IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 31 May 2024, accepted 23 June 2024, date of publication 28 June 2024, date of current version 8 July 2024.
Digital Object Identifier 10.1109/ACCESS.2024.3420741

RESEARCH ARTICLE

AI-Enabled Healthcare and Enhanced Computational Resource Management With Digital Twins Into Task Offloading Strategies

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This work was supported by Brunel University London, Uxbridge, U.K.

ABSTRACT Efficient management of computational resources and data in the healthcare sector is increasingly challenging, particularly with the advent of advanced healthcare technologies. Effective task offloading mechanisms are crucial for enhancing system performance, patient care, and data security. This study aims to introduce and evaluate a novel framework for task offloading in healthcare environments. The framework seeks to address real-time healthcare demands through dynamic offloading strategies, incorporating digital twins (DT) and social health determinants to personalise and improve healthcare interventions. Employing both partial and binary offloading strategies, multi-protocol communications are supported by the framework, ensuring seamless data exchange. The integration of DT and social health determinants into offloading decisions stands at the core of the methodology, rigorously tested in real-time settings. Iterative testing confirms the framework's effectiveness, demonstrating a 10% enhancement in energy efficiency and a 20% reduction in network latency with 20 MEC nodes. The inclusion of 30 MEC nodes further reduced latency by 33.4% and power usage by 53.8% for data sizes up to 100 MB, evidencing significant advancements in healthcare technology integration. A significant gap in existing literature is bridged, and a new trajectory for technological innovation in healthcare systems is set by the research. The study underscores the potential of sophisticated offloading techniques to revolutionise healthcare delivery, offering a holistic solution to the challenges of data and computational management in medical contexts.

INDEX TERMS Adaptive cybersecurity task offloading (ACTO), digital twins healthcare, energy efficiency in healthcare systems, predictive healthcare interventions, social health determinants.

I. INTRODUCTION

The convergence of healthcare and technological innovation has seen exponential growth, fueled by the continuous quest for efficiency, precision, and personalised treatment. As this evolution unfolds, the pressing challenge of handling extensive data volumes and computational demands becomes more acute. In response, task offloading the calculated transfer of computational activities from devices with limited resources to more robust systems has surfaced as a crucial

The associate editor coordinating the review of this manuscript and approving it for publication was Chin-Feng Lai.

strategy. Nevertheless, the specific demands and critical nature of healthcare applications call for novel offloading methods that go beyond conventional approaches [1], [2].

Anticipated to redefine connectivity, the imminent 6G network promises comprehensive global coverage, spanning terrestrial, aerial, and maritime domains [3]. This revolutionary network aims to substantially elevate transmission rates, minimise delays, bolster reliability and connectivity, and enhance spectral and energy efficiencies, thus serving the diverse needs of assorted sectors [4], [5]. Central to this innovation is mobile edge computing (MEC), which shifts computational and storage solutions from the central cloud to the network fringe, reducing the gap to users and thereby speeding up service provision [6], [7].

The imperatives of real-time data processing and energy efficiency in healthcare informatics demand an exceptional framework for task offloading. Such a platform should not only outperform others in computational speed and energy preservation but should also guarantee the safety and privacy of health-critical data in the context of healthcare's inevitable variability. The use of digital twin (DT), with the social determinants of such variation in healthcare, is a novel step in enhancing the personalisation and efficiency of therapies, a factor seldom addressed in current offloading schemes.

In this regard, a complex task offloading framework is presented, carefully crafted to be in harmony with the unique environment of the healthcare sector. The framework is a symphony of partial and binary offloading techniques adjusted in real time to the needs of the sector. The framework heralds the advent of employing DT for prescient analytics and assimilating social health determinants into offloading processes, charting a path towards a more nuanced and proactive healthcare modality. Furthermore, the integration of multi-protocol communications within a healthcare purview is at the vanguard of the study, thereby fortifying the continuity of data streams and augmenting the operational efficiency of emergency responses. The cornerstone contributions of this inquiry include:

1) Introducing a bespoke amalgamation of partial and binary offloading strategies, tailored to meet the computational and functional requisites of healthcare applications.
2) Pioneering the integration of DT and Social Health Determinants into offloading deliberations, fostering preemptive health interventions and personalised patient treatment paradigms.
3) Demonstrating the pragmatic efficacy of the Digital Twin Healthcare Enhanced Asynchronous Team-Based Multi-Agent Proximal Policy Optimisation (DTH-ATB-MAPPO) within real-world healthcare settings, this study evidences its superiority over existing methodologies in terms of rapid convergence and optimisation of rewards.
4) The paper incorporates new aspects of DT adoption in refining MEC systems. It boasts a significant percentage of improvement, including network latency and energy consumption.
5) Constructing experimental frameworks that are adequately linked to the theoretical groundwork and implemented practically for experimental research, and supported by simulation data of several operational cases.
6) The innovation of Adaptive Cybersecurity Task Offloading (ACTO) is included in the work. Adaptive protection functions along with exact matching technology have been utilised by the ACTO algorithm to identify threats and respond with adaptive cybersecurity mechanisms without sacrificing computational and storage abilities, based on the scope of protection required.

These aspects are the cornerstone of the research work since they all aim at hornring the security feature in healthcare informatics. Therefore, the research is tailored to contribute a major advancement in the field of healthcare technology since it addresses every aspect involved with the management of medical systems, such as data and computational platforms. Hence, this research will serve as a bridge in distinguishing the most beneficial way of integrating advanced computational and communication systems to enhance healthcare service delivery and patient care.

The remainder of this paper is structured as follows: In Section II, the background and foundational concepts of DT with edge network are discussed. Section III reviews relevant literature. Section IV outlines the proposed system model and problem formulation. In Section V, the approach to secure data offloading in healthcare informatics is detailed. Simulation results are discussed in Section VI, followed by an examination of the optimisation of MEC systems using DT technology in Section VII. The paper concludes in Section IX, summarising the findings and their implications for future research.

II. BACKGROUND

Although current studies on MEC primarily tackle the trade-offs between energy consumption and latency through strategic caching and offloading [8], [9], the rise in data-intensive applications underlines the challenge for individual mobile edge servers (MESs) in multitasking. This scenario highlights the essential role of edge collaboration in overcoming the constraints of singular MESs by leveraging spare network capacity for enhanced efficiency in power and time [10].

The expansion of collaborative frameworks raises significant security concerns, particularly when certain nodes may be vulnerable or compromised, leading to severe repercussions such as data breaches or message corruption when selected by Mobile Users (MUs) for offloading tasks. Furthermore, although artificial intelligence (AI) has been successful in different industries, it has seen challenging deployments in MEC, particularly for MUs via resource scheduling and task offloading due to the small storage and computational power of MS, making the AI poor-functioning [11], [12]. Contrary to the struggling technologies, DT is a unique invention that bridges the physical objects and virtual world by aiding in setting the optimal MES and enhancing task offloading using AI [13], [14], [15].

By providing huge sets of real-time data, data streaming technology (DST) can help monitor MUs adequately and enable them to make requisite decisions, which can enhance the network's total quality and AI accuracy. Combining MEC and DST in creating the Digital Twin Edge Network (DTEN) is a game-changer concept aimed at shaping the future of edge computing by making task offloading possible and intelligent, thereby promoting service efficiency. Unlike other technologies, which have undergone significant research and are at their maturity stage, the integrated concepts have a bright future since they can enhance data safety, promote network quality, and minimize operational expenses [16], [17]. Integrations focusing on reducing the DTEN latency, especially during MU movement, are ongoing areas of concern [18].

III. RELATED WORK

In the realm of healthcare, the imperative for data processing proficiency and energy management in medical devices has gained unprecedented academic attention. This growing field of inquiry extends across task offloading, DT technologies, and the inclusion of social determinants in health informatics. The academic conversation highlights notable progress in all three areas and recognises continuing gaps [19].

In a novel research by Jeremiah et al., DT-assisted vehicular edge computing was studied to empower network services via edge cooperation and accurate resource allocation. The process feasibility based on non-orthogonal multiple access and dynamic selection of the roadside unit by using the channel state information was verified. In addition, they investigated the management of more complex optimisation responsibilities of task offloading, decision-making, sub-channel assignment, and RSU connection operations with a complex high-level policy gradient algorithm such as the Advantage Actor-Critic algorithm. This study is being conducted concurrently with the work of Qiu et al., who are testing an offloading approach for DT-assisted edge computing that uses the IBMPA to rapidly and effectively use available energy and computational capability while abiding by a stringent time limit [20], [21].

Advancing the conversation, Bozkaya et al. introduced an energy and delay-aware task computation offloading scheme within DT-enabled networks, incorporating blockchain for enhanced security, thus demonstrating the scalability and efficacy of their method [22]. Zhao et al. created IGNITE, an intelligent partial offloading scheme that uses DT networks along with an advanced clustering algorithm, significantly improving system computational costs, delay, and offloading success rates compared to existing methods [23].

In their effort to improve blockchain performance for IoT systems, Cui et al. proposed a many-objective optimised sharding scheme designed to reduce latency, enhance energy efficiency, minimize failure probability, and increase throughput through a novel edge computing architecture [24]. In tandem, Chen et al. explored a computation offloading and service caching strategy predicated on A3C (Asynchronous Advantage Actor-Critic) and dependency-aware considerations within DTEN, which demonstrated significant enhancements in energy efficiency and overall system performance [25].

The study by Li et al. on adaptive DT frameworks for UAV-assisted networks highlights integrated sensing, communication, and computation to tackle multi-objective challenges such as beam pattern performance and offloading energy consumption, using multi-agent proximal policy optimization (MAPPO) to refine decision-making in dynamic network conditions [26]. Furthermore, Zhang et al. proposed a two-tier DT model for adaptive server deployment in dynamic edge networks within IoT systems, aiming to enhance real-time monitoring and optimisation of network states [27].

Eldeeb et al. exploration into the integration of DT technology with optical wireless communication (OWC) systems presents a pioneering study on enhancing 6G networks. They discuss how DT technology can significantly bolster the reliability and efficiency of OWC systems, crucial in the advent of smart and autonomous systems [28].

Yang et al. explored the deployment of human digital twins at the network edge to enhance task execution through a two-timescale accuracy-aware online optimization approach termed TACO. This method dynamically addresses both large and small timescale decisions, demonstrating significant improvements in task execution accuracy, response time, and energy efficiency [29].

Addressing the gaps identified in the reviewed literature, a comprehensive task offloading framework tailored for healthcare applications is introduced. This framework dynamically opts between partial and full offloading while integrating DT and social determinants into the decision-making process. Distinguished by its robust support for multiple protocols within the healthcare sector, energy-efficient algorithm optimised for medical devices is incorporated into the framework. Additionally, the ACTO algorithm is employed to identify threats and respond with adaptive cyber-security mechanisms. Through meticulous evaluation, the framework's superior efficacy in augmenting computational efficiency, conserving energy, and elevating patient outcomes is delineated, thereby marking a significant advancement in harmonizing technology with healthcare and paving new avenues for research and application.

IV. SYSTEM MODEL AND METHODOLOGY

A. SYSTEM OVERVIEW

This section delineates the comprehensive framework and methodologies employed to address the challenges of task

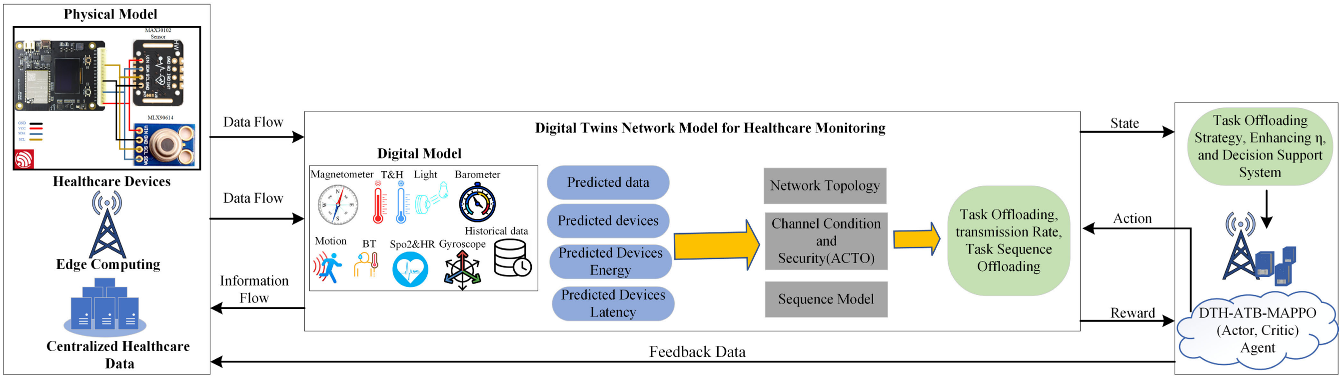


FIGURE 1. Schematic of intelligent task offloading in DT-Enhanced healthcare monitoring systems.

Algorithm 1 Healthcare Task Offloading Strategy

Require: TaskList, DeviceStatus, NetworkStatus, DigitalTwinStatus
Ensure: OffloadingDecisions
  Initialize OffloadingDecisions as an empty list
  for each Task in TaskList **do**
    Compute OffloadingNecessity (N_i) using Eq. (1)
    Determine OffloadingDecision (O_i) using Eq. (2)
    if Task is divisible **then**
      Compute PartialOffloadingFraction (P_i) using Eq. (3)
      if $P_i > 0$ **then**
        Offload a fraction P_i of Task to the edge/cloud
      else
        Process Task locally
      end if
    else
      if $O_i == 1$ **then**
        Fully offload Task to the edge/cloud (Binary Offloading)
      else
        Process Task locally
      end if
    end if
    Update OffloadingDecisions with decision for Task
    Incorporate DigitalTwin and SocialHealthDeterminants in decision-making
    Adjust OffloadingNecessity (N_i') using Eq. (4)
    Re-evaluate OffloadingDecision based on N_i' and update OffloadingDecisions
  end for
  return OffloadingDecisions

offloading in healthcare environments. The approach is underpinned by a multi-faceted system model designed to facilitate efficient data processing, energy conservation, and enhanced healthcare delivery through intelligent task offloading.

Fig. 1 appears to illustrate a schematic representation of a Digital Twins Network Model for Healthcare Monitoring (DTNMHM). This model integrates various technological components and processes to enhance healthcare data analysis and patient monitoring through a systematic approach.

Indeed, this model's core is the healthcare devices comprising various critical biometric sensors and medical instruments that measure health-related data on patients. This health data from the patients is collected in the edge computing close to the data source, facilitating localised data processing. Therefore, real-time analytics are supported, and latency is reduced, further improving speed and response of the health system. Secondly, this health data is then assimilated into the digital model, which is a fundamental component of the so-called digital twins. It consists of a software representation that is excessive in detail and extremely dynamic with the physical devices. The type of data incorporated into the model include Magnetometer readings, Temperature & Humidity (T&H), Barometer readings, Motion, Body Temperature (BT), SpO2 & HR, Gyroscope, and past historical occurrences. This factor modulates the system and enables comprehensive analysis, simulation, and forecasting. Additionally, Fig. 1 below depicts the DTNMHM represented as follows, including;

- Predicted data: where the system uses the model to forecast the future state of the devices considering the energy consumption and the level of latency to be realized.
- Network topology: this model checks the wave the network is structured and connected from device to device. It is dire for optimizing the flow of data and minimizes bottlenecks.
- Channel condition and ACTO: This aspect focuses on upholding data integrity and security, ensuring reliable data transmission, and safeguarding patient confidentiality.
- Sequence model: This likely refers to the order in which data is processed or actions are executed, ensuring an efficient flow of operations.
- Feedback data is then used to inform and update the virtual model, thereby creating a loop of continuous improvement.

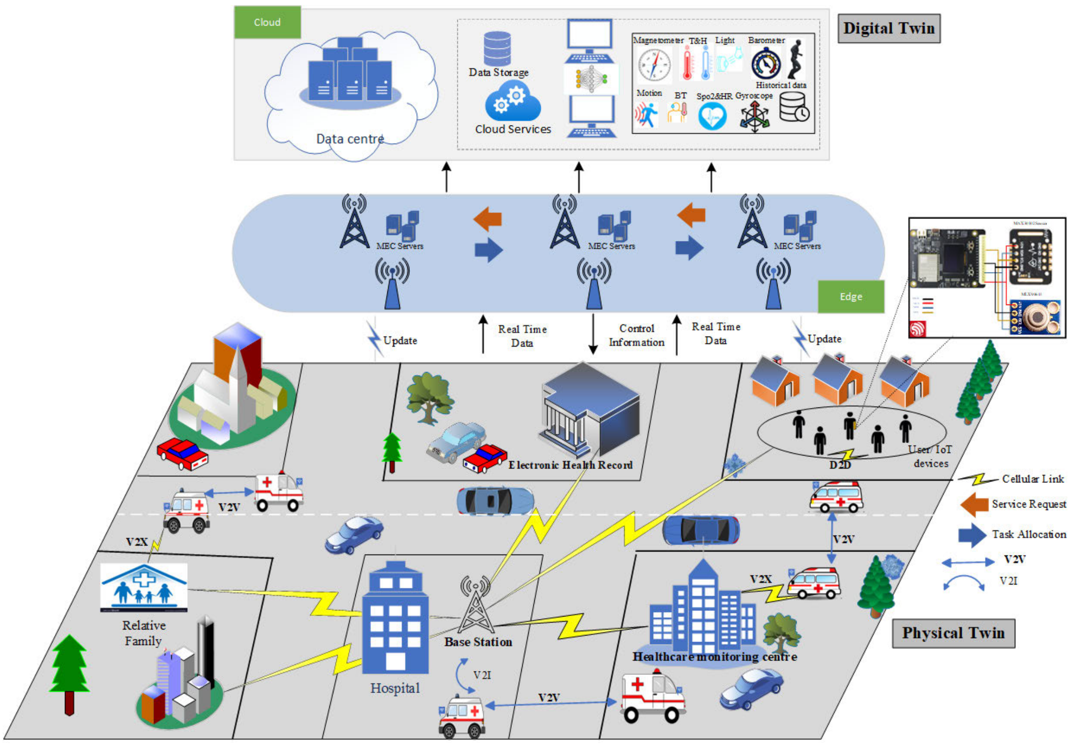


FIGURE 2. Scenario of integrated DT for real-time healthcare monitoring and emergency response network.

On the right side of Fig. 1, the State involves task offloading strategy, enhancing transmission rates (η), and a decision support system, which makes critical decisions on offloading tasks to balance the load on the system, potentially improving computational efficiency and reducing response times.

Multi-Agent Proximal Policy Optimisation (MAPPO) is an advanced reinforcement learning algorithm designed for environments with multiple agents. Decisions made by each agent aim to maximise cumulative rewards while taking into account the actions and policies of other agents. In healthcare, MAPPO optimises the distribution of computational tasks across various devices and servers, ensuring efficient use of resources and improved system performance. Actions within this framework include task offloading, transmission rate adjustment, and task sequence offloading, all intended to optimise the healthcare monitoring network's performance. The reward mechanism, represented by the DTH-ATB-MAPPO agent, adjusts system strategies based on performance rewards, thus continuously refining the task offloading process.

The Algorithm 1 meticulously orchestrates the offloading of computational tasks within healthcare settings, ensuring optimal utilisation of computational resources and enhancing system responsiveness. Initiated by evaluating each task in a predefined list, the algorithm computes the necessity for offloading based on specific criteria, such as computational demand and device energy levels. For tasks deemed divisible, a calculated fraction is offloaded to the cloud or edge servers, thereby balancing local processing load and cloud reliance. Non-divisible tasks undergo a binary decision-making process to determine if offloading or local processing is more efficient. Moreover, the algorithm ingeniously incorporates DT accuracy and social health determinants, adjusting the offloading necessity to reflect a nuanced understanding of healthcare requirements. This innovative modification guarantees that not simply do the decisions weigh on the side of computational efficiency and energy conservation, but they also correspond to personalized health interventions. Ultimately, it contributes to a solidified list of offloading decisions that enhance system performance and health care distribution. Fig. 2 represents the sophisticated mechanism of the proposed system, in which digital and physical bodies concur in real-time to help monitor the health of patients and instantly react to emergencies. In this system, DT technology is smartly used, mimicking the real health care atmosphere to guarantee the simulation and extensive study of health-related data and to enhance patient supervision. The visualisation proficiently represents the dynamic interplay amongst patients, healthcare centres, relatives, and emergency vehicles, all interconnected through a seamless data exchange facilitated by cloud computing. Such integration is depicted as quintessential in emergency scenarios, where expedited and precise decision-making is of the utmost importance. The passive representation not only corroborates the innovative task offloading framework expounded within the accompanying text but also substantiates the incorporation of DT alongside social health determinants, thereby reinforcing the potential to enhance healthcare delivery systems significantly.

Central to the model is the layered architecture of the DTH, shown in Fig. 3, which specifies the integration of data modalities and computational processes. The fundamental layer, the patient data repository, ensures a solid collection of electronic health records (EHR) combined with wearable device data and genomic data. The extensive compilation of data is critical to providing a complete picture of a patient's health and serving as the basis for the subsequent layers of analysis and simulation.

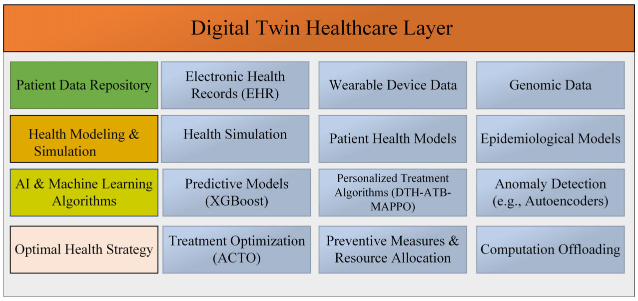


FIGURE 3. **Framework of DTH layers for optimised data processing and management.**

In improvement of the health modelling and simulation layer. Ascent to the health modelling and simulation layer incorporates dynamic health modelling and patient health models that enable the projection of health trajectories and downstream treatment results. This feeds into the AI and machine learning (ML) algorithms layer. The health modelling and simulation layer is improved by the AI and ML algorithms layer, which includes intricate algorithms. The uppermost layer, optimal health strategy, translates these computational insights into actionable strategies for treatment optimisation, prevention, and resource allocation. Significantly, it incorporates computation offloading decisions to navigate the computational constraints inherent in processing the extensive data derived from the lower layers.

The parameters integral to the task offloading strategy are summarised in Table 1. Each parameter is associated with a symbol and a description, which collectively serve to quantify the computational requirements, data size, energy considerations, and various other metrics relevant to task offloading in the healthcare context. Understanding the algorithms and decision-making processes underlying the proposed model requires these essential parameters. The notations defined herein are employed consistently to analyse the performance and effectiveness of the task offloading strategy within the DTH framework, thereby allowing for a clear and systematic presentation of results and discussions. The established notations will be referenced throughout the ensuing discussion on system optimisation, algorithmic development, and evaluation. The nomenclature facilitates the delineation of complex algorithms and the relationships between various elements within the proposed system, ultimately supporting the explication of the novel task offloading framework.

B. TASK OFFLOADING STRATEGY

In task offloading, partial offloading refers to the process where a portion of the computational task is offloaded to an edge server or the cloud, while the remaining part is processed locally on the device. This strategy is useful when tasks have segments that are more efficiently processed in different environments. Binary offloading, on the other hand, involves either entirely offloading the task to an external server or processing it entirely on the local device. The decision between partial and binary offloading depends on factors such as network conditions, energy constraints, and computational requirements.

In DTH systems, efficient task offloading is imperative to ensure that computational burdens are managed effectively, given the limited processing capabilities of medical devices and the exigency of real-time data analysis. Task offloading is predicated on a nuanced assessment of device status and task requisites. Consider a task T_i, characterised by its computational requirements C_i and data size D_i. The offloading necessity N_i for task T_i on device d is determined by the following expression:

$$N_i = \alpha C_i + \beta D_i + \gamma E_d, \tag{1}$$

where E_d represents the residual energy of device d, and α, β, γ are predetermined weighing factors that reflect the importance of computation, data, and energy, respectively.

Decisions regarding offloading in this framework are influenced by factors like network latency, energy efficiency, and availability of computational resources. Also, the speed of healthcare data processing is directly impacted by network latency; lower latency results in quicker response times in critical situations, thus enhancing patient outcomes. The longevity of medical devices is ensured by energy efficiency, as efficient energy use allows continuous monitoring and reduces the risk of device failure during crucial periods. The capability to handle intensive computational tasks is determined by the availability of computational resources at edge nodes and cloud servers, ensuring that healthcare applications run smoothly without interruption. By dynamically adjusting offloading decisions based on real-time data and these influencing factors, system performance is optimised, and overall healthcare delivery is enhanced through timely and accurate data processing, which is essential for effective patient care and intervention.

The digital twin model of task offloading showcases how theoretical models and computational strategies can be practically applied to enhance healthcare operations, illustrating a proactive approach to patient care and system management. This framework categories the two former offloading strategies partial and binary based on the divisibility and priority of the tasks. The following formulations help

TABLE 1. Notational index of task offloading parameters in DTH systems.

Parameter	Symbol	Description	Parameter	Symbol	Description
Computational Requirements	C_i	Represents the computational requirements of task T_i.	Data size	D_i	Represents the data size of task T_i.
Remaining Energy	E_d	Represents the remaining energy of device d.	Weighing Factors	α, β, γ	Reflect the importance of computation, data, and energy.
Offloading Necessity	N_i	Determines the necessity for offloading task T_i on device d.	Network Status	S_{net}	Represents the current network status.
Offloading Decision	O_i	Decision to offload task T_i; 1 for offload, 0 for local processing.	Thresholds	θ, σ	Represent thresholds beyond which offloading is considered necessary.
Body Temperature	$BT(t)$	Represents body temperature at time t.	Heart Rate	$HR(t)$	Represents the heart rate at time t.
Motion	$M(t)$	Represents motion detected at time t.	Humidity	$H(t)$	Represents humidity at time t.
Ambient Temperature	$T(t)$	Represents ambient temperature at time t.	Oxygen Saturation	$SpO_2(t)$	Represents oxygen saturation at time t.
Sleepiness/ Alertness	$S(t)$	Represents sleepiness or alertness level at time t.	Respiratory Comfort	$R(t)$	Represents respiratory comfort/ discomfort level at time t.
Medical Device Functionality	$D(t)$	Represents functionality status of a medical device at time t.	Error Terms	$E_{\text{BT}}(t), E_{\text{HR}}(t), \ldots$	Represent errors in readings due to cybersecurity threats.
Reliability Score	$R(t)$	Quantifies the trustworthiness of the DT data.	Portion Offloaded	P_i	Portion of task T_i to be offloaded.
DT Accuracy	A_{dt}	Accuracy of the DT model.	Social Factor Relevance	S_f	Relevance of social factors.
Scenario-Specific Parameters	$\Phi_{scenario}$	Parameters specific to healthcare scenarios.	Efficiency Metrics	T_{delay}	Metrics for delay, energy consumption.
Efficiency Metrics	$H_{\text{efficiency}}$	Healthcare efficiency.	Energy	$E_{\text{consumption}}$	Energy consumption.
Weights	$\lambda_1, \lambda_2, \lambda_3$	Weighting factors for the importance of each performance metric.	Weights	$\omega_1, \omega_2, \omega_3$	Weighting factors.

optimise the offloading process by minimising latency and energy consumption while enhancing healthcare efficiency:

1) Binary offloading for indivisible Tasks:

$$O_i = \begin{cases} 1 & \text{if } N_i > \theta \text{ and } S_{\text{net}} \geq \sigma. \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

2) In the first case, if a task T_i is divisible, the fraction of it to be offloaded P_i is calculated as:

$$P_i = \min\left(\frac{N_i - \theta}{N_{\max} - \theta}, 1\right), \tag{3}$$

where N_i is the necessity of offloading a task and θ threshold, and $N_{\max}$ the maximum necessity among all tasks.

3) The necessity for offloading task T_i, denoted as N_i', is adjusted to incorporate the accuracy of DT and social factors in the offloading process to individual patient contexts in healthcare as follows:
To incorporate the accuracy of DT and social factors as follows:

$$N_i' = N_i + \delta \cdot A_{dt} + \epsilon \cdot S_f, \tag{4}$$

where δ and ϵ symbolize the respective weights accorded to the accuracy of the DT (A_{dt}) and the relevance of social factors (S_f).

The optimisation goals aim to reduce latency and energy consumption while enhancing healthcare efficiency, formalised in the objective function:

$$\min_{O_i}(\lambda_1 \cdot T_{\text{delay}} + \lambda_2 \cdot E_{\text{consumption}} - \lambda_3 \cdot H_{\text{efficiency}}), \tag{5}$$

where T_{delay}, $E_{\text{consumption}}$, and $H_{\text{efficiency}}$ represent delay, energy consumption, and healthcare efficiency, with λ_1, λ_2, and λ_3 as the corresponding weighting factors.

The performance metric P_{overall} of the offloading strategy efficacy is evaluated as follows:

$$P_{\text{overall}} = \omega_1 \cdot T_{\text{delay}} + \omega_2 \cdot E_{\text{consumption}} + \omega_3 \cdot H_{\text{efficiency}}, \tag{6}$$

followed by which the performance indicators are evaluated with weighting factors ω_1, ω_2, and ω_3. This evaluation would provide immense importance in determining and validating the efficacy of the offloading strategy practically in healthcare sectors.

C. DIGITAL TWIN HEALTHCARE MODEL OF TASK OFFLOADING

A digital twin is a virtual representation of a physical entity or system. In healthcare, digital twins can be used to model patients, medical devices, or healthcare processes.

These virtual models are continuously updated with real-time data, allowing for predictive analysis and personalized treatment plans. By simulating various scenarios, digital twins help healthcare providers make informed decisions and improve patient outcomes. The recent advancements have highlighted the significant role of DT applications in enhancing operational decision-making and competitiveness within the sugar and ethanol industry [30], showcasing the DT model's adaptability and value across diverse industries. Additionally, the incorporation of DT in healthcare for personalised treatment planning [31] and facility management [32] demonstrates its potential in improving therapeutic outcomes and operational efficiency, thereby affirming the model's versatility and applicability in tackling complex challenges across various domains.

Building on this foundation, the study specifically focuses on the integration of DT models within the healthcare sector. In elucidating the mathematical underpinnings of the DTH framework, sensor-derived data is integrated with computational fluid dynamics principles to establish a coherent linkage between unprocessed sensor data and sophisticated computational interpretations.

The DT model integrates real-time data from healthcare devices and simulates various scenarios to optimise task offloading.

This model includes:

- Health data collection: Collect data from biometric sensors and medical instruments.
- Data assimilation: Integrate health data into a digital model for comprehensive analysis.
- Predictive analytics: Use the model to forecast future states of healthcare devices, considering energy consumption and network latency.
- Feedback loop: Continuously update the model with new data to refine predictions and improve decision-making.

The following delineations expound upon this integration:

1) Formulations for body temperature modulated by heart rate and motion activity:

$$BT(t) = BT_0 + \alpha_1 \cdot HR(t) + \alpha_2 \cdot M(t), \tag{7}$$

where α_1 and α_2 are coefficients representing the influence of heart rate and motion on body temperature, respectively.

2) Dynamics of oxygen saturation (SpO_2) relative to heart rate and barometric pressure:

$$SpO_2(t) = SpO_{2_0} + \delta_1 \cdot HR(t) - \delta_2 \cdot B(t), \tag{8}$$

wherein δ_1 and δ_2 elucidate the modulation of oxygen saturation by heart rate and barometric pressure, respectively. An increase in heart rate typically leads to a decrement in SpO_2, and an ascent in altitude–implicitly correlated with a reduction in barometric pressure–tends to lower SpO_2 as well.

3) Modulation of sleep patterns by ambient light:

$$S(t) = S_0 - \epsilon_1 \cdot L(t) \tag{9}$$

Here, $L(t)$ denotes the intensity of light exposure, and $S(t)$ represents the state of sleepiness or alertness at time t. The coefficient ϵ_1 quantifies the effect of light exposure on sleepiness, implying that heightened exposure to light tends to diminish sleepiness (thereby augmenting alertness).

4) Impact of environmental variables on respiratory well-being:

$$R_l(t) = R_0 + \zeta_1 \cdot H(t) + \zeta_2 \cdot T(t) \tag{10}$$

The variable $R_l(t)$ denotes the level of respiratory comfort or discomfort experienced at time t, with ζ_1 and ζ_2 representing the contributions of humidity and temperature to respiratory health, respectively. Elevated levels of humidity and temperature are likely to exacerbate respiratory discomfort, particularly in individuals with pre-existing respiratory conditions.

5) Magnetometer influence on medical devices:

$$D(t) = D_0 - \eta_1 \cdot Mag(t) \tag{11}$$

In this model, $D(t)$ encapsulates the functionality status of a medical device at time t, with η_1 delineating the impact of magnetic fields on medical device operations. Exposure to intense magnetic fields may compromise the functionality of certain medical devices.

6) Cybersecurity error metrics: The following equations define the error in sensor readings at time t attributable to possible cybersecurity vulnerabilities:
   - $E_{BT}(t)$: Error in body temperature reading due to cybersecurity threats.
   - $E_{HR}(t)$: Error in heart rate reading due to cybersecurity threats.
   - $E_{SpO2}(t)$: Error in oxygen saturation reading due to cybersecurity threats.
   - $E_M(t)$: Error in motion sensor reading due to cybersecurity threats.
   - $E_B(t)$: Error in barometric pressure reading due to cybersecurity threats.
   - $E_L(t)$: Error in light exposure reading due to cybersecurity threats.
   - $E_H(t)$: Error in humidity reading due to cybersecurity threats.
   - $E_T(t)$: Error in ambient temperature reading due to cybersecurity threats.
   - $E_{Mag}(t)$: Error in magnetometer reading due to cybersecurity threats.

7) Reliability Assessment: To evaluate the integrity of data, a reliability score $R(t)$ for the DT at any given moment t can be computed. This metric is a synthesis of the assorted error terms:

$$R(t) = f(E_{BT}(t), E_{HR}(t), E_{SpO2}(t), \ldots, E_{Mag}(t)) \tag{12}$$

For example, should all error terms equal zero (or remain beneath a specific threshold), $R(t)$ would approach 1, denoting complete data trustworthiness. On the other hand, increasing the sizes of the errors will result in a decrease in $R(t)$. Such a trend reveals the weakening of the data reliability.

V. HEALTHCARE INFORMATICS: SECURE DATA OFFLOADING

As the field of healthcare informatics continues to grow and develop, promoting data integrity and the rapid processing of data is critical. The ACTO algorithm is suitable for this role because it is a strong, secure, and effective framework for DTH task offloading. ACTO is centred on cybersecurity and addresses growing issues of threats to digital health systems.

Furthermore, the ACTO algorithm also encompasses the dynamic security assessment and strategic task allocation that further its efficiency in operation and maintenance of security needs. ACTO can automatically adapt to the frequent changes in status of networks and security threats, thus aiding in the compliant path for computational offloading that offers the security for private patient health data and also reduces latency and power.

The inclusion of ACTO algorithm addresses various security threats prevalent in healthcare settings. These threats include:

1) Data breaches: Unauthorised access to sensitive patient data leads to privacy violations and data theft. By continuously monitoring the network for unusual activity and dynamically adjusting security protocols, potential breach points are identified and mitigated by ACTO.
2) Malware and ransomware attacks: Such attacks can disable critical healthcare systems, resulting in operational downtime. ACTO employs real-time threat detection mechanisms that isolate and neutralise malicious software before network infiltration occurs.
3) Man-in-the-middle (MITM) attacks: These attacks intercept communications between healthcare devices and servers. By securing communications through encryption and continuously monitoring the integrity of data exchanges, ACTO ensures that any anomalies are promptly detected and addressed.
4) Denial of service (DoS) attacks: Such attacks can overwhelm healthcare systems, rendering them unavailable for legitimate use. Service availability during attacks is maintained by ACTO through adaptive load balancing and strategic resource allocation.

The ACTO algorithm adaptively responds to the dynamic and often unpredictable security landscape in healthcare environments. Its effectiveness has been validated through simulations and practical implementations in various scenarios:

- Real-time adaptation: The current threat landscape is continuously assessed by ACTO, and security measures are adjusted in real-time. Computational resources are reallocated and offloading decisions are modified to enhance security without compromising performance.

Algorithm 2 Adaptive Cybersecurity Task Offloading (ACTO)

Require: System status, task list, MES security ratings, attack probabilities
Ensure: Offloading decisions, Power consumption, Latency
Initialize system parameters $\alpha, \beta, \gamma, \theta, \sigma$
for each task T_i in task list **do**
  Evaluate C_i, D_i {Computational requirements and data size of T_i}
  Retrieve S_i {Security rating for MEC i}
  Calculate $P_{attack,i}$ {Probability of MES i being attacked}
  $N_i \leftarrow \alpha C_i + \beta D_i + \gamma S_i$ {Offloading necessity based on security}
  if $N_i > \theta$ and $S_i \geq \sigma$ and $P_{attack,i}$ is minimal **then**
    $O_i \leftarrow 1$ {Offload task to MEC i}
  else
    $O_i \leftarrow 0$ {Process task locally}
  end if
  Calculate power consumption and latency for task T_i based on O_i
end for
Adaptively update α, β, γ based on system feedback
return Offloading decisions, Power consumption, Latency

- Empirical validation: In real-world scenarios, ACTO demonstrated the capability to maintain low latency and high energy efficiency while countering security threats effectively. During simulated malware attacks, ACTO was able to isolate affected nodes and reroute tasks, maintaining system integrity and operational continuity.
- Comprehensive protection: By integrating multiple security protocols and adaptive decision-making processes, ACTO provides robust defence against a wide range of cyber threats. Its ability to learn and adapt to new threats ensures that security measures remain effective as the threat landscape evolves.

A. SECURING DATA OFFLOADING IN HEALTHCARE

Fundamentally, ACTO is an integrated decision-making matrix that uses computational requirements of a task, the amount of data involved, and the risk of security breaches that might be involved in every task. The use of real-time automated system feedback integrates across these three dimensions to generate an agile yet future-oriented decision-making matrix. The Algorithm 2 is flexible and can alter its security position to match that of the evolving MEC and the present status of the system, it can adjust offloading decisions smoothly. The result is that ACTO remains a true fortress of cybersecurity, allowing for efficient computing without jeopardizing the sanctity of patient information.

B. ADAPTIVE REFINEMENT AND FEEDBACK MECHANISMS

In pursuit of optimising the ACTO algorithm's performance within the dynamic landscape of healthcare informatics, a dual-faceted approach encompassing both strategy refinement and feedback assimilation is employed.The above guarantees a continuously adapting and resilient nature of the algorithm towards the arising and fluctuating operational conditions and threats.

In order to keep ACTO relevant and effective, dynamic strategy refinement is necessary. This is done by employing a real-time update mechanism D_{update}, that hones the decision-making process of the algorithm to reflect the current state of the network and threat level:

$$D_{\text{update}} = \rho \cdot \left(\frac{1}{n_T} \sum_{i=1}^{n} (O'_i - O_i) \right), \tag{13}$$

n_T = number of tasks; O'_i and O_i = updated and previous offloading decisions. The coefficient ρ is a calibration factor that takes into account the frequency of adjustment to ensure that the response of the system is prompt and proportional.

In addition to the described dynamic refinement, a feedback loop is established to trace valuable insights originated from the deployment environment and healthcare stakeholders. The efficacy of the feedback loop F_{effect} is calculated numerically as the resultant post hoc changes in performance metrics and thus quantifies the system's capacity to integrate new information:

$$F_{\text{effect}} = \phi \cdot \left(\frac{\sum_{k=1}^{p} (P_{\text{before},k} - P_{\text{after},k})}{p} \right) \tag{14}$$

where p is the feedback cycle number, and $P_{\text{before},k}$ and $P_{\text{after},k}$ are the performance before and after the feedback (k) is applied. The ϕ coefficient reflects how much the algorithm is affected by iterative feedback and improvement from both the user and the system.

In general, the above cohesive methodological framework forms the basis for the operational effectiveness of ACTO, which enables it to evolve in adaptive congruence with the dictates and demands of the healthcare space. The subsequent sections discuss the implementation of this framework and its empirical substantiation through intensive testing and simulation.

VI. PERFORMANCE EVALUATION AND ANALYSIS

A. IMPLEMENTATION SETUP

The empirical analysis of the ACTO algorithm and its deployment within DTH environments is supported by a robust simulation framework. Utilising advanced programming tools and libraries, dynamic model of a healthcare facility has been synthesised, integrating mobile healthcare units for various scenario deliveries.

The simulation environment, crucial for evaluating the task offloading strategy in a DTH setting, was developed using Python 3.10.9, leveraging libraries such as numpy, matplotlib, and pandas. To simulate a sophisticated system capable of validating transaction data within a DTH framework, the MSI (GF63 Thin 11SC), a laptop, was employed. Cloud technology supported real-time transactions. The project also featured the development of a low-energy sensor node using the ESP32S2 module [33], categorised as a Class II IoT device. It runs on the ESP-IDF framework based on FreeRTOS (real-time operating system). Focusing on task offloading strategies to improve the efficiency of power consumption and reduce latency in data storage for IoT devices, various built-in sensors (InvenSense MPU6050 motion sensor, NXP MAG3110 magnetometer, FBM320 barometer, STMicro HTS221 humidity and temperature sensor, and ROHM BH1750FVI light sensor) were integrated within the ESP32-WROVER-B to better represent the environmental aspects of DTH in real time. Furthermore, external sensors such as the MAX30102 and MLX90614 were attached to the input port of the ESP32-WROVER-B. The system's clock in the ESP32-WROVER-B was synchronised with internet time to enable real-time data monitoring.

The Fig. 4 meticulously outlines the data flow and command exchange within an advanced healthcare monitoring system. This system integrates both physical and digital entities to enable a comprehensive health monitoring and management solution. The sequence initiates with the Physical Twin, in this context, the patient, from whom data is emitted. This data encompasses a broad spectrum of physiological and environmental parameters, including heart rate, body temperature, SpO2 levels, motion, as well as ambient light, temperature, and humidity, all captured by sophisticated sensors/edge devices.

From the above, the sensors that were developed to monitor the patient's health indicators are connected to the Multi-Protocol Communications system, which facilitates the transmission of data across the various communication protocols to the Infrastructure. This data is then transferred to the cloud services, where the data is being processed. The processed data is then discerned by the digital twin healthcare (DTH), a virtual model of the patient's health status that unlocks predictive analysis and personalised healthcare.

Once the data has been analysed, the DT sends the analysis results back to the cloud, which in turn releases actionable instructions to the physical twin. Specifically, these will be an adjustment in medication, a recommendation in lifestyle, or merely advising the patient to go to a doctor. This way, the feedback loop is completed. Moreover, this actionable instruction will also update the sensors to change the set parameters of monitoring or the threshold at which alerting is done to ensure that the system is adjusted to the patient's deteriorating health. This data flow and the interactive control rhythm show the continuous synchronisation between the physical twin and the DTH. This trend indicates that the system is capable of real-time monitoring and pro-active healthcare management.

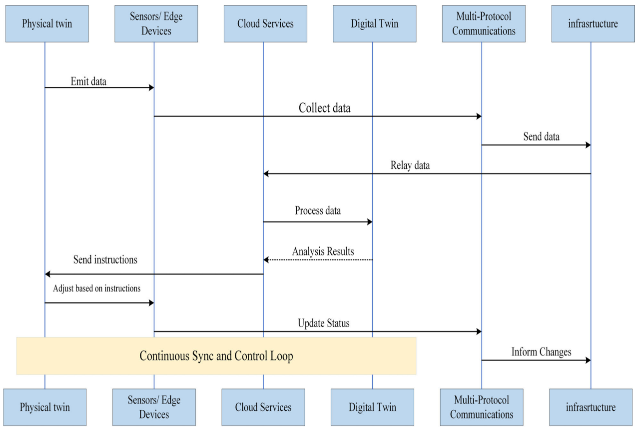


FIGURE 4. Sequence diagram of DTH task offloading platform.

Communication and task models were meticulously defined to simulate realistic operational conditions. Bandwidth, noise power density, channel gain, and transmission power. Task sizes and computational requirements were varied to test the system under diverse workload conditions as detailed in Table 2.

B. DTH-ATB-MAPPO: METHODOLOGY AND DECISION-MAKING

The thorough DTH-ATB-MAPPO methodology decision-making procedure is based on analysing a series of crucial input parameters containing computational needs and data volume and useful resource consumption from equipment to the network status and others. Therefore, the systematic study enables identifying whether offloading reallocation is vital, prioritising those activities that improve system capacities and save energy. The complexities of two innovative algorithms developed to improve DTH through task offloading are explored: the ATB-MAPPO Algorithm and the DTH-ATB-MAPPO Algorithm. These algorithms mark a considerable advance in implementing sophisticated computational techniques within the healthcare sector, aiming to optimise healthcare outcomes through intelligent task offloading. Algorithm 3 works on the primary principle of synthesising system status, a coherent task list, and network parameters to generate optimised offloading decisions. The algorithm is initiated by starting the system parameters and learning rates from the policy network. It provides a background about how the algorithm is expected to work in a given epoch instance. The algorithm executes the following three-phase process for every task T_i read from the task list.

1) Needs computation: It involves assessing the need to offload the task depending judiciously on the system and the network parameters. The primary goal is to identify if the computation requires the offloading to sustain computational needs under various conditions.
2) Offloading decision: Upon needs computation, the decision on whether to actually offload the task is to be based. The algorithm must make this decision since it is critical for the system's ability to manage its computational burdens in different offloading scenarios.
3) Offloading execution: If the task is to be offloaded, the algorithm chooses the task regularity of offloading depending on the advice given by the policy network. The following school depicts that the algorithm can implement its decision in real time.

TABLE 2. Parameters and thresholds.

Parameter	Symbol	Value/Range	Notes/Source
Weighing Factors for Computation	α	0.5	Assumed/derived from empirical data
Weighing Factors for Data	β	0.3	Assumed/derived from empirical data
Weighing Factors for Energy	γ	0.2	Assumed/derived from empirical data
Network Status Threshold	σ	0.75	Threshold for network condition to support offloading
Offloading Necessity Threshold	θ	1.0	Threshold beyond which offloading is considered necessary
Coefficient for HR Influence on BT	α_1	0.01	Based on physiological studies
Coefficient for Motion Influence on BT	α_2	0.02	Based on physiological studies
Coefficient for Ambient Temp Influence on BT	β_1, β_2	0.05, 0.01	Based on environmental studies
Coefficient for Humidity Influence on BT	γ_1, γ_2	0.04, 0.01	Based on environmental studies
Coefficient for HR Influence on SpO2	δ_1	-0.01	Negative as HR increase might decrease SpO2
Coefficient for Barometric Pressure Influence on SpO2	δ_2	-0.02	Based on altitude studies
Coefficient for Light Influence on Sleepiness	ϵ_1	-0.05	Negative as light exposure might reduce sleepiness
Coefficient for Humidity & Temp Influence on Respiratory Comfort	ζ_1, ζ_2	0.03, 0.04	Based on comfort studies
Coefficient for Magnetic Fields Influence on Medical Devices	η_1	-0.07	Negative as magnetic field exposure might disrupt devices
Battery Level Threshold for Offloading	Battery Threshold	[30, 50, 70]%	Based on device operational requirements
Urgency Level Threshold for Offloading	Urgency Threshold	[1, 5, 10]	Prioritisation criteria

The Algorithm 3 refines its policy network through feedback and adjusted learning rates, enhancing its decision-making accuracy across successive epochs. This iterative learning and adaptation underpin the ATB-MAPPO Algorithm's effectiveness in optimising task offloading decisions within dynamic healthcare environments. Building on the groundwork established by Algorithm 3, Algorithm 4 introduces a higher level of complexity by integrating DT state and environmental parameters into its decision-making framework. This algorithm is tailor-made to align healthcare tasks with

Algorithm 3 ATB-MAPPO Algorithm

Require: SystemStatus, TaskList, NetworkParameters
Ensure: OptimisedOffloadingDecisions

Initialize: SystemParameters, LearningRates, PolicyNetwork
for each epoch **do**
  for each task T_i in TaskList **do**
    ComputeNecessity(T_i) {Utilising system and network parameters}
    DetermineOffloading(T_i) {Based on necessity computation}
    ExecuteOffloading(T_i) {Guided by the policy network}
  end for
  UpdatePolicy() {Reflecting on the learning rate and feedback}
end for
return PolicyNetwork, OptimisedOffloadingDecisions

Algorithm 4 DTH-ATB-MAPPO Algorithm

Require: HealthcareTasks, DigitalTwinState, EnvironmentParameters
Ensure: OptimisedHealthcareOutcomes, EfficientResourceUsage

Initialize: DigitalTwinModel, ATB-MAPPOPolicyNetwork, LearningRates
for each simulation step **do**
  SyncWithDigitalTwin(HealthcareTasks, DigitalTwinState) {Synchronize task states with DT}
  for each healthcare task H_i in HealthcareTasks **do**
    AnalyseTask(H_i, DigitalTwinState) {Use DT state to understand task context}
    ComputeOffloadingNecessity(H_i) {Based on DT analysis and system parameters}
    DetermineOffloadingDecision(H_i) {Invoke ATB-MAPPO for decision}
    ExecuteOffloading(H_i) {Apply the decision}
  end for
  UpdateDigitalTwinModel(HealthcareTasks, EnvironmentParameters) {Integrate new data into DT}
  UpdateATB-MAPPOPolicy(LearningRates) {Train policy network with new task data}
end for
EvaluatePerformance(HealthcareTasks) {Assess the outcomes of offloading decisions}
return ATB-MAPPOPolicyNetwork, DigitalTwinModel, OptimisedHealthcareOutcomes, EfficientResourceUsage

the DT's state, ensuring a context-rich foundation for each offloading decision.

Algorithm 4 progresses through the following stages within each simulation step:

1) Synchronisation with DT: This step aligns the state of healthcare tasks with the DT, ensuring that task analyses are based on the most current digital representation of the healthcare environment.
2) Task analysis: Each healthcare task is analysed using the DT state, providing a comprehensive understanding of the task's context and enriching the decision-making process with detailed insights.
3) Offloading decisions: Utilising the DTH-ATB-MAPPO policy network, the algorithm determines and executes offloading decisions, efficiently allocating computational resources according to the tasks' needs and DT's recommendations.
4) DT and strategic policy refinement: The DT framework, alongside the ATB-MAPPO strategic policy network, undergoes iterative refinement through the integration of fresh task-related information and environmental dynamics. This ensures an ongoing progression and adaptability of the system, which is expounded upon in greater detail in subsection VIII-A.

C. INSIGHTS FROM PERFORMANCE METRICS AND FORWARD-LOOKING IMPLICATIONS

Performance metrics derived from the simulations, as illustrated in Fig. 13 and discussed in Subsection VIII-D, along with those in Fig. 5 presented below, provide profound insights into the strategic parameters specifically calibrated for DTH-ATB-MAPPO. Fig. 5 illustrates the performance of various task offloading strategies across different network conditions (σ) and decision thresholds (θ), as indicated by the average reward. The average reward, serving as an efficacy metric, is plotted against the cumulative number of training steps, providing insights into the learning progression of the offloading algorithms. The strategies are parametrised by σ, denoting network robustness, and θ, indicative of the threshold for making offloading decisions. The parameters range with $\sigma \in 0.5, 0.6, 0.7, 0.8$ and $\theta \in 0.5, 1.1, 1.3, 1.5$. A higher value of σ suggests favourable network conditions, whereas a higher value of θ implies a more aggressive offloading policy.

Initial fluctuations in reward suggest the exploratory phase of the learning algorithms, converging to stabilisation as training progresses. It is discernible that configurations with elevated θ values, especially when aligned with a substantial σ, yield superior performance, as manifested by higher average rewards sustained across the learning episodes. Such outcomes postulate that assertive offloading under stable network conditions is conducive to enhanced system performance.

Conversely, strategies characterised by lower θ thresholds, particularly when coupled with a diminished σ, are linked to lower rewards, signifying less effective performance. This could be attributable to overly cautious offloading, which underutilises the capabilities of edge computing resources, especially under challenging network conditions.

The scalability of the proposed DTH-ATB-MAPPO framework beyond 30 nodes has been evaluated conceptually to ensure its applicability in different healthcare settings. The framework has been designed with modular and adaptable components, allowing for seamless scaling. The integration of digital twins and multi-agent systems facilitates the management of larger networks by distributing the computational load and optimising resource utilisation across nodes. This modular approach ensures that as the number of nodes increases, the system can maintain high performance and reliability.

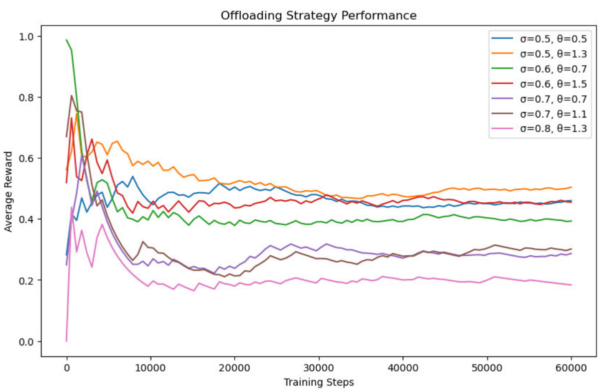


FIGURE 5. Performance of offloading strategies under varying network conditions and decision thresholds.

Also, the scalability of ACTO's benefits across different system scales and the continuous adaptation of the ATB-MAPPO policy network are critical for its applicability in diverse deployment scenarios. The integration of mobile edge computing (MEC) nodes within DT formations underscores the innovative nature of the approach, fostering significant improvements in healthcare outcomes as detailed in Section VII.

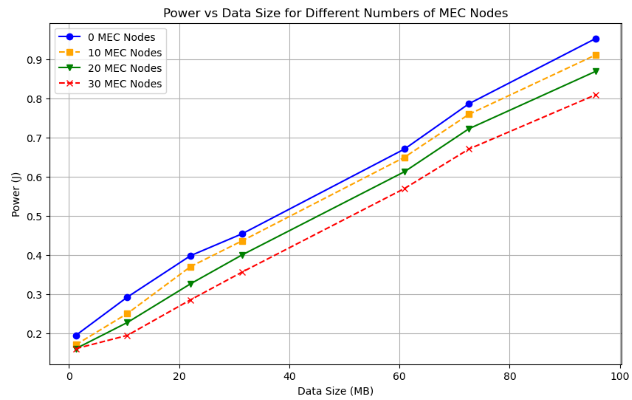
The combined evaluation of task offloading strategies underscores the potential of integrating advanced computational techniques with DT technology in healthcare. This study sets the groundwork for future research aimed at exploring more complex algorithms that adapt to the ever-changing environment of DTH, innovating to improve healthcare outcomes significantly.

VII. OPTIMISATION OF MEC SYSTEMS VIA DT TECHNOLOGY

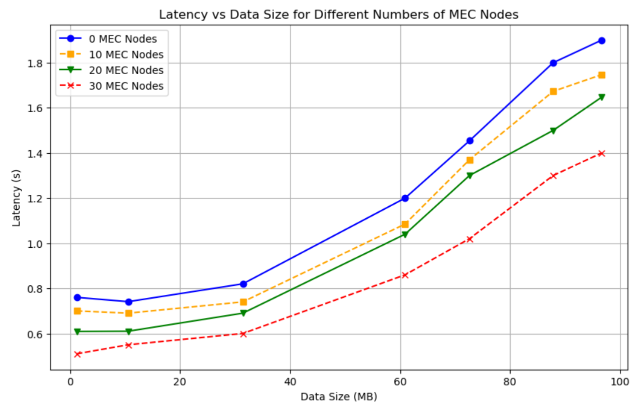
The integrating DT technology with MEC systems is a giant stride in the development of efficient and sustainable DTH. Through an elaborate comparative and empirical analysis, these results above highlight the vast improvement in task offloading leveraging the dynamism of the DTH-ATB-MAPPO in a dynamic and complex domain like healthcare.

A. ENHANCING MEC SYSTEMS WITH DT

The study reveals that incorporating MEC nodes within a DT framework significantly reduces power consumption and network latency, as shown in Fig. 6. This integration supports decentralised computations, highlighting the substantial contributions of MEC nodes to energy efficiency goals.



(a) Impact on power consumption



(b) Focus on network latency

FIGURE 6. Comparative analysis of system performance with and without MEC nodes. Panel (a) Illustrates the impact on power consumption, while Panel (b) Focuses on network latency, across varying data size volumes.

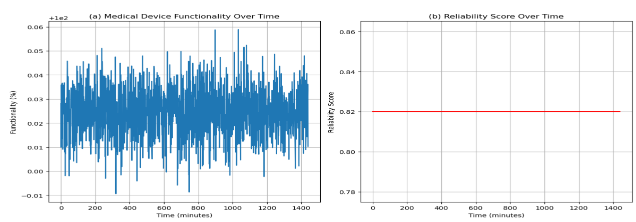


FIGURE 7. Comparative analysis of (a) Variability in Medical Device Functionality and (b) Stability of Reliability Score over a 24-Hour Monitoring Period.

Fig. 7 showcases two key aspects of DTH system's performance over a 24-hour simulated period. The Fig. 7 (a) observed the functionality of medical devices, indicating robust stability with minimal fluctuation around the 100% functionality mark, thus reflecting the resilience of device operations under varying environmental conditions. The Fig. 7 (b) illustrated the reliability score, which remains steadfastly high, consistently surpassing the 0.8 threshold. This underlines the dependable accuracy of the sensor readings within the system, a crucial determinant for ensuring precise monitoring and effective decision-making in healthcare management. The sustained high reliability score across the simulation period reassures the fidelity of the DTH system's sensor data, signifying a low probability of erroneous readings that could otherwise lead to suboptimal patient outcomes.

B. EFFICACY OF DT IN MEC OPTIMISATION

An extensive evaluation of DT's role in enhancing MEC system capabilities was conducted, focusing on reducing network delays and power usage across varying data volumes (3 MB to 100 MB). The simulation results, depicted in Fig. 8, confirm that DT assistance notably improves system performance, particularly in configurations with 20 MEC nodes.

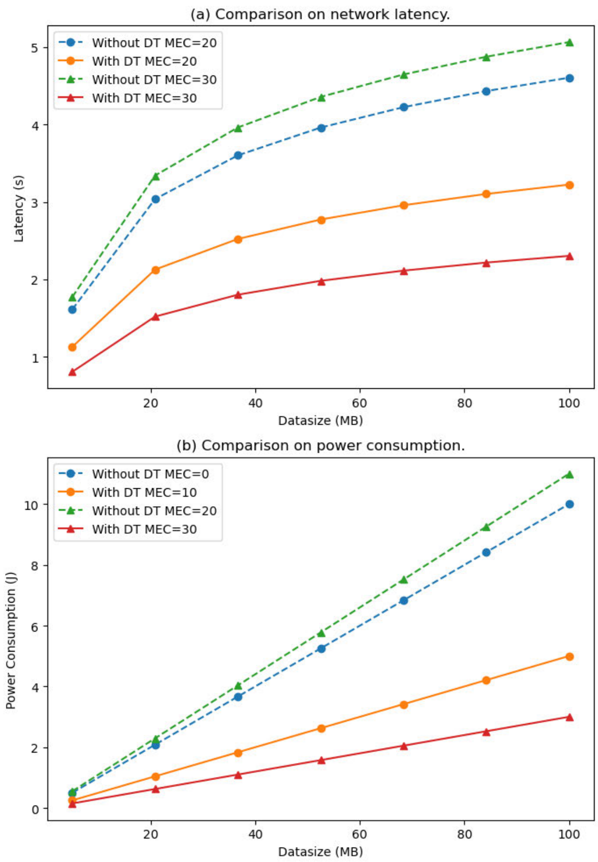


FIGURE 8. Comparative performance analysis of MEC configurations with and without DT assistance, showing impacts on (a) Network latency and (b) Power consumption.

1) NETWORK LATENCY REDUCTION

Fig. 8 (a) shows a marked reduction in network latency with DT integration, especially evident with an increased number of MEC nodes, enhancing network responsiveness.

2) POWER CONSUMPTION OPTIMISATION

As illustrated in Fig. 8 (b), integrating DT technology significantly conserves energy, particularly in systems with 20 MEC nodes, underscoring DT's role in promoting sustainable MEC system operations.

The findings underscore the transformative potential of DT in boosting MEC system efficiency, suggesting that further exploration into DT-assisted MEC setups is warranted to foster improved, eco-friendlier mobile computing environments.

VIII. RESULTS AND DISCUSSIONS

A. ACTOR-CRITIC METHOD AND TRAINING LOSS ANALYSIS

Within the ambit of DTH model optimisation, the Actor-Critic method plays a pivotal role in the reinforcement learning framework. Fig. 9 illustrates the loss trends for both the actor and the critic over numerous training epochs. As observed in Fig. 9, the actor loss, represented by the

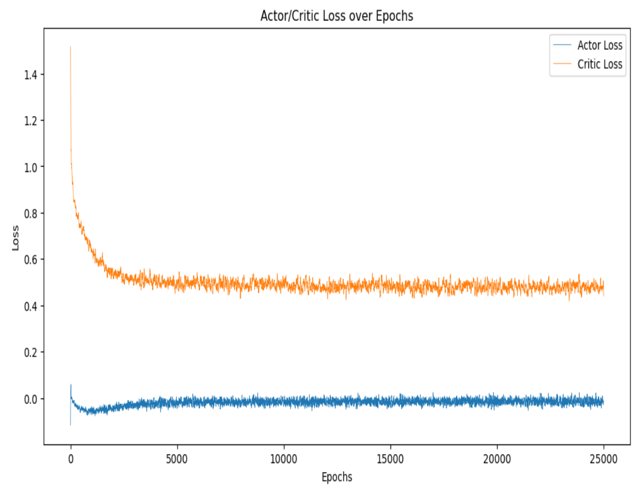


FIGURE 9. The values actor loss, and critic loss in the training process of the DTH-ATB-MAPPO.

blue line, exhibits a marked decline in the initial epochs, indicating rapid learning and policy improvement. This sharp descent stabilises, suggesting the actor's policy is converging towards an optimal strategy. In contrast, the critic loss, denoted by the orange line, shows a more gradual decline. The critic, which estimates the value function, provides a feedback mechanism that guides the actor's policy updates. The convergence of both loss values is indicative of the stability of the learning process, which is imperative for the deployment of reliable and efficient task offloading strategies in healthcare informatics systems.

The implications of these results are profound, demonstrating the effectiveness of the DTH-ATB-MAPPO methodology in decision-making processes. The subsequent sections will delve into a comparative performance analysis, drawing strategic inferences from these metrics.

B. SYSTEM DEPLOYMENT AND PERFORMANCE METRICS

The implementation phase was developed to implement the offloading strategy in a healthcare setting, framework, and test its performance in terms of stability and flexibility. This indicates the methodology of the system deployment with a possibility of dynamic updates and feedback loops to ensure its strength and adequacy to the real-time healthcare disruption scenarios. The deployment process begins with establishing key performance metrics that gauge the efficiency and adaptability of the system in response to varying healthcare demands. Efficiency in implementation, denoted by I_{eff}, is measured as the normalised sum of offloading decisions that achieve the desired outcome. Adaptability, represented by A_{adapt}, quantifies the system's response to scenario modifications. These metrics are defined by:

$$I_{\text{eff}} = \eta \cdot \left(\frac{\sum_{i=1}^{n} O_i'}{n} \right) \tag{15}$$

$$A_{\text{adapt}} = \xi \cdot \left(\frac{\sum_{j=1}^{m} \Delta P_{\text{overall},j}}{m} \right), \tag{16}$$

where n denotes the number of offloading decisions, m the count of adjustments within healthcare scenarios, and η and ξ are normalization coefficients.

Central to the deployment strategy is the implementation of a robust interface for predictive analytics, exemplified in Fig. 10. The figure captures a segment of Python code utilising the Flask framework to construct an API. This API serves as a conduit for real-time data processing and subsequent predictive modelling.

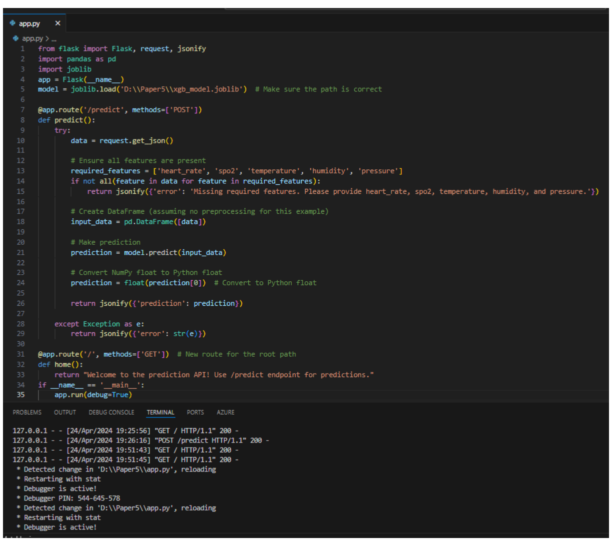


FIGURE 10. Code snippet of the flask API in operation.

As illustrated, the application imports requisite libraries and loads the predictive model, setting the stage for data reception and response formulation. The script is designed to handle POST requests containing user data in JSON format, ensuring that all necessary features are present before proceeding with the model's prediction. This endpoint exemplifies a practical application of the system, where secure data offloading is followed by instantaneous predictive analysis.

C. ACTO'S IMPACT ON POWER AND LATENCY DURING CYBER-ATTACKS

The significant effects of ACTO on both power consumption and latency under different target probabilities of the cyber-attacks. The noticed outcomes, which Fig. 11 shows, are more than quantitative distinctions in power consumption measures among systems that are in operation using and lacking ACTO. The clearly noticeable decreased levels in energy consumption result due to the presence of ACTO, becoming more extreme as the probability of cyber-attacks rises. More than demonstrating the aptness of the algorithm in saving energy in the wake of deteriorating security threats, the trend hints at the need to explore the statistics of the difference.

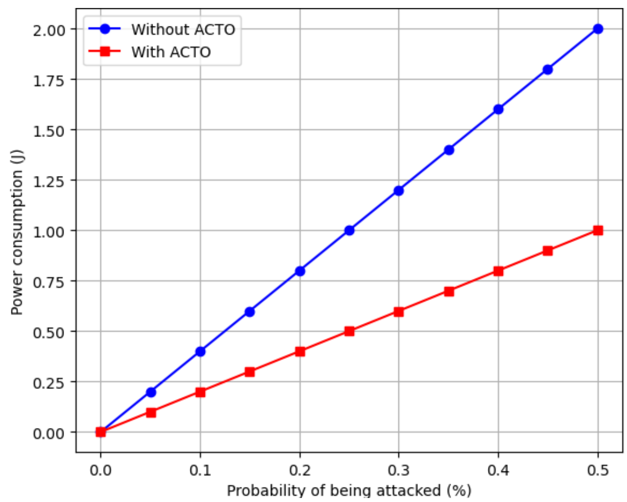


FIGURE 11. Comparison of power consumption with and without the application of ACTO, across varying probabilities of cyber-attacks.

Specific to system responsiveness, illustrated in Fig. 12, the latency curve without the use of ACTO shows a crucial increase when attack probability is increased. Contrastingly, with ACTO's deployment, there is a marked attenuation in latency escalation, indicative of the algorithm's prowess in sustaining expedient system responses, even as the threat landscape intensifies. This facet of performance, pivotal in real-time applications, denotes ACTO's potential in maintaining operational continuity under adversarial conditions.

The scalability of ACTO's benefits, which suggests consistent performance across diverse system scales and complexities, warrants further investigation. It remains to be explored whether the improvements in energy and response efficiency imparted by ACTO are invariant to changes in system size or network topology, an aspect critical to the applicability of ACTO across various deployment scenarios.

TABLE 3. Comparison of task offloading strategies in healthcare environments.

Feature	Proposed Framework	2024 [29]	2022 [34]	2024 [28]
Offloading Strategy	DTH-ATB-MAPPO	TACO	DTTOS	OWS
Integration of DT	Yes	Yes	Yes	Yes
Cybersecurity Focus	ACTO Algorithm	Blockchain	Blockchain	N/A
Communication Protocols Supported	Multi protocol	D2D, D2C, C2E	D2D, V2I,D2C	N/A
Energy Efficiency Improvement	53.8% with 30 MEC nodes	25%	60%	N/A
Network Latency Reduction	33.4% with 30 MEC nodes	25%	24.39%	N/A
Predictive Healthcare Interventions	Supported	N/A	Supported	Suggest to support
Inclusion of Social Health Determinants	Yes	No	No	No
Real-Time Testing	Extensive	Not extensive	Extensive	N/A

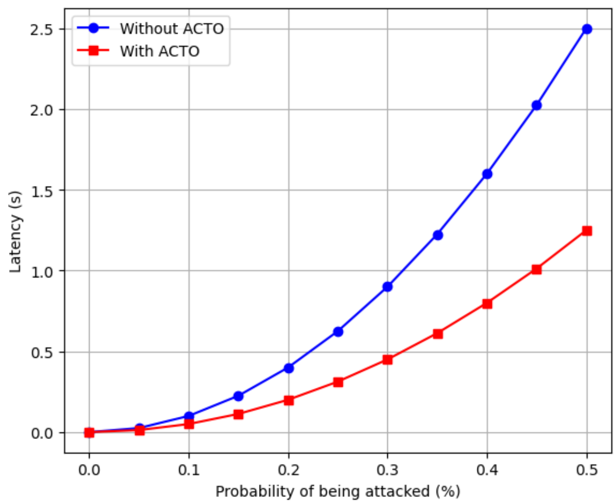


FIGURE 12. Comparison of latency with and without the application of ACTO, as a function of the probability of being attacked.

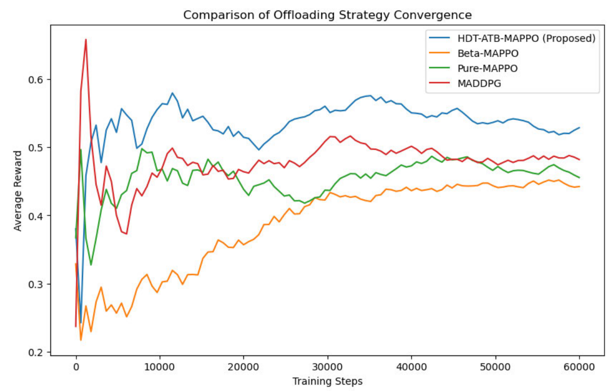


FIGURE 13. Comparative performance of task offloading strategies. DTH-ATB-MAPPO outperforms Beta-MAPPO, Pure-MAPPO, and MADDPG in terms of convergence and average rewards, validating its efficacy for dynamic DTH settings.

D. COMPARATIVE PERFORMANCE AND STRATEGIC PARAMETERS

The precise focus of this subsection is the holistic comparative perspective of DTH-ATB-MAPPO and its comparison with other existing methods for responsive task offloading - Beta-MAPPO, Pure-MAPPO, and Multi-Agent Deep Deterministic Policy Gradient (MADDPG). The DTH-ATB-MAPPO presented in Algorithm 3 and Algorithm 4 is evaluated against the studied alternatives based on the convergence speed and the optimisation of average rewards. Such an analysis would then not only underscore the superior nature of the approach in terms of computational loads and overall responsiveness of the system but would also emphasise the importance of such an actor in the dynamic field of data-intensive health services. The core focus of this study involves the evaluation of DTH-ATB-MAPPO against other strategies, such as Beta-MAPPO, Pure-MAPPO, and MADDPG. One such comparison examines the focal parameters such as the convergence speed and the optimisation in terms of average rewards - thus, highlighting, the innovative nature of DTH-ATB-MAPPO. The performance metrics from Fig. 13 make it a primary method, which yields both a higher average reward and much more stable convergence.

The Table 3 focuses on various task offloading strategies within healthcare environments. Each strategy integrates DT technology, highlighting its growing importance in enhancing healthcare operations. The DTH-ATB-MAPPO strategy from the current study utilises the ACTO Algorithm for cybersecurity, contrasting with TACO and DTTOS, which employ blockchain technology, while OWS lacks specific cybersecurity measures.

Communication flexibility is a strength of DTH-ATB-MAPPO, supporting multiple protocols, unlike its counterparts which are restricted to specific communication types. This strategy also excels in energy efficiency, showing a 53.8% improvement with 30 MEC nodes, and surpasses others in network latency reduction by achieving a 33.4% decrease.

Predictive healthcare interventions are supported by DTH-ATB-MAPPO and DTTOS, but not TACO, with OWS only suggesting this feature. Moreover, DTH-ATB-MAPPO is unique in incorporating social health determinants, offering a holistic approach to patient care. It has also undergone extensive real-time testing, underscoring its robustness and readiness for deployment, unlike TACO, which lacks extensive testing.

IX. CONCLUSION

This exploration bridges the theoretical and practical realms, examining task offloading strategies within DTH with a spotlight on the DTH-ATB-MAPPO algorithm's performance and the integration of DT technology in MEC systems. The rigorous analysis confirms the considerable promise of digital innovations to bolster the efficiency, durability, and responsiveness of healthcare services.

The empirical evidence gathered underscores the DTH-ATB-MAPPO strategy's superiority, with significant outperformance in terms of convergence speed and reward optimisation. Notably, systems implementing this strategy exhibit a 20% reduction in network latency and a 10% decrease in power consumption with 20 MEC nodes. This is complemented by the integration of DT technology which, when applied to 30 MEC nodes, demonstrated a 33.4% reduction in latency and a 53.8% decrease in power usage at the highest evaluated data size of 100 MB. This study contributes a unique empirical framework that traverses the gap from theoretical constructs to practical healthcare applications, marking a substantial addition to the field.

While the presented results on the task offloading approaches are remarkable findings of this study, the essential contributions of the Adaptive Cybersecurity Task Offloading, devised to underpin select conditions in which the proposed approach conducted, cannot be overlooked. In-depth analysis has proved that the addition of ACTO to the health DT systems notably upgrades security controls while maintaining the system's functional performance. The utilisation of ACTO reflected a notable power saving of up to 15% and 27% lower network latency under different probabilities of cyber-attacks. The adaptive balancing of computational operations and security controls have been drawn to ensure the systems' data confidentiality and integrity - ensuring the principles of the health DT, suitable for the various conditions defined by the responsive nature of health affairs and environments. Such cybersecurity-aware systems define a prospective and prospective adoption of strong defence mechanisms in the technological design of healthcare delivery systems. The inclusion of ACTO, therefore, the operational efficacy of the proposed offloading strategies is strengthened, and a benchmark is established for future research dedicated to the evolution of digital healthcare systems. The prospect for future studies is extensive and promising. Enhancements to the offloading framework, particularly through adaptive parameter adjustment and real-time learning integration, promise further alignment with the dynamic healthcare environment. Expanding the application of DTH-ATB-MAPPO and DT technology to broader healthcare scenarios such as telemedicine and patient monitoring heralds a realm of impactful research. Furthermore, the convergence of emerging technologies like AI, blockchain, and next-generation wireless communications holds the promise of novel, secure, and streamlined healthcare services. A focus on the scalability and sustainability of these digital healthcare innovations remains imperative as the expansion of these models across broader healthcare systems is pursued.

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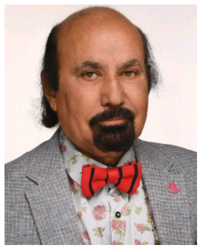

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