tasks in IoMT-based smart homes.
- Its ability to learn and adapt dynamically, driven by individualized data from each digital twin, allows for highly tailored healthcare strategies.
- DDSAC's nuanced approach in balancing healthcare optimization with risk mitigation sets it apart in delivering personalized healthcare services, ensuring effective and safe patient care.

These results affirm the potential of DDSAC with HDT integration in transforming the landscape of personalized healthcare services, highlighting its adaptability, efficiency, and effectiveness in meeting the unique healthcare needs of individuals in smart home environments.

C. Optimizing Denoising Steps

Our experiments, which involved various denoising steps (T) values including $\{1, 2, 3, 4, 5, 10, 15\}$, tailored specifically for HDT scenarios, indicated a critical balance. As T values increased, there was a notable improvement in accuracy; however, this was accompanied by a rise in computational time, a crucial factor in time-sensitive healthcare applications. Intriguingly, the rewards plateaued beyond $T = 5$, suggesting that this value offers an efficient compromise for HDT applications. This key insight implies that in systems where HDT is employed within IoMT, a lower denoising step count is not

TABLE III: DDSAC and Benchmark Performance Comparisons (totaling 1000 steps)

Policy Type	Policy Name	Train Reward	Test Reward	Total Time (h)	Time to Baseline (h)	Step to Baseline
Heuristic	Random	-20	-34	0.73	N/A	N/A
	Round Robin	270	277	0.75	N/A	N/A
	Crash Avoid	392	405	0.78	0.0	0
	Prophet	600	598	N/A	N/A	N/A
DRL	DQN	420	505	1.8	0.8	465
	Prioritized-DQN	390	458	1.7	1.1	475
	DRQN	382	428	3.0	2.1	695
	REINFORCE	397	465	1.2	0.8	855
	PPO	355	479	1.2	1.2	945
	Rainbow	416	452	2.7	2.3	$\{135, 845\}$
	SAC	416	438	2.8	1.3	435
Our Method	**DDSAC**	**530**	**539**	**6.9**	**1.4**	**195**

TABLE IV: Comparison of Accumulated Rewards for General Benchmark Tasks

Policy Type	Policy Name	Acrobot-v1	CartPole-v1	CoinRun-v0	Maze-v0
DRL	DQN	-82.10 ± 16.80	499.85 ± 0.20	6.20 ± 4.70	2.90 ± 4.50
	Prioritized-DQN	-104.70 ± 15.00	498.80 ± 1.40	5.20 ± 4.80	1.90 ± 3.90
	DRQN	-81.90 ± 13.50	133.00 ± 70.00	-	-
	REINFORCE	-105.00 ± 15.00	499.95 ± 0.05	0.05 ± 0.05	0.05 ± 0.05
	PPO	-77.50 ± 9.00	499.92 ± 0.08	0.10 ± 0.10	1.80 ± 3.80
	Rainbow	-157.50 ± 56.00	478.50 ± 30.00	5.10 ± 4.90	1.90 ± 3.90
	SAC	-120.50 ± 35.50	499.95 ± 0.05	9.90 ± 0.10	2.80 ± 4.40
Online [38], [39]	A2C	-86.50 ± 25.00	499.85 ± 0.15	-	-
	ACER	-91.00 ± 33.00	498.50 ± 24.00	-	-
	ACKTR	-91.00 ± 32.50	487.00 ± 64.00	-	-
	PPO2	-85.00 ± 26.00	499.95 ± 0.05	-	-
	DQN	-88.00 ± 33.00	499.95 ± 0.05	-	-
	TRPO	-	485.00 ± 71.00	-	-
	PPO + IMPALA	-	-	9.00	$\mathbf{9.70}$
	Rainbow + IMPALA	-	-	5.40	4.20
Ours	**DDSAC**	**-70.50±4.00**	**499.95±0.05**	**10.10±0.10**	**7.10± 4.50**

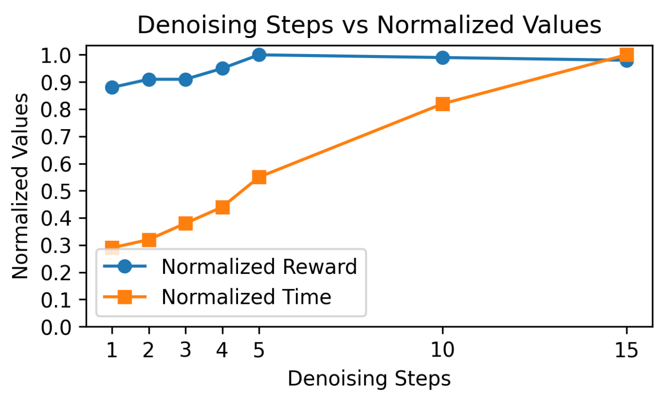

Fig. 4: Denoising is used to set step effects on training time and rewards to their greatest value.

only feasible but also aligns computational efficiency with the exigency of timely healthcare interventions.

The reverse diffusion process generates actions from noise, beginning with an action probability distribution characterized by high uncertainty. As the process progresses, this distribution gradually narrows, leading to a more focused and certain selection of actions that align closely with the unique requirements of individual HDTs. This evolutionary trajectory of the action probability distribution underscores the effectiveness of reverse diffusion within the DDSAC framework for personalized healthcare decision-making. It adeptly adapts and refines choices to cater to the varied and dynamic needs of different human digital twins in the IoMT environment, demonstrating its suitability and precision in providing patient-specific healthcare solutions.

These observations emphasize DDSAC's distinctive approach in diffusion-based DRL, particularly when adapted for HDT in IoMT. They showcase its capabilities not only in operational efficiency but also in making precise, informed decisions in discrete action spaces, crucial for personalized healthcare applications.

D. Optimal Action Prediction and Exploration Balance

DDSAC demonstrates a crucial capability to accurately predict optimal actions for personalized healthcare, as evidenced by its performance in later training phases (Table V). The algorithm's handling of denoising steps plays a vital role in striking a balance between exploration and exploitation, a feature particularly significant in HDT applications. Fewer denoising steps lead to increased exploration, beneficial for comprehending a variety of health scenarios, while more steps can limit exploration, potentially affecting the adaptability to unique HDT requirements. This balance in discrete action spaces, where DDSAC navigates between exploring new healthcare strategies and exploiting known effective ones, marks a significant advancement in providing tailored healthcare solutions within IoMT environments, catering specifically to the needs of HDTs.

DDSAC effectively incorporates action entropy regularization, controlled by the entropy temperature coefficient α. This feature is crucial for balancing exploratory and exploitative

TABLE V: Benchmarks and DDSAC Task Performance Comparisons

Policy Type	Policy Name	Finished Rate	Obtained Utility	Crashed Rate	Lost Utility
Heuristic	Random	69.8%	212	28.5%	95
	Round Robin	90.5%	306	7.8%	33
	Crash Avoid	97.5%	355	0.2%	1
	Prophet	97.5%	545	0.2%	1
DRL	DQN	97.5%	477	0.2%	1
	Prioritized-DQN	97.5%	430	0.2%	1
	DRQN	94.1%	430	4.0%	18
	REINFORCE	95.6%	455	2.1%	12
	PPO	96.8%	454	0.9%	5
	Rainbow	97.5%	416	0.2%	1
	SAC	94.1%	410	3.7%	13
Ours	**DDSAC**	**96.4%**	**492**	**1.3%**	**6**

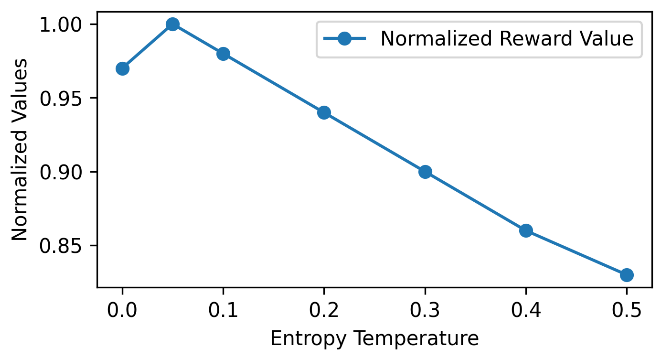

Fig. 5: Entropy regularization's effects at various temperatures. By using their maximum, values are normalized.

strategies in healthcare interventions specific to HDTs. The entropy temperature significantly influences DDSAC's policy learning for HDT applications, as depicted in Figure 5. An optimal setting of α is essential for efficiently tailoring policies to the unique needs of individual HDTs. However, the adjustment of α presents a delicate trade-off: lower values tend to result in deterministic actions, potentially missing out on innovative healthcare solutions, whereas higher values might introduce too much randomness, thereby prolonging the policy learning process for HDT-specific scenarios. This balance is critical for ensuring the effectiveness and adaptability of DDSAC in the dynamic and personalized realm of HDT healthcare management.

These insights into DDSAC's exploration-exploitation management through action entropy regularization and denoising steps highlight its innovative approach in discrete action spaces tailored for HDT in IoMT. This nuanced balance is crucial for DDSAC's effective policy learning, rendering it a powerful tool for complex healthcare scheduling tasks in IoMT-based smart homes.

VII. Conclusion

This paper delves into the integration of AIGC within the IoMT in smart homes, synergizing with HDT concepts. We introduce the AIGOD algorithm, incorporated into the DDSAC framework, to select AISP effectively in IoMT environments catering to HDTs. Our innovative AIGC-as-a-Service (AIGCaaS) architecture leverages edge networks for scalable, personalized AI services crucial for nuanced patient care and HDT application. In IoMT scenarios, DDSAC demonstrates superior performance over traditional DRL models, particularly in managing patient-specific needs and HDT requirements. It adeptly balances individual HDT utility with efficient resource management, showcasing its versatility in adapting to dynamic HDT needs and evolving IoMT conditions. This research significantly advances IoMT, AIGC, and HDT fields, underscoring the potential of diffusion models in complex healthcare decision-making. Extending beyond mere AI integration in patient care, it paves the way for future exploration in diffusion-based deep learning across various sectors. Ultimately, this study propels AI-driven, patient-centric services in smart homes, integrating HDT concepts and setting new standards in personalized healthcare delivery and management.

Future research could apply our framework to smart cities and industrial IoT, enhancing operational efficiency and user experience. Investigating advanced privacy-preserving techniques and their integration with AIGCaaS could strengthen data security. Our research advances IoMT, AIGC, and HDT fields, showcasing the potential of diffusion models in healthcare. This study sets the stage for diffusion-based deep learning across various sectors, driving AI-driven, patient-centric services in smart homes and setting new standards in personalized healthcare delivery.

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