Digital-Twins-Based Internet of Robotic Things for Remote Health Monitoring of COVID-19 Patients

Sangeen Khan, Sehat Ullah, Habib Ullah Khan, *Member, IEEE*, and Inam Ur Rehman

***Abstract*—The deadly coronavirus disease (COVID-19) has highlighted the importance of remote health monitoring (RHM). The digital-twins (DTs) paradigm enables RHM by creating a virtual replica that receives data from the physical asset, representing its real-world behavior. However, DTs use passive Internet of Things (IoT) sensors, which limit their potential to a specific location or entity. This problem can be addressed by using the Internet of Robotic Things (IoRT), which combines robotics and IoT, allowing the robotic things (RTs) to navigate in a particular environment and connect to IoT devices in the vicinity. Implementing DTs in IoRT, creates a virtual replica [virtual twin (VT)] that receives real-time data from the physical RT [physical twin (PT)] to mirror its status. However, DTs require a user interface for real-time interaction and visualization. Virtual reality (VR) can be used as an interface due to its natural ability to visualize and interact with DTs. This research proposes a real-time system for RHM of COVID-19 patients using the DTs-based IoRT and VR-based user interface. It also presents and evaluates robot navigation performance, which is vital for remote monitoring. The VT operates the PT in the real environment (RE), which collects data from the patient-mounted sensors and transmits it to the control service to visualize in VR for medical examination. The system prevents direct interaction of medical staff with contaminated patients, protecting them from infection and stress. The experimental results verify the monitoring data quality (accuracy, completeness, and timeliness) and high accuracy of PT's navigation.**

***Index Terms*—Coronavirus disease (COVID-19), digital twins (DTs), Internet of Robotic Things (IoRT), Internet of Things (IoT), remote health monitoring (RHM), robot navigation, virtual reality (VR).**

I. Introduction

The DIGITAL-twins (DTs) paradigm creates a virtual-physical system that allows bidirectional data exchange between a physical entity (device, equipment, object, or human) and its virtual counterpart using a communication network [1], [2], [3], [4]. More specifically, a DTs system consists of three major elements: the physical artifact, its virtual replication, and the bidirectional communication link between them [5]. DTs can link the virtual and physical spaces in real time, allowing more accurate and realistic measuring of unpredictable events [6]. A high-level mapping connects physical and virtual entities to convert the behavior of real objects into virtual objects [7], [8]. The real-time data exchange between the DTs allows continuous monitoring of the physical artifact [9]. Many researchers suggest that DT is a virtual model updated continuously to depict the behavior of a physical entity. However, DT is not just a virtual replica, it is a paradigm that incorporates multiple high-tech fields and executes various advanced technologies [10]. DTs have been implemented in different domains, including industrial production, building smart cities, aerospace, immersive shopping, and healthcare [11]. Over the preceding decade, DTs technology has transformed the healthcare industry, resulting in more intelligent, personalized, and realistic healthcare solutions [12]. Among the key solutions are simulation of hospitals' physical spaces, modeling of organizational processes, and virtualization of clinical processes or individuals' genetic/physiological/lifestyle characteristics [13].

The recent coronavirus disease (COVID-19) pandemic has increased the importance of DTs. DTs systems predict and manage contagious disease outbreaks more efficiently and improve hospital management and healthcare services [14]. Unlike earlier pandemics like middle east respiratory syndrome (MERS) and severe acute respiratory syndrome (SARS), COVID-19 has a high and asymptomatic transmission capability. Consequently, its treatment becomes quite challenging for the medical staff [15]. Healthcare workers are highly exposed to this infection because they interact daily with COVID-19 patients to measure vital body signs, such as body temperature, blood oxygen level, heart rate, and respiratory rate, to monitor patient health status [16], [17], [18]. This problem has increased the importance of remote health monitoring (RHM), which collects and transmits patient health information to a remote server for medical examination [19], [20].

DTs infrastructure is a better choice for RHM during the COVID-19 outbreak [21]. DTs can enable medical professionals to monitor and treat patients remotely by providing real-time health-related information [22]. They exploit various technologies, including artificial intelligence (AI), blockchain, cloud computing, and the Internet of Things (IoT) [23], [24], [25], [26]. IoT is considered a building block for DTs as it employs different sensors to gather information about patients'

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health and transmit it to the virtual counterpart for analysis [27], [28]. The real-time data analysis allows RHM, the treatment of infected patients, and the prediction of epidemic evolution [29], [30]. However, most IoT systems are based on devices with passive sensors that monitor and organize various systems and their functionalities. Although the frameworks are effective, more transformational and advanced aspects of IoT solutions must be explored for the ubiquitous connectivity and communication among intelligent devices to further enhance these initiatives [31]. Therefore, the DTs lay their foundation on using the Internet of Robotic Things (IoRT) [32] for RHM of infected patients. IoRT is a new field that combines IoT and robotics [33]. Unlike IoT devices, robotic things (RTs) are dynamic and can operate freely in real-world scenarios [34]. Robotic technologies can be applied in regions with a high risk of infection, such as hospitals, public places like parks, shopping malls, and markets during this epidemic situation and in the future [35]. They can identify IoT devices in their surroundings and obtain real-time information to facilitate the medical workers, avoiding unnecessary intervention or supporting healthcare activities in crucial situations [36]. Robotic devices can also help supply foodstuff [37], deliver medicines, and remove dirty laundry and waste within the hospital [38]. When implemented in the IoRT, the DTs paradigm creates a virtual model of the physical robot that obtains real-time information from the physical robotic device during its lifespan and acts like a real robot. The physical robot is known as a physical twin (PT), whereas the virtual robot is referred to as a virtual twin (VT) [32]. The PT communicates with the VT and with other RTs and IoT devices in the real environment (RE).

Although a DTs system provides the best possible performance for a specific application, it is unlikely to be fully autonomous. Human intervention is often required to operate the system or redesign a specific process. Accordingly, an intuitive interface is desirable to enable real-time interaction between humans and DTs. Virtual reality (VR) has the natural capabilities of visualizing and interacting with the DTs [39]. VR interface allows the users to observe the VT that uses the received information to mirror the real-world status of the PT [40]. The three-dimensional (3-D) virtual representation of the PT and its surroundings provides the operator with a live virtual view of the RE and physical entity [41].

This research proposes an RHM system for COVID-19 patients using DTs-based IoRT and VR. The system obtains real-time health-related data from patient-mounted biomedical sensors using the PT and transmits it to the control center for medical examination. The proposed system replaces the traditional medical care systems, where passive IoT devices or medical personnel who physically interact with isolated patients perform patient care and monitoring. This article also provides a detailed analysis of the PT's navigation. The VR-based interface visualizes the PT and its surrounding environment, providing the operator with better perception and real-time user interaction. The interface also displays health monitoring data and PT's navigation information, such as distance traveled, obstacles detection, and obstacles' distance from the PT.

The proposed system uses the DTs architecture presented in [42] that describes the functionalities of each component of a DTs system. The model comprises five entities.

1) The *Physical entities* comprise the real assets in the physical environment and their interactions.
2) The *Virtual entities* comprise the virtual models that receive real-time data from physical entities.
3) The *DTs data* includes data obtained from the real world through sensors.
4) The *Services* are the applications of the DTs, such as simulation, real-time monitoring, navigation, diagnosis, and prognosis.
5) The *Connections* are the links among the components of the system.

A. Motivation

Due to the rapid spread of the COVID-19 pandemic, the existing healthcare systems are overburdened. The situation resulted in various complications, including inadequate patient health status monitoring, human errors in health parameters, and unavailability of medical staff in an emergency. Most healthcare professionals endure long working shifts and deal with the common hazard of getting infected, which results in mental and physical stress. As medical professionals are the backbone of every nation, this research aims to protect medical professionals by exploring and using advanced technologies in medical systems. Monitoring contagious patients remotely without having a direct physical connection can help the caretakers to avoid infection and mental stress.

B. Contribution

This research presents a real-time framework for remotely monitoring COVID-19 patients using DTs-based IoRT and VR. The main contributions of the study are as follows.

1) In general, DTs systems use passive IoT sensors to update the status of the virtual counterpart, which restricts their applications to specific sites or entities. We implemented the DTs paradigm in the IoRT to uncover the dynamic aspect of the existing systems. Our physical entity (PT) allows bi-directional communication with the virtual model (VT) and communicates with other PTs and IoT devices while moving around in the RE.
2) We developed an RHM system that can monitor contagious patients in real time without direct physical contact of the medical workers with the patients, protecting the health carers from infection.
3) We employed a VR-based user interface that provides a better perception of the PT's surroundings and real-time user interaction with the DTs.
4) We presented and evaluated a robot navigation technique that uses DTs and a VR-based user interface, our method is not constrained by the limitations of camera-based navigation techniques, such as restricted field-of-view, low-quality video feedback, communication delay, two-dimensional (2-D) prospect, poor performance in low lighting, visual data transmission, and processing load [43], [44], [45], [46].

5) We developed a real-time mechanism to detect and visualize stationary and moving obstacles and their distances from the PT, allowing situational awareness of the RE.
6) Our system functions off-line using the radio transceiver (NR24L01+) and Bluetooth modules, eliminating the limitations posed by Internet cloud-based communication, including increased energy consumption, high communication latency, and security issues [47], [48].

The remaining part of this article is organized as follows: Section II discusses the related work, Section III describes the proposed system, Section IV discusses the experimental setup, Section V describes performance evaluation, Section VI presents the discussion of the results, and Section VII describes the conclusion and future directions.

II. Related Work

Because of the increasing number of medical complications and emerging infectious outbreaks, the importance of digital technologies has grown significantly. The DTs paradigm employs various computing, communication, and visualization technologies, such as AI, cloud computing, blockchain, IoT, IoRT, and VR. Therefore, it is considered a significant breakthrough for improving industrial, engineering, and medical infrastructures and processes. Researchers have implemented DTs in different fields to improve living standards.

De Benedictis et al. [13] provided a detailed review of the role of DTs in healthcare and proposed a generalized DTs architecture for identifying the essential functional components of a DTs system. They also presented CanTwin, the DT of canteen service, designed to monitor social distancing, queue status, table occupancy, and worker counting and tracking during the COVID-19 pandemic. The proposed architecture is based on six layers.

1) The *Physical layer* consists of sensors that transmit the collected data to an aggregator.
2) The *Data layer* comprises the data obtained from the aggregator.
3) The *Connectivity layer* allows both the physical and virtual worlds to exchange information.
4) The *DTs layer* includes the geometric model of the canteen enriched with points representing the number of workers, their respective distances, and the number of served workers.
5) The *Service layer* consists of real-time monitoring, social distancing, table occupancy, and served workers.
6) The *Security layer* provides authentication and authorization mechanism to facilitate device identity and access management.

Bondoc et al. [49] proposed LIVE DT, a model-based solution to create DTs through sensor data for asset management. LIVE consists of four basic phases: 1) Learn; 2) Identify; 3) Verify; and 4) Extend. It relies on the proper allocation and placement of various sensors on the physical entities to allow bi-directional communication with the simulated model. The designed DT is used for prognostic and health management of the Light Rail Transit system. The data collected from the physical structure is based on acceleration and vibration. The phases of the LIVE model are defined as follows.

1) The *Learn* phase gathers basic knowledge and information about the physical object to create a virtual model.
2) The *Identify* phase generates a low fidelity (LF) model, which is further optimized with the high fidelity (HF) model using the parameters to identify sensors locations.
3) The *Verify* phase synchronizes the physical and virtual assets for real-time communication to analyze the physical assets' health and allow fault detection based on the LF model.
4) The *Extend* phase uses the HF model to suggest plans for eliminating the faults diagnosed during the previous stage.

Dang et al. [50] introduced a DTs-based system using deep learning and cloud computing to monitor the structure's health and proactive maintenance. The system uses cloud computing and a Web-based interface to enable data interaction among the users, virtual model, and physical structure. The framework is validated for a toy bridge in the lab and a real bridge structure. The system model has four components.

1) *Physical Structure:* This component includes structural entities, auxiliary elements, external excitation, and measurement devices.
2) *Virtual Structure:* It represents the virtual replica mirroring the physical structure's status using sensor data.
3) *Cloud Computing:* This element includes hybrid cloud computing (private fog and public cloud). First, the private fog performs data preprocessing, such as data cleaning and training of the virtual model. After that, the processed data and model are deployed to the public cloud.
4) *User Application:* It consists of a Web-based interface to allow human–computer interaction and real-time monitoring and controlling. The application presents structural data (stress, vibration, and temperature) as graphical carts.

Yu et al. [51] presented a hybrid monitoring system for the health of the cable-stayed bridge. The system employs an orthotropic steel deck fatigue-assessment method appropriate for ambient temperature actions, traffic loads, and welding residual stress. The DTs concept is used to understand the stress of fatigue-vulnerable deck areas during heavy traffic flow, and the submodel is implemented for a long-span bridge. The method allows data to flow from the monitoring unit to the numerical model. The deck is fixed in the middle lane of the bridge to measure the stress.

Of the additional advances, AI, IoT, and IoRT have various advantages, including potential computing, reduced human errors, cost efficiency, unbiased decisions, zero errors, and remote access via a communication network, enabling RHM, and treatment of patients. Many researchers have employed these technologies for RHM, patient assistance, and medicine delivery to minimize the direct exposure of medical staff to contaminated patients.

Wang et al. [52] presented an AI-based robotic system that can deliver parcels to customers autonomously. The robot can also deliver medicine to COVID-19 patients, reducing human contact with infected patients and freeing up valuable time for medical staff. The system employs a user authentication mechanism based on PIN code and biometrics verification (voice print and face recognition) to ensure safe delivery to the correct customers. When the customer places an order, the server receives the request and provides verification data to both the robot and the client. The robot loads the information and navigates to the target position. On reaching the destination, the customer is asked for cooperative authentication (PIN code). If the PIN code is provided, and one of the biometrics is verified, the parcel is handed over. If the PIN is incorrect, the robot switches to the noncooperative mode, i.e., facial identification. However, face recognition is one of the vital identification elements. Therefore, the system inherits the limitations of visual computing.

Hamim et al. [53] proposed an IoT-based remote patient health monitoring system. The health information acquired by the biomedical sensors is transferred to cloud storage. An Android application is developed to access the cloud and show a graphical representation of the health parameters. However, the system uses passive IoT sensors and cloud services, thus inheriting their limitations.

Akhund et al. [54] proposed an IoT-based robot for collecting patients' health-related data and helping disabled or infected patients. The robot recognizes hand gestures measured with the Accelerometer/Gyroscope sensor (MPU-6050) rather than using the image processing techniques. The system utilizes a 433-kHz radio transceiver for data communication. However, the system functions merely when the robot is in a visual line of sight. There is no user interface for operating the robot beyond the visual range. Also, the system's accuracy is measured only for gesture recognition; there is no actual implementation and evaluation of the health monitoring mechanism.

Leila et al. [55] proposed an IoRT-based health monitoring system to combat the COVID-19 pandemic. The system uses a physical robotic device that moves in the hospital's corridor, collects clinical parameters from the medical sensors attached to the patient, and transmits them to the Internet cloud through Wi-Fi. The health service obtains the information from the cloud using the Internet. The body sensors collect clinical data and send it to an aggregator device using the ZigBee module. The aggregator transmits the aggregate data to the room controller (RC) using another ZigBee module. The RC receives information from multiple aggregators. Communication between the RC and the RT is performed by using the Bluetooth technology. However, the system uses cloud services to communicate clinical information from RT to the medical service, thus inheriting the demerits of cloud computing. Furthermore, there is no clear description regarding the interface for controlling or navigating the RT in the corridor. Also, the clinical data passes through various gateways to reach the health service; as a result, the system suffers from latency issues.

Bhardwaj et al. [56] developed a smart health monitoring system based on the IoT technology. The system can distantly monitor the health parameters (body temperature, heart rate, blood pressure, oxygen level) of COVID-19 patients. The collected information is displayed on a monitor and transmitted to a cloud server using Wi-Fi for monitoring by doctors or physicians. Medical service receives an alert message if the system detects abnormal values. However, the system is based on passive IoT sensors and cloud services, thus inheriting their limitations.

Ruman et al. [57] proposed a remote patient monitoring system using the IoT technology. The health-related parameters (blood pressure, ECG, and body temperature) are collected via sensors and transmitted to the cloud via Wi-Fi. The stored data is retrieved by authorized personnel or doctors for monitoring using an Android application. However, the system depends on cloud service, consequently, it suffers from latency issues.

El-Rashidy et al. [58] introduced a real-time system for remote monitoring of COVID-19 patients in hospitals and homes. The system uses wireless sensors, cloud and fog computation, and deep learning-based clinical decision support to create comprehensive disease detection and monitoring model. A mobile application is developed to retrieve the stored data from the cloud for patient monitoring. However, the system consumes high power during sensing and transmission. Introducing fog nodes to the network infrastructure may cause complexity. Maintenance of the distributed fog storage nodes is another complex problem.

Various architectures have been suggested in the literature to create DTs for different applications. A thorough analysis leads to the common conclusion that DTs frameworks comprise physical and virtual elements connected through sensor data for a particular application. Our proposed method uses the same standard architectural components, i.e., physical entities, virtual entities, DTs data, services, and connectivity. However, it differs from the existing DTs systems that use passive IoT sensors and require a direct connection between the physical and virtual assets for updating the status. The proposed system employs IoRT to create a dynamic framework whose applications are not restricted to a specific entity or location. Furthermore, it does not require every physical asset to be directly synchronized with a virtual entity. The PT, which has a virtual replica, collects data from different real-world assets and transmits it to the virtual space to display or synchronize with a simulated model. It acts as an intermediary between the virtual space and other assets in the physical world. The PT can be easily upgraded to perform additional functions in real-world scenarios, such as diagnosing and maintaining faults in physical assets and their communication links.

COVID-19 has put the lives of doctors and other medical personnel in extreme danger because they have daily physical interactions with the infected patients to collect vital body signs (heart rate, oxygen level, body temperature). This research proposes a real-time system for remotely monitoring infected patients without physical contact to protect healthcare workers from infection and stress. The proposed system employs VR and DTs-based IoRT for RHM of COVID-19 patients. The VR interface visualizes the PT and its surroundings and allows real-time interaction with the DTs, lacking in previous studies. Unlike the existing IoT and IoRT systems,

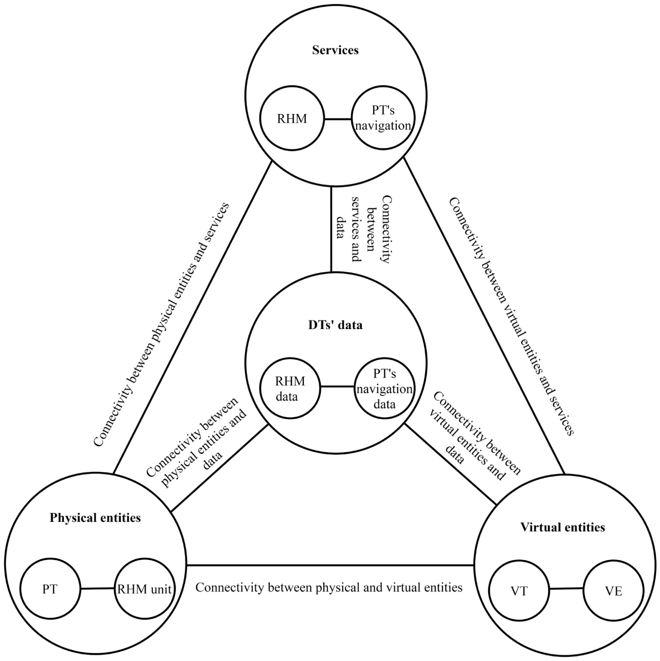


Fig. 1. Architecture of the proposed system.

the proposed method does not depend on Internet clouds or vision-based interfaces, thus preventing inheriting their limitations.

III. Proposed System

The proposed approach describes a real-time RHM system that uses DTs-based IoRT and VR. The framework uses the PT that moves around in the RE and collects health data from IoT sensors attached to the patient's body. The data collected by the system is then transmitted to the health service for medical evaluation, thereby eliminating direct contact between medical professionals and COVID-19 patients. This not only protects medical professionals from infection but also relieves them of physical and mental stress. Additionally, this study provides a comprehensive evaluation of PT's navigation. It includes a real-time obstacle detection and visualization mechanism that provides situational awareness during navigation. The VR interface developed in this study visualizes the PT and its surroundings, providing a better perception of the physical environment and real-time user interaction. The proposed system consists of five components, as shown in Fig. 1.

A. Physical Entities

Simulating a physical entity requires knowledge of the physical asset and access to real-time data. Sensors, actuators, and controllers handle data collection, processing, and control. Sensors perceive events in the physical environment, actuators alter the physical world, and controllers analyze data and allow the data to flow between devices. The proposed system comprises two physical entities, i.e., PT and an RHM unit. The PT includes various sensors, including a speed sensor (LM393) for measuring the rotational speed of the wheel to locate the PT in the RE, an Accelerometer/Gyroscope (MPU-6050) to calculate the orientation of the PT in real space, ultrasonic distance sensor (HC-SR04) to determine the obstruction's distance from the PT in the physical environment. It includes a microcontroller device (Arduino Uno) for analyzing the sensor data. It also comprises actuators (wheel motors) to navigate the PT to the target position. It can be easily upgraded for remote operations by introducing a mechanical hand, sanitizing spray pump, or lifting platform for medicine delivery. The main components of the RHM unit consist of biomedical sensors, i.e., a temperature probe (DS 18B20) for monitoring the patient's body temperature, a pulse oximeter, and a heart rate sensor (MAX30100) to compute oxygen level in blood and heart rate of the patient. The RHM unit also comprises a microcontroller device allowing sensor connectivity and data analysis. The physical entities include communication devices (NRF24L01+, HC-05) that will be discussed in the *Connectivity* phase.

B. DTs Data

This component includes the parameters collected by physical entities in the RE and transmitted to the virtual space to reflect the changes in the physical asset. The data also comprises the responses generated by the virtual entities to alter the physical assets. Our system's data represent the parameters (position, orientation, and detected obstacles) collected by the PT's sensors from the physical space to provide situational awareness during navigation. It also includes the information (blood oxygen level, heart rate, and body temperature) obtained by the PT from various RHM unit sensors and the commands the end-user issued to navigate and control the PT in the RE.

C. Virtual Entities

The virtual replica is expected to reflect the physical object's behavior accurately. Therefore, it continuously receives and integrates sensor data from the physical space for real-time mapping and control. The virtual entities comprise the virtual model of the tangible assets and the engine that makes data communication and synchronization possible. It also includes a user interface that allows visualization of the virtual model and real-time interaction with the DTs. Our virtual space consists of a simulated model (VT) of the PT that feeds on real-world information from different sensors, including a speed sensor, ultrasonic distance sensor, and Accelerometer/Gyroscope. Based on the obtained data, the VT depicts the PT's status (position, orientation, and detected obstacles) for the navigation task. The virtual entities also comprise a VR-based user interface that simulates the PT and its real-world scenario, allowing intuitive interaction with the DTs. The interface is used to visualize the detected obstacles in the path of PT, along with their distance parameters, based on the collected data from the ultrasonic distance sensors. Another purpose of the interface is to exhibit the patient health data (blood oxygen level, heart rate, and body temperature) collected by the PT from the biomedical sensors of the RHM Unit. The doctors and physicians can use the information to examine the health status of the infected patients.

D. Connectivity

This part enables the exchange of information between physical and virtual entities in real time. According to [59], communication between the DTs is based on the following two criteria.

1) Intratwins Connectivity: It is the link between the physical objects that use sensors to collect real-time data regarding the physical environment and the virtual model that employs the gathered data to mirror the status of the actual asset.

2) Intertwins Connectivity: It enables communication between different tangible entities in the real world.

To allow real-time data transmission actual communication network is required. In the proposed system, we used the NRF24L01+ communication modules for intratwins connection, avoiding Internet-based communication to eliminate the disadvantages of online methods. The modules enable the PT and VT to exchange information about PT's navigation and real-time patient monitoring. We used the Bluetooth modules (HC-05) for intertwins communication to transmit patient monitoring data to PT, which then sends it to the virtual space using the intratwins connection.

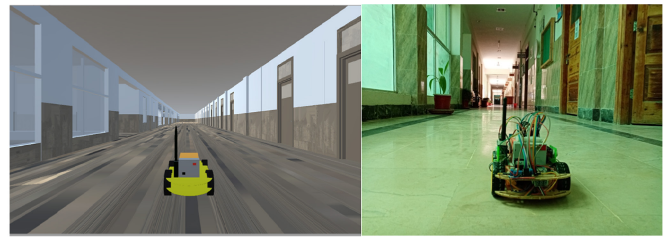
E. Services

Services are the real applications of the DTs systems. Tao et al. [60] identified 18 services of DTs. The major applications include simulation, remote monitoring, navigation, training, and tele-operation. We used DTs-based IoRT and VR to create a real-time system that monitors the health of COVID-19 patients. The method avoids direct interaction between healthcare professionals and infected patients, protecting them from infection. We presented and analyzed the navigation of PT by operating its VT for collecting patient health data remotely. Our proposed system can be easily upgraded for tele-operation service by mounting a mechanical arm, or disinfecting unit.

F. Implementation

The proposed system uses DTs-based IoRT and VR for RHM of the infected patients. Robot navigation is the first step of the health monitoring process because it allows the PT to access the monitoring unit and collect patient data for medical inspection. Therefore, we developed a robot navigation system that used VT to navigate the PT in the RE and provided a detailed analysis to validate the design.

1) PT's Navigation Task: The navigation system utilizes a user interface based on the VT and VR technology to navigate the PT in physical space, rather than relying on traditional camera-based navigation techniques. This approach enables real-time user interaction and provides a more accurate perception of the surrounding environment. Additionally, the system incorporates a real-time obstacle detection and visualization mechanism to enhance the user's situational awareness. All data processing and virtual rendering are carried out by a laptop computer. Unlike other navigation systems, the proposed system does not rely on additional devices or sensors to locate the PT in the physical environment. Instead, the VT accurately reflects the PT's real-world status, as illustrated in Fig. 2.



(a) (b)

Fig. 2. (a) VT in the VR. (b) PT in the RE.

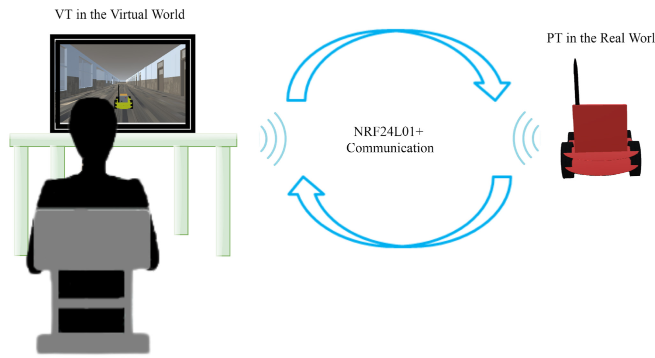


Fig. 3. Graphical abstract of the navigation system.

To simulate the physical robot and its surroundings, we utilized the Unity-3-D game engine. Mapping between the DTs enabled the PT's navigation. The proposed framework is independent of the Internet data transmission and control service. It employs the NRF24L01+ communication modules to allow data exchange between the DTs. We mounted three ultrasonic sensors (HC-SR04) on the robot's left, right, and front sides to detect static or moving obstacles. When the PT detects a stationary obstruction with less than 1 m from it, the system displays a solid cube in the VR interface at the same distance from the VT. The method visualizes a moving obstacle if the distance is less than 2 m. As the moving obstruction approaches the physical robot in the RE, the system updates its position in virtual space. The VR interface displays the obstacle distance and labels (front, left, and right) to provide additional information about the robot's navigation. The Accelerometer/Gyroscope sensor (MPU-6050) determines the direction of physical RT. The virtual robot visually represents any change in the PT's direction, while the speed sensor calculates the distance traveled by the real robot. To provide the operator with additional information, the VE displays this data. The arrow keys on the laptop keyboard are used to navigate the PT rather than any special and expensive interaction devices. The up and down keys move the robots forward and backward, respectively. Right and left keys control left and right turns, respectively. The abstract view of the PT's navigation system is shown in Fig. 3, and the data flow between the components is shown in Fig. 4.

2) RHM Task: The primary purpose of the research is to present a real-time system that monitors the health of isolated patients with COVID-19. Doctors and other medical personnel are at high risk of infection because they directly

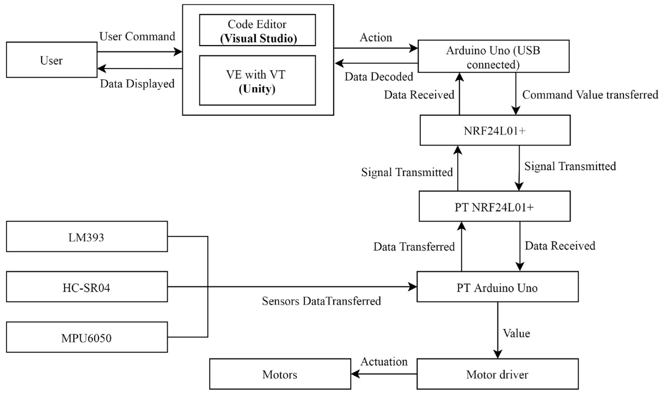


Fig. 4. Data flow between the components of navigation system.

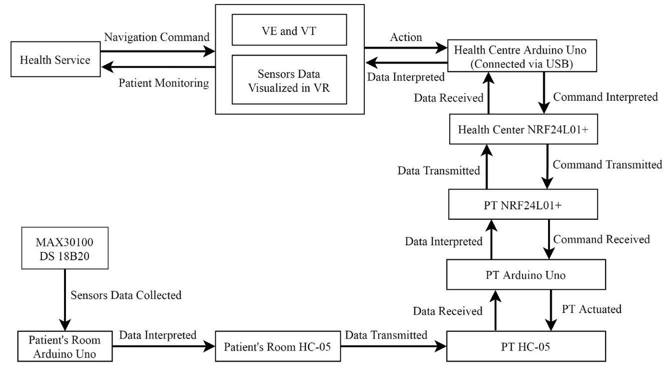


Fig. 6. Data flow between the components of the proposed RHM system.

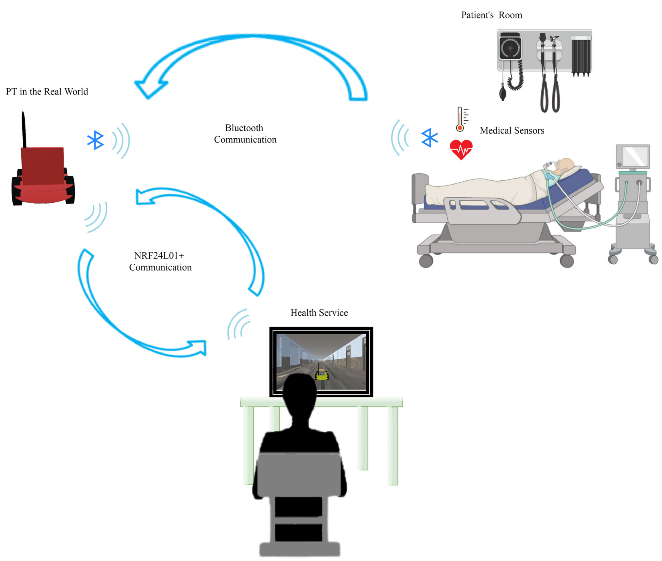


Fig. 5. Graphical view of the RHM system.

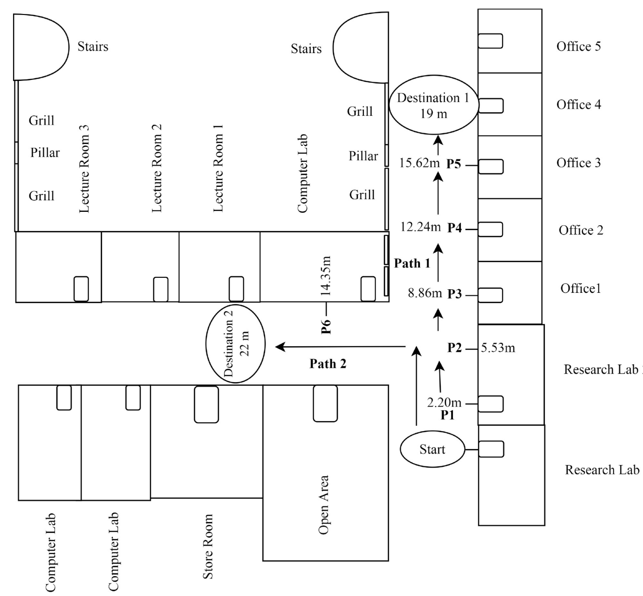


Fig. 7. Scenario of the experimental environment.

contact the contaminated patients. The proposed method uses the PT as a nurse robot that navigates freely in the corridor for data collection. When the PT arrives at the patient isolation room (Destination), it connects to the medical sensors (DS-18B20 and MAX30100) attached to the patient's body using the Bluetooth module (HC-05). It collects health-related data, which is sent to the control center for visualization in VR. The medical staff can easily control the PT, examine clinical information, and take necessary action. The abstract view of the RHM system is shown in Fig. 5. The data flow between the components of the RHM system is illustrated in Fig. 6.

IV. Experimental Setup

We installed the experimental setup in research lab 1 (control room) of the Department of CS & IT, University of Malakand. The PT was placed in the corridor outside the control room. To the right of the corridor are various offices, and stairs and grills to the left, as shown in Fig. 7. A laptop PC was used to implement the virtual setup. The PT and its surroundings were rendered in VR using the Unity 3-D game engine. We performed several trials that perfectly synchronized DTs for the designed settings. The medical sensors were installed. The objective was to use the VT to navigate the PT to various points, collect real-time health data from medical sensors, and transmit it to the control center for visualization in VR. We created two setups to assess the quality of the monitoring data.

A. Setup 1

The medical sensors were installed in office 4 (Destination 1) at 19 m from the start.

B. Setup 2

The sensors were mounted in Lecture room 1 (Destination 2) at 22 m from the start.

V. Performance Evaluation

A. Experimental Protocol and Task

1) PT's Navigation: To evaluate the proposed system's performance, we conducted a user study involving ten volunteers. The study collected both quantitative data and qualitative feedback on the system's accuracy and usability. All users were male, and their ages ranged between 25 and 35. They had already experienced computer gaming using keyboard,

Fig. 8. Real-time detection and visualization of obstacles during navigation.

mouse, and touch screens, but no one was familiar with DTs and VR. We instructed all the participants about the functionality and use of the proposed system. After that, they performed the tasks. Each of the ten participants completed six tasks, resulting in a total of 60 tasks. To evaluate the system's obstacle-detection performance, we placed plant pots as stationary obstructions at various positions in the corridor. Additionally, we used a cardboard box as a moving obstacle, which was dragged toward the PT at roughly the same speed as the PT. The experimentation comprised the following tasks.

Task 1: To follow path 1 from start to Destination 1 (see Fig. 7) with no obstacles in the way.

Task 2: To follow path 2 from start to Destination 2 (see Fig. 7) with no obstacles in the way.

Task 3: To follow path 1 from start to Destination 1 with one stationary obstacle placed at point 4 (P4).

Task 4: To follow path 2 from start to Destination 2 with one static obstacle placed at point 6 (P6).

Task 5: To follow path 1 from the start to Destination 1 with 3 stationary obstacles (as seen in Fig. 8) placed in a zigzag. The distance between each obstacle was set to 1 m.

Task 6: To follow path 1 from the start to Destination 1 with moving obstacles at two different locations: when the PT reaches point 2 (P2), the obstacle is moved from point 3 (P3), and when the PT approaches point 4 (P4); the obstacle is moved from point 5 (P5).

2) RHM: We divided the experimentation into two tasks to evaluate RHM performance. Each participant performed the tasks that resulted in a total number of 20 trials.

Task 1: Navigating the PT to Destination 1 by following Path 1 (with no obstacles) and acquiring data from the medical sensors for transmitting to the control station.

Task 2: Navigating the PT to Destination 2 by following Path 2 (with no obstacles) and acquiring data from the medical sensors for transmitting to the control station.

B. Results Analysis

We evaluated the performance of the proposed system using objective and subjective metrics. The time factor has a significant impact on the robot's navigation performance. Also, errors may occur over the distance traveled by the PT because of various factors, such as wheel drift, improper turns, and low power supply to motors. Therefore, the task completion time and errors in the traveled distance were used to calculate the accuracy of PT's navigation. The quality of monitoring data was assessed using the three most commonly used data-quality (DQ) dimensions (accuracy, completeness, and timeliness) described in [61].

TABLE I
ACCURACY AND TIME FOR PT'S NAVIGATION

Tasks	Time (sec)	% Accuracy
Task 1	55.30	98.71
Task 2	67.10	97.90
Task 3	76.10	96.97
Task 4	88.10	97.06
Task 5	75.70	97.29
Task 6	70.20	97.46

TABLE II
ANOVA TEST RESULTS

	F	df	p-value
Time	22.36	5	.040
Errors	36.50	5	.020

1) Objective Analysis of Navigation Task: The PT's navigation accuracy is measured using the difference between the total distance and the traveled distance (i.e., error) and the time for each task. Table I shows the percent accuracies and mean time for each task.

We used analysis of variance (ANOVA) [62], which determines the statistical difference among groups. ANOVA test calculates the F ratio (or simply F), which refers to the ratio of how much variance exists among groups compared to variability within groups. If the null hypothesis is true, there is no difference between groups, and the ratio is close to the value of 1. The larger value of F shows a more significant difference among the groups. The groups are treated as equal if the alpha level (p-value) is greater than 0.05, showing that the difference between the averages of all groups is not statistically significant. However, the difference is significant if the p-value is less than 0.05. The degrees of freedom (df), i.e., number of participants minus 1, are included in the test's outcome, written after F in Parentheses.

The ANOVA test results in Table II show a significant variation $F(5, 54) = 22.36$, $p = 0.000$, and $F(5, 54) = 36.50$, and $p = 0.000$ among the Means of time and errors, respectively.

TABLE III
MEAN AND SD OF TASKS COMPLETION TIME (SEC) AND ERRORS IN THE TRAVELED DISTANCE (CM)

Tasks	Mean (Time)	*SD* (Time)	Mean (Errors)	*SD* (Errors)
Task 1	55.30	3.97	24.50	3.44
Task 2	67.10	5.26	46.20	4.64
Task 3	76.10	4.79	57.50	7.60
Task 4	88.10	10.4	64.60	9.72
Task 5	75.70	7.93	51.40	6.99
Task 6	70.20	8.98	48.20	8.43

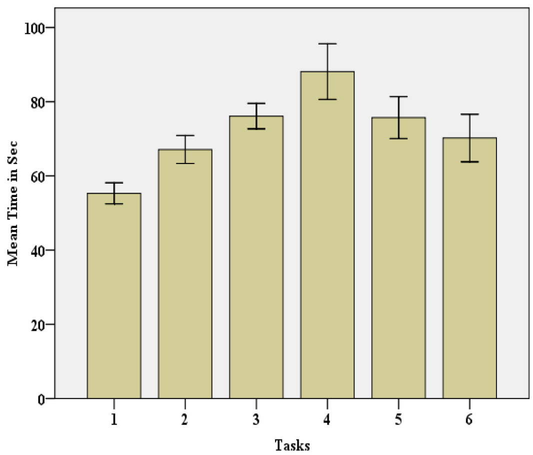


Fig. 9. Mean and SD of task completion time.

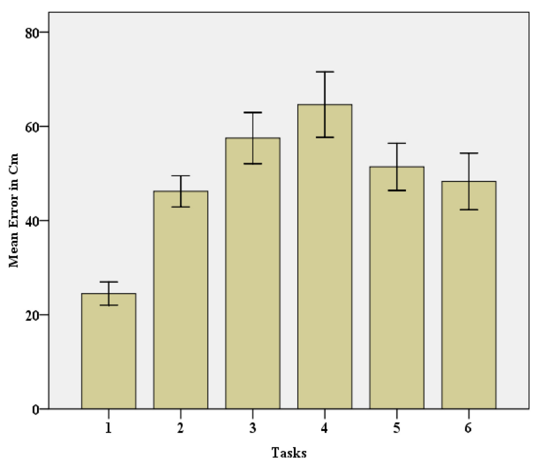


Fig. 10. Mean and SD of errors.

The Mean and standard deviation (SD) of time and errors are listed in Table III and shown in Figs. 9 and 10, respectively.

2) Objective Analysis of Monitoring Data Quality: The DQ dimensions ensure that the acquired data is consistent with the actual sensors' readings (i.e., accuracy), no expected data is lost (i.e., completeness), and the acquired data is up-to-date (i.e., timeliness).

The experimentation was performed by obtaining the monitoring data for a time slot of 10 s. To assess the system's overall performance in RHM, the DQ parameters for Tasks 1 and 2 were calculated and averaged.

The accuracy and completeness of the health monitoring data are calculated using the equations described in [63]

$$\text{Accuracy} = 1 - \left(\frac{r_e}{r}\right) \tag{1}$$

where r_e is the number of erroneous data records and r is the total number of acquired data records.

The data units' completeness is measured using the following equation:

$$\text{Completeness} = 1 - \left(\frac{r_c}{r}\right) \tag{2}$$

where r_c is the number of not-null records and r is the total number of received records.

The monitoring data's timeliness is computed by using the equation described in [64]

$$\text{Timeliness} = 1 - \left(\frac{r_o}{r}\right) \tag{3}$$

where r_o is the number of data records obtained within a defined time slot and r is the total number of records in the same time slot.

The comparative analysis of DQ dimensions for the existing and proposed systems is given in Table IV.

3) Subjective Analysis: The system's usability was measured using the system usability scale (SUS) [65]. The SUS includes ten items; each has a 5-point response ranging from strongly disagree to strongly agree. The odd-numbered items (1, 3, 5, 7, and 9) have values from strongly disagree = 0 to strongly agree = 4, whereas even-numbered items (2, 4, 6, 8, and 10) have values from strongly agree = 0 to strongly disagree = 4. The score contribution for items with odd numbers is the scale position minus 1. The score contribution for items with even numbers is 5 minus the scale position. The SUS provides scores having a range of 0 to 100. To measure the SUS score, the values from each item are summed up and then multiplied by 2.5 to obtain the overall usability score. The results show a high usability score for the proposed system, as shown in Table V.

VI. RESULTS DISCUSSION

Generally, DT is regarded as a virtual replica representing a physical artifact. However, this idea is unclear and general, narrowing down the concept of DTs. In a broader sense, the DTs paradigm combines different state-of-the-art technologies, including IoT, IoRT, VR, AI, and cloud computing, to create a virtual model that mirrors the real-world status of a physical artifact through real-time data exchange. DTs have their specific applications in different fields of life. However, depending on the application, their architecture remains the same with a slight component difference. The primary standard components of a DTs system are physical entities, virtual entities, DTs data, connectivity, and services. De Benedictis et al. [13] suggested an additional security layer to improve the safety and performance of the DTs frameworks. Our system employs the five-layer architecture proposed in [42] because it operates offline without relying on insecure public Internet service, preventing the need for an online security layer. The existing

TABLE IV
COMPARATIVE ANALYSIS OF THE EXISTING AND PROPOSED RHM SYSTEMS: THE DQ DIMENSIONS ARE EVALUATED USING TEMPERATURE SENSOR VALUES

Systems	Technologies	Connectivity	User interfaces	Services	Accuracy	Completeness	Timeliness
[53]	IoT	Internet cloud	Android application	RHM	x	x	x
[54]	IoRT	Radio tranceiver 433kHz	x	RHM, Patient assistance	x	x	x
[55]	IoRT	Internet cloud, Wifi, ZigBee, Bluetooth	Not mentioned	RHM	x	x	x
[56]	IoT	Internet cloud, Wifi	Android application	RHM	0.970	x	x
[57]	IoT	Internet cloud, Wifi	Android application	RHM	0.974	x	x
[58]	IoT	Internet cloud computing, Fog computing	Android application	RHM	0.979	x	x
Proposed system	DTs-based IoRT	NRF24L01+, Bluetooth	VR	RHM, Robot navigation	0.979	0.986	0.811

TABLE V
RESULTS OF SUS. THE AVERAGE SUS SCORE IS 38.3, AND THE TOTAL SCORE IS $38.3 \times 2.5 = 95.75$

Items	SUS Statements	Strongly Disagree 1	2	3	4	Strongly Agree 5	Average Score
1	I think I would like to use this system frequently.			1	1	8	3.8
2	I found the system unnecessarily complex.	8	2				3.8
3	I thought the system was easy to use.				1	9	3.9
4	I think that I would need the support of a technical person to be able to use this system.	7	3				3.7
5	I found the various functions in this system were well integrated.				2	8	3.8
6	I thought there was too much inconsistency in this system.	10					4
7	I imagine that most people would learn to use this system very quickly.				1	9	3.9
8	I found the system very cumbersome to use.	8	1	1			3.7
9	I felt very confident using the system.				2	8	3.8
10	I needed to learn a lot of things before I could get going with this system.	9	1				3.9

systems enable the physical asset to update the virtual models by sending sensor data straight to the latter. There is a one-to-one connection between virtual and physical entities. Our proposed DTs-based IoRT allows the PT to receive data from other real-world devices and transmit it to the virtual space for visualization or synchronization with another virtual model. The PT bridges the virtual world and the other physical entities in the real world. We displayed RHM data (body temperature, blood oxygen level, and heart rate) in VR rather than embedding it with a virtual model because it contains numerical parameters that medical staff can easily understand.

Although many systems have been developed for remote patient monitoring, the majority of them lack experimental details. Hamim et al. [53] explored the functionality of sensors by altering environmental or behavioral factors to observe how each sensor responds to these changes. However, none of the DQ dimensions is used to validate the quality of health monitoring data. In [54], gesture recognition accuracy is calculated, but the DQ dimensions are not verified. The system proposed in [55] is not tested for DQ dimensions. In [56], the sensors' accuracy is verified with commercially available medical devices, but no information about the completeness and timeliness of health data is provided. The health monitoring system proposed in [57] has analyzed the accuracy of sensors; however, completeness and timeliness are not measured. Similarly, the system presented in [58] is analyzed for the accuracy of monitoring data, but no details regarding the other two dimensions of DQ are given. Unlike the existing systems, the proposed system is subjected to detailed experimentation to evaluate the robot's navigation performance. The ANOVA results rejected the null hypothesis, indicating significant differences among the Means of experimentation groups. The comparative analysis verified that the proposed system is equally or more accurate than the existing systems for RHM. Furthermore, it outperforms all existing approaches because it is validated for data completeness and timeliness.

VII. CONCLUSION AND FUTURE DIRECTIONS

This article presented a real-time system for remotely monitoring the health of isolated patients and navigating the robotic device in the RE using a VR-based user interface and DTs-based IoRT. A predefined virtual space is used to visualize the PT and its surrounding environment and to display health-related parameters. Implementing the DTs paradigm in IoRT allows real-time control of the physical RT. The PT works as a nurse robot, an intermediary between the patient and the health service collecting health information without physically contacting the infected patient. The obstacle detection and visualization mechanism responds in real time if an obstruction is repositioned or a new obstacle is introduced in the RE. The experimental results validate the proposed system's high performance and usability. Future work will be focused on autonomously navigating the DTs to collect and transmit health information. Also, to implement AI for predicting future abnormalities based on the collected data. Additionally, more precise measures for the synchronization of DTs will be made to achieve the real advantage of the system over longer distances.

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