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Medical Data Integration and Interoperability through Remote Monitoring of Healthcare Devices

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Abstract

In the age of intelligent gadgets and interconnected communities, the widespread surveillance and provision of healthcare to patients are made feasible through the Internet of Medical Things (IoMT). The number of implanted electronic devices that can be monitored remotely is increasing, leading to a rise in the amount and intricacy of biological data. The collected data can offer valuable diagnostic information that can be used to intervene and maintain implanted devices promptly, therefore enhancing the quality of treatment provided. Current remote monitoring processes are not fully using device diagnostics because of the lack of compatibility and data integration between exclusive applications and Digital Health Record (DHR) platforms. Establishing a technology framework that establishes information and enhances interoperability has the potential to strengthen remote monitoring. This article introduces the Medical Data Integration and Interoperability via Remote Monitoring of Healthcare Devices (MDII-RMHD) framework, which facilitates the collaboration of healthcare devices. MDII-RMHD enhances a cloud-based IoMT system using conversion resources at the network's boundary. This is achieved through the use of inquiring and

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conversion agents. The investigating devices keep track of a list of MDII-RMHD devices on the regional network and allow one device to seek information conversion from another gadget when the requesting device cannot do the task independently. The converting agent transforms the data into the necessary format and returns it to the original entity. These agents enable IoMT devices to utilize their surplus computational capabilities for data translations, reducing the need for cloud access. Conventional devices are compatible with fog resource managers that have MDII-RMHD support. We assess the MDII-RMHD framework by rigorous experimentation under different scenarios. The obtained results demonstrate that the proposed framework decreases the amount of uplink traffic and enhances the response time. This improvement in response time is significant for real-time healthcare applications.

Keywords: IoMT, Medical Data, Integration, Interoperability, Remote Monitoring, Healthcare Devices, Cloud Devices.

1 Introduction

The progress made in engineering and computer science has resulted in notable enhancements in the functionalities of implanted medical devices and remote monitoring systems. The transition towards a patient-centered healthcare paradigm has opened up novel opportunities for leveraging data derived from Healthcare Devices (HDs) to enable patients to effectively take charge of their health and actively participate in their healthcare (Gilbert & Laporte, 2023; Muralidharan, 2020). The existing remote monitoring strategy is predominantly focused on the system, with patients receiving minimal or negligible individual information from their devices. The initial stage of evaluating patient-centered remote monitoring involves transmitting patients' device data in a discreet format (Rudin et al., 2021; Yashir Ahamed et al., 2023). Moreover, data standards and interoperability are necessary to develop technological solutions that can facilitate the comprehension of implanted device data by both patients and healthcare practitioners (Juma et al., 2023; Trivedi et al., 2023).

Cronin and Varma characterized remote monitoring as a significant transformation in the 21st century, emphasizing its ability to enhance effectiveness and efficiency compared to in-clinic assessments (Fraiche et al., 2021). Nevertheless, remotely monitoring HDs presents difficulties in data integration and interoperability due to the utilization of exclusive data formats by various device makers (Stevovic et al., 2018). HDs offer essential data, including indications of device operation and physiological health data. The provided data offers significant insights about the device, including the state of the battery and leads, as well as alarms indicating potential worsening in health, such as arrhythmia and ventricular treatments. Previously, individuals using HDs were obligated to visit the medical facility to undergo device assessments. To enhance operational effectiveness, medical clinics have introduced remote monitoring systems to gather, assess, and analyze data obtained from implanted medical devices in the interim periods between patients' visits to the clinic. The remote monitoring technique enables the prompt identification of device situations, irregular heartbeats, improper shocks, and incidents. Engaging patients in remote monitoring has been shown to result in enhanced survival rates and economic outcomes for patients following the implantation of HDs (Chew et al., 2022; Sakthive et al., 2019; Sofiene et al., 2023).

The prevalence of individuals using HDs is rising, while the intricacy of medical equipment and the data they generate continuously evolve in response to technological advancements. The utilization of remote monitoring has the potential to offer diagnoses that closely approximate real-time results, hence decreasing the time required for therapy due to early identification. Nevertheless, clinics must handle extensive datasets obtained from device interrogations effectively. The clinic personnel review, triage, summarize, and store the data inside a DHR for further evaluation by a healthcare professional. To ensure the provision of high-quality healthcare, clinics must promptly follow up with patients when actionable data is available.

Additionally, if patients fail to send data as scheduled, it is incumbent upon the clinic to initiate communication with them to address any missing transmissions. Although remote monitoring has several benefits and is generally well-received, patient adherence to this approach remains suboptimal (Piccini et al., 2016; Papalou, 2020). One further obstacle in managing remote monitoring data is the exclusive format of the data obtained from various device suppliers (Daley et al., 2023). The management of data entails the integration of distinct proprietary platforms and the electronic storage of reports in the Portable Document Format (PDF) within the DHR. Therefore, the data is not readily accessible discretely and may be easily utilized (Daley et al., 2023; Nielsen et al., 2020). The growing abundance of health data necessitates the utilization of technology to enhance data management for patient safety and optimizing clinical workflow. There is a pressing need to establish a universally accepted methodology to include remote monitoring data in the DHR. This integration should adhere to a set of observations that remain constant across various devices.

There has recently been a notable transformation in the healthcare sector, characterized by the widespread adoption of medical equipment and the progress made in remote monitoring systems. The rapid increase of medical data derived from various sources, such as HDs, DHRs, and multiple healthcare systems, brings out unique prospects and obstacles (Dinh-Le et al., 2019). This study explores the crucial field of medical data integration and interoperability, specifically emphasizing the smooth communication enabled by remote surveillance of HDs. Integrating these many data sources is crucial to extract significant insights, improve patient care, and fully harness the value of HD.

The dynamic ecosystem of HDs, encompassing a wide range of smart wearables and Internet of Things (IoT) enabled HDs, has brought about a new era in which patients' health may be continually monitored beyond the confines of conventional clinical environments (Al-Turjman et al., 2020; Sonya & Kavitha 2022; Bobir et al., 2024). This technology has not only facilitated the active engagement of individuals in their physical well-being but has also resulted in the generation of a substantial volume of real-time data. Nevertheless, the fragmented structure of various data sources frequently presents difficulties when effectively integrating and transferring information. The establishment of interoperability is paramount in developing a unified healthcare infrastructure that facilitates the seamless access of healthcare practitioners to complete and precise patient data, enhancing the quality of decision-making via increased knowledge and awareness.

The present study investigates the technical framework that enables the integration and interoperability of medical data. This study explores the significance of remote monitoring in acquiring patient data in real-time. It investigates the impact of advanced technologies, including cloud computing, data standards, and interoperability systems, on developing a linked healthcare ecosystem.

2 Related Works

This part starts with examining the pertinent literature, followed by an exposition of the underlying motivation for our study.

Rubí and Gondim propose a technique for creating an interoperable IoMT platform for e-health applications (Priyanka et al., 2023; Kodric et al., 2021; Rubí & Gondim, 2020). The execution method involves creating a platform for efficient and uninterrupted communication between medical devices with different functions. Results show improved interoperability, enabling data exchange across devices.

Increased healthcare ecosystem connectivity improves patient care. Establishing uniform communication protocols across medical equipment may be difficult.

Philip et al. propose IoT-based in-home health tracking systems. The implementation process involves reviewing recent advances and overcoming obstacles in deploying IoT technology for residential health monitoring (Philip et al., 2021; Stephen et al., 2023). The findings provide valuable insights into the discipline's current state and suggest future research directions. A complete analysis of in-home health surveillance is one benefit of this approach. Standardization may be difficult for IoT systems in different residential contexts.

Jayaratne et al. provide a data integration platform for patient-centered e-healthcare and medical decision support. The implementation process includes creating a patient data platform to improve healthcare decision-making (Jayaratne et al., 2019; Chow et al., 2017). The results show improved data integration in customized healthcare. One benefit of this approach is better decision assistance. However, data privacy and security issues must be considered.

Muzny et al. propose a method to assess the current state and requirements of mobile health surveillance system stakeholders, focusing on wearable sensors and data sharing. The implementation process evaluates the needs and expectations of many mobile health monitoring stakeholders (Muzny et al., 2020). The study sheds light on wearable sensor specifications and current state. This approach helps understand stakeholders' many needs and interests. However, this approach may have drawbacks, particularly in meeting stakeholders' diverse needs.

In remote patient monitoring, Abdolkhani et al., (2019) discuss the many challenges of handling patient-generated health data. The implementation process includes developing strategies to manage and ensure the quality of remote patient health data. The result shows remote patient monitoring challenges and solutions. Patient-generated data can improve quality. Maintaining multiple data sources can be difficult, so there may be drawbacks (Klein et al., 2023).

IoT-based e-health platforms can use Healthcare Device Interoperability (HeDI) from Pathak et al. The method involves creating a conceptual structure to improve healthcare equipment's IoT ecosystem compatibility (Pathak et al., 2021). This shows improved device compatibility in e-health platforms. This phenomenon improves connectedness but may make it difficult to standardize interoperability frameworks.

Jaleel et al. propose fostering collaboration between healthcare devices to achieve medical data interoperability (Jaleel et al., 2020). The implementation process promotes healthcare equipment collaboration to facilitate data exchange. Results show improved medical data-sharing interoperability. One benefit of this approach is improved collaboration. Drawbacks include the difficulty of achieving widespread device collaboration. Daley, Toscos, and Mirro study data integration and interoperability for remote monitoring of cardiovascular implantable electronic devices (Daley et al., 2019; Camgözlü & Kutlu, 2023), focusing on patient-centered care. The method involves creating a remote monitoring system that integrates patient data. The results show improved remote monitoring. This approach improves patient-centered treatment, but integrating cardiovascular equipment may be difficult.

This research is motivated by the potential impact of modern technology on healthcare. Wearable devices, IoMT technologies, and remote monitoring systems offer unprecedented opportunities to use real-time health data for personalized and preventative treatment. However, the fragmented nature of healthcare data sources hinders medical data integration, preventing the smooth and comprehensive flow of information needed for holistic patient care. This issue must be resolved to improve healthcare processes, patient outcomes, and data-driven medical insights. The complexity of integrating and interoperating medical data is the focus of this study. This research aims to create a connected healthcare ecosystem that uses remote monitoring technologies to improve patient health and healthcare efficiency.

3 Medical Data Integration and Interoperability via Remote Monitoring of Healthcare Devices (MDII-RMHD) Framework

The healthcare sector is currently undergoing a significant shift towards digital transformation. In this context, the integration and interoperability of medical data play crucial roles in enabling comprehensive and patient-centric care. This paper explores the challenges and opportunities associated with remote monitoring technologies, highlighting the potential for significant transformation in healthcare through the seamless integration of healthcare devices and systems. This integration has the potential to improve patient care and healthcare outcomes greatly.

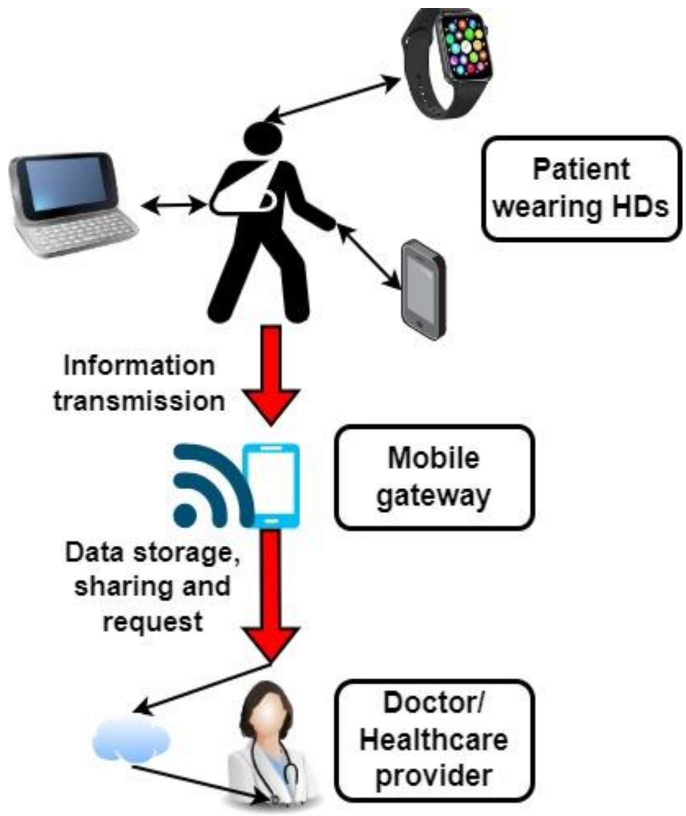

Figure 1: Patient Health Monitoring through IoMT and HDs

Figure 1 shows the patient health monitoring through IoMT and HDs. Utilizing a medical application (App) enables establishing a connection between a healthcare provider and the IoMT devices belonging to their patient. This scenario is visually depicted in Figure 1. In this context, the patient's smartphone functions to access the corresponding cloud platform. The system facilitates the process of data retrieval and dissemination. However, to address the issue of disparate data formats, the cloud infrastructure must provide support for data translation. Failure to do so would render the data ineffective or of limited use. This study centers on the practical application of the IoMT in medicine, emphasizing the importance of maintaining a balanced perspective on the issue.

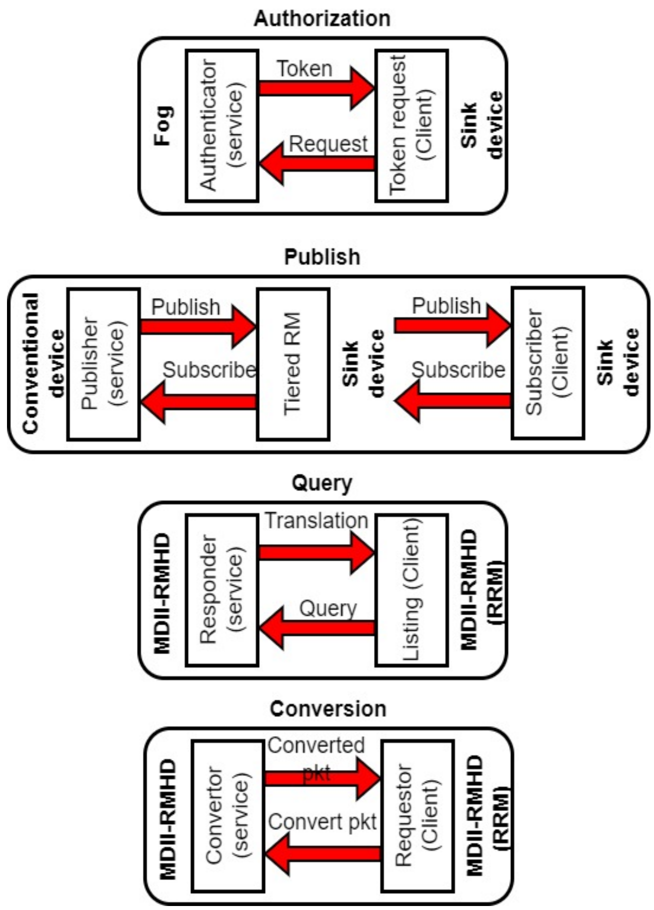

Figure 2: The Proposed MDII-RMHD Framework

The MDII-RMHD framework is founded on the fundamental concept of addressing data format discrepancies across IoMT devices either inside the requesting device itself or with assistance from other IoMT devices within the regional network.

The MDII-RMHD framework is depicted in Figure 2. The MDII-RMHD framework enhances the functionality of traditional IoT interfaces, such as authorization, follow, and publishing, by facilitating collaboration across IoMT devices. This is achieved by utilizing its Query and Interpretation interfaces, seamlessly linked with tiered resource management. The graphic illustrates interfaces that facilitate the operation of autonomous and collaborative software agents, enabling them to access and utilize the services provided through these interfaces. The agents are strategically implanted within the IoMT devices, which are classified according to the underlying assumptions.

- Conventional devices are designed to utilize traditional interfaces for authorization, subscription, and publishing alone.
- MDII-RMHD devices are equipped with Probe and Translation interfaces specifically designed for MDII-RMHD. These interfaces facilitate resource sharing by enabling data translation services.
- Source devices encompass various sensors responsible for generating and collecting a patient's medical data. This study postulates that the source devices under consideration are legacy devices and possess intrinsic limitations in terms of available resources. Consequently, their capacity is limited to producing data in forms particular to their respective vendors.

- Sink devices encompass a range of technological instruments, namely monitors, analytics, and transducers, designed to receive and process medical data about a patient. These devices encompass the wallets of patients and doctors and other gadgets that offer the computational power to handle the data. Therefore, the primary emphasis of our study is on these gadgets. The sink devices of the MDII-RMHD system provide the capability to facilitate the conversion of medical information from one format to another utilizing their conversion interface. The computational resources are listed using the Query interface for this objective. MDII-RMHD devices can be classified as Edge devices.
- The hierarchical structure of the Resource Manager (RM) consists of the Fog RM (FRM) at the highest level, the edge RM (ERM) at the middle levels, and the regional RM (RRM) at the LAN levels. The ERM and RRM cache the relevant sections of resource tables obtained from the FRM. Furthermore, they offer fundamental translation services to outdated gadgets. In this manner, ERM/RRM might be classified as managers of Fog resources.

Authorization

This interface enables a sink device to obtain access privileges from a source device. The most straightforward method is deploying an authorization server in the cloud. This server manages a Resource Table (RT), which contains each patient's device's login privileges and information permissions. An HD is assigned and cataloged with its Unvarying Resource Identifier (URI). After the authentication process, devices have the capability to publish their own data and get data from other devices in their original format, utilizing the cloud RM.

Publish

This interface offers a Subscriber agent that enables a sink device to obtain healthcare data from a source device once the authorization procedure has been completed. This agent operates on HD, including the doctor's digital wallet. The data query is initiated by utilizing the URI of the source device together with the authorization token. When a conventional device sends a data request through its Subscriber agent, the RM receives the information from the Publisher agent of the source device. If necessary, the data is converted into the supported format of the sink device. Finally, the RM sends the information over to the Subscriber.

Inquiry

MDII-RMHD enables resource distribution through its Query and conversion agents. Specifically, the query agents possess a Conversion Resource Table (CRT) that describes the capacities and current status of the accessible MDII-RMHD. The queues are arranged based on the Weight Factors (WF) of each MDII-RMHD, with the device having the smallest WF placed at the top. The WF indicates the computing resources currently accessible in an MDII-RMHD system. To populate and update its CRT, the Query interface offers two agents: the list or and the Query Responder.

Conversion

The Conversion interface facilitates the process by which MDII-RMHD allows a competent device to conduct data conversion by employing its redundant computational resources. The system keeps a solitary feature known as the WF, which indicates the current use of resources, encompassing CPU time and memory usage. The conversion interface consists of two agents: a Requester and a Convertor.

Let's assume that D is an MDII-RMHD with a computing capacity of ND Million Instructions Per Second (MIPS). The WF of device D is calculated using the formula:

$$WFD = WFID + [WCQ \times CAvg]/ND \quad (1)$$

Here, $WFID$ denotes the inherent weight on the device D, WCQ is the duration of Conversion Requests in the queue, and $CAvg$ is the mean cost of conversion methods in $MIPS$. The WF represents the anticipated duration for the task queue to be completed and can be used to mediate between MDII-RMHD for conversion services. When a Query request is made, the WF called Response time $given\ as$ $[WFID + \frac{[CAvg]}{ND}]$ is provided to indicate the response time of a later conversion request.

$$Response\ time = [WFID + \frac{[CAvg]}{ND}] \quad (2)$$

After the conversion is finished, the number of pending translations in the queue is reduced by 1, and the updated WFD is sent back to the Requester to adjust its CRT appropriately.

4 Description of the Experimental Configuration

In this study, a thorough Monte Carlo simulation approach is used. We continuously construct the iFogSim configurations by adjusting important simulation factors, such as the number of information requests and conventional/ MDII-RMHD in an RRM. Data sinks have produced one data request per second on a typical basis, with a Gaussian distribution culminating at ten requests per second. Furthermore, the MDII-RMHD and RM handle several conversion requests about their MIPS ratings. A comparison of response time and uplink data traffic has been made using 3 IoMT configurations: zero MDII-RMHD (MDII-0), one MDII-RMHD (MDII-1), and all MDII-RMHD (MDII-total).

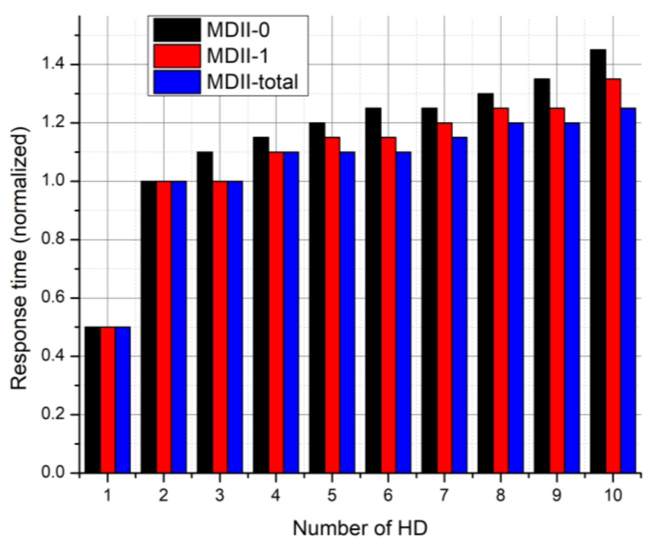

Figure 3: Normalized Response Time from RRM for 3 Configurations (MDII-0, MDII-1, and MDII-total)

Figure 3 presents the normalized response time data obtained from the RRM for three different IoMT setups, namely MDII-0, MDII-1, and MDII-total, under different numbers of healthcare devices. The response time is standardized concerning the baseline configuration MDII-0, a reference for a single healthcare equipment. With the growing number of healthcare devices, there is a uniform pattern in the time it takes to respond, regardless of the specific setup. MDII-1 and MDII-total provide comparable or enhanced reaction times compared to MDII-0, highlighting the efficiency and scalability of the suggested setups. The results demonstrate that the system adeptly manages heightened healthcare device workloads, underscoring its resilience and dependability for integrating and interoperating medical data via remote monitoring of healthcare equipment.

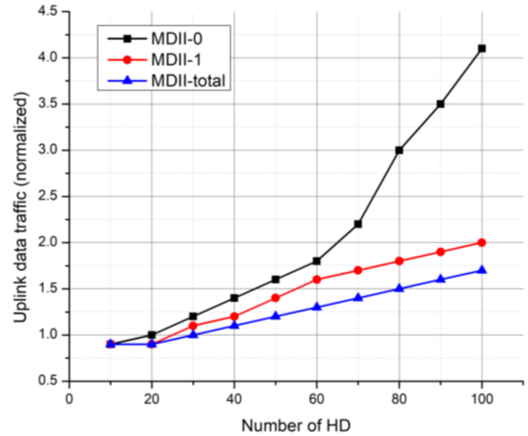

Figure 4: Normalized Uplink Data Traffic from RRM for 3 Configurations (MDII-0, MDII-1, and MDII-total)

Figure 4 displays the standardized uplink data traffic from the RRM for three IoMT configurations—MDII-0, MDII-1, and MDII-total—across varying quantities of HD. The uplink data flow is standardized concerning the standard configuration MDII-0, which corresponds to 10 HDs. With the growing number of HDs, there is a noticeable and consistent growth in the normalized uplink data traffic across all configurations. MDII-1 and MDII-total typically exhibit reduced normalized uplink data traffic compared to MDII-0, suggesting a more effective usage of network resources. These findings indicate that the suggested configurations can manage higher HD workloads while enhancing network efficiency. This is critical for integrating medical data and ensuring interoperability through remote monitoring of healthcare equipment.

5 Conclusion

This article aims to provide the Medical Data Integration and Interoperability via Remote Monitoring of Healthcare Device (MDII-RMHD) framework, enabling healthcare equipment cooperation. The MDII-RMHD improves a cloud-based IoMT system by utilizing the network's perimeter transformation resources. This is accomplished by employing inquiry and converting agents. The investigative devices maintain a registry of MDII-RMHD devices within the local network and enable one device to request data conversion from another when the asking device cannot do the operation independently. The converting agent then changes the data into the required format and returns it to the originating entity. These agents allow IoMT devices to employ their extra computing capabilities for data translations, lowering the need for cloud connections. Fog resource managers with MDII-RMHD support are compatible with conventional devices. It has been evaluated the MDII-RMHD architecture through thorough testing across three IoMT scenarios (MDII-0, MDII-1, and MDII-total). MDII-1 and MDII-total provide comparable or enhanced reaction times compared to MDII-0, highlighting the efficiency and scalability of the suggested setups. The results illustrate that the suggested framework reduces the volume of uplink traffic and improves the response time. The improvement in response time is important, especially for real-time healthcare applications.

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