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Visualization of Remote Patient Monitoring System Based on Internet of Medical Things

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Abstract: Remote patient monitoring (RPM) has become a crucial tool for healthcare professionals in the monitoring and management of patients, particularly for patients with chronic illnesses. RPM has undergone improvements in its capability to deliver real-time data and information to healthcare practitioners as the Internet of Medical Things (IoMT) devices have become more widely available. However, managing and analyzing such a large volume of data still remains a difficult task. The visualization method suggested in this article enables healthcare professionals to examine data gathered by IoMT devices in real-time. Healthcare professionals may monitor patient health status and identify any data irregularities thanks to the system's dashboard. To assess the system's usability and user satisfaction, we employed both the Post-Study System Usability Questionnaire (PSSUQ) and the System Usability Scale (SUS). The outcomes of the PSSUQ and SUS assessments revealed that the suggested visualization system scored higher than the control group, demonstrating the system's usability, accuracy, and dependability as well as its user-friendliness and intuitive interface. The visualization system can boost the effectiveness and efficiency of remote patient monitoring, resulting in better patient care and lower healthcare costs.

Keywords: visualization; remote patient monitoring; Internet of Medical Things; usability

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1. Introduction

The Internet of Things (IoT) has made substantial contributions toward the transition of the healthcare sector into a technologically advanced field to improve patient care. The Internet of Medical Things (IoMT), or IoT in healthcare, integrates various medical equipment and sensors with the Internet to allow for the real-time collection and analysis of patient data. Remote patient monitoring (RPM), which enables healthcare providers to gather and analyze patient data remotely, represents one of the most promising applications of IoMT. RPM can reduce the need for frequent visits to healthcare facilities, help patients by providing eHealth solutions, and also reduce healthcare costs [1]. The RPM system relies on the integration of various medical devices that collect data related to vital signs, medication adherence, and other health-related parameters [2]. For chronic diseases such as COVID-19, heart disease, cancer, etc., to be effectively managed, data collection and analysis in healthcare are essential. Healthcare professionals may find it difficult to manage and analyze the massive amounts of associated data, particularly if they lack data analytics training [3]. Numerous visualization systems have been developed to address this issue, enabling healthcare professionals to track and evaluate patient data [4–8]. RPM has become a potential solution that additionally helps address sustainability in healthcare by utilizing IoT standards as discussed in [9,10]. RPM reduces the need for frequent visits to healthcare facilities, lowering the healthcare infrastructure burden and facilitating the process remotely. Additionally, RPM supports sustainable healthcare by enabling eHealth solutions and remote data collection [11]. This allows patients to receive more accessible and effective care, regardless of location. These elements work together to optimize resource use and reduce healthcare expenses, consistent with sustainability ideals [12,13]. The proposed study seeks to improve the user experience while supporting long-term sustainability goals by quickening data analysis and enhancing the capacity of healthcare professionals to provide effective and efficient care. Modern visualization techniques have made it necessary to offer better visualization schemes for a variety of data, including real-time data produced by IoT-based healthcare systems. This study is a continuation of studies being conducted in the field of IoMT, where initially, a detailed and systematic literature survey was conducted focusing on authentication [14]. Later, we proposed a graphical password-based authentication scheme for the security and privacy of users engaging with IoT-enabled health infrastructure [15]. In this article, we propose a novel IoMT-based RPM visualization system to enhance the user experience. The rest of the article is organized as follows: Section 2 reviews the existing literature on IoMT, RPM, and different visualization systems proposed for IoMT. In Section 3, we build our motivation toward the proposed RPM visualization system, and the details of the proposed work are also mentioned. In Section 4, we explain the methods and materials utilized to perform the experiments. The results, their explanations, and discussion are presented in Section 5. Lastly, Section 6 provides concluding remarks and elaborates on future research directions.

2. Literature Review

In recent years, the Internet of Things has drawn significant attention due to its ability to link and automate various systems and devices, allowing for real-time data monitoring and analysis. From smart cities and transportation to agriculture and industry, IoT has the potential to instill change across a wide range of industries. By linking gadgets to the internet and other sensing and communication devices, IoT can increase safety, decrease costs, and improve productivity.

IoT-based technologies in healthcare have gained significance as a result of their capacity to enhance patient health while boosting productivity and lowering treatment costs, particularly in healthcare systems. Doctors and other healthcare workers can gather and analyze data thanks to the seamless integration of medical equipment, sensors, and other monitoring systems made possible by these technologies. The demand for IoT-based health solutions will continue to rise in the upcoming years due to its potential to revolutionize healthcare procedures.

2.1. Internet of Medical Things

The Internet of Things is a technological paradigm that connects and communicates numerous systems, sensors, and devices to accomplish various goals [16]. The Internet of Medical Things is a use of IoT technology in the healthcare industry that collects and transmits medical data to healthcare providers, patients, and care providers through sensors, medical devices, and other equipment or systems. By offering remote monitoring, real-time patient data, and individualized healthcare, the IoMT is transforming healthcare delivery.

The field of IoMT includes a variety of subparts or sub-areas, such as wearable health monitoring devices, implantable medical devices, mobile health (mHealth) apps, telemedicine and telehealth systems, big data analytics, artificial intelligence for healthcare, and remote patient monitoring (RPM), as discussed in many survey articles [2,17,18]. Smartwatches, activity trackers, and medical sensors are examples of wearable health monitoring technology that are currently in use. In [19], the ontology-based learning framework leverages predefined ontologies and activity data logs to identify new activities, conditions for evolution, and learn behaviors, enhancing personalized assistance in adaptive smart homes. Such sensors and frameworks help in tracking patients' vital indicators such as heart rate, blood pressure, and breathing rate [20]. On the other hand, implantable medical devices [21] are surgically implanted devices used to analyze patient health metrics while treating them for various medical conditions, such as pacemakers for heart rhythm disorders and cochlear implants for hearing loss. Mobile health apps provide patients with access to health information and personalized care and can track symptoms and medication use [22]. Telemedicine and telehealth systems [23,24] allow patients to consult with healthcare providers remotely and can include remote monitoring of patient health status. Big data analytics can help identify patterns and trends in patient data, informing clinical decision-making and improving patient outcomes [25]. Artificial intelligence for healthcare involves the use of machine learning algorithms to analyze large amounts of patient data and assist with diagnosis, treatment planning, and drug discovery [26]. Thus, RPM is a model of providing quick and remote analysis for treatment using modern connectivity standards different from traditional healthcare settings, such as hospitals or clinics [27].

2.2. Remote Patient Monitoring

As illustrated in Figure 1, remote patient monitoring is a standard of healthcare delivery built upon modern connectivity standards to monitor patients from remote locations [1]. It can assist patients with critical conditions to receive proper treatment and manage their health by providing real-time monitoring and feedback. RPM can also reduce healthcare costs by reducing hospital re-admissions and emergency department visits.

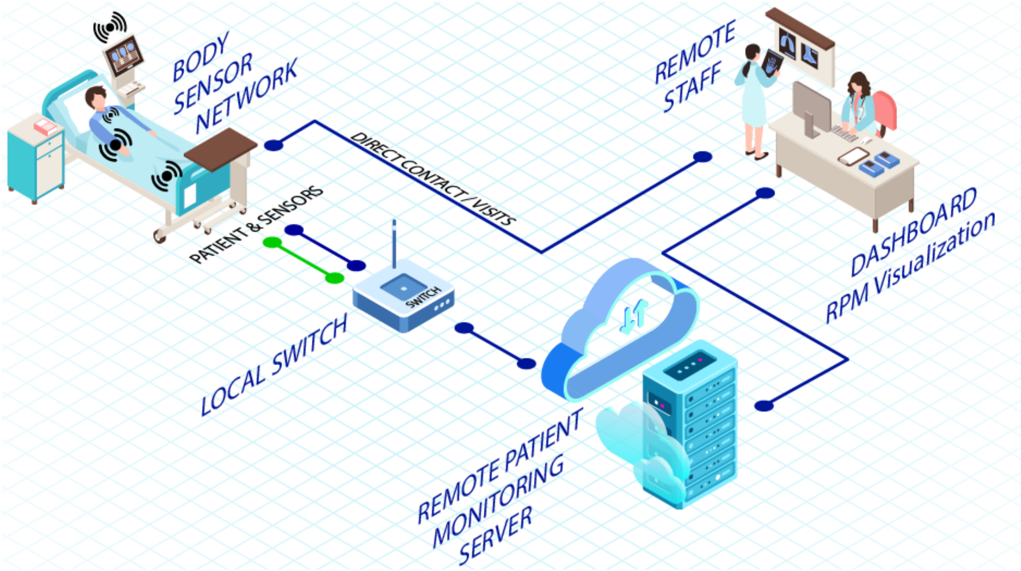


Figure 1. Architecture of a generic remote patient monitoring system [1].

Various approaches have been proposed for RPM-based healthcare systems. One of which, i.e., [28], presents a device dedicated to Super Specialty Hospital in Puttaparthi that offers auto backup, multi-environment, and bi-directional communication features. However, potential weaknesses and further details on its extension plans are lacking. It was reported that the device takes only a few seconds to store data in the relevant database, whereas, for any specific patient, approximately 20 MB of space is acquired in the database yearly. The authors intend to extend upon their work by adding small sensors embedded with mobility features to help patients carry the device for greater periods of time. In [29], challenges were encountered while developing an eHealth system that can integrate different sensors seamlessly as discussed. A modular approach was adopted to ensure improved stability and simplified addition of extra sensors. The data are sent through WebSocket protocol to address the bulk of sensor data, enabling real-time data transmission. The system aims to train neural networks for health problem identification and treatment recommendations, using the recorded data for future analysis. The article highlights the importance of fault-tolerant systems in IoT and concludes by stating that the eHealth system successfully integrates multiple devices and allows for early warnings and improved treatment efficiency.

As discussed in [30], a patient monitoring app was developed to allow doctors and nurses to view the ECG signals of patients remotely from a computer or mobile device without physically attending the wards. The system has the potential to improve healthcare services throughout the country, especially for patients from rural areas. Future work includes implementing an ECG identification algorithm to detect abnormal signals and incorporating additional e-health sensors to gather more health parameters. Further improvements are required to reduce issues concerning delay and jitter. The removal of noise from the signal is also needed to improve system performance. Ref. [31] proposes a smart healthcare system for IoT-enabled healthcare infrastructure. The system will help doctors monitor patients' basic vital signs and observe other conditions related to the infrastructure in real-time using five different sensors. The system is effective in healthcare monitoring and can be viewed by medical staff in real-time, even if the patient is outside the hospital. The system is also claimed to be helpful in times of epidemics or crises. It provides the technical means to analyze unprocessed medical data within a short span of time. The prototype is designed in a simple way in order to increase usability, as it can improve the current healthcare system, possibly protecting numerous lives. The system's success rate was found to be greater than 95% for all cases, and the error percentage was within a specific limit (<5%) for each case.

2.3. Visualization of IOMT for RPM

One of the primary goals of IoMT systems is to collect and process data generated abundantly and rapidly by various medical devices and sensors. However, such data collection would be almost useless unless presented meaningfully and easily for healthcare providers and patients [32]. Therefore, data visualization plays a crucial role in IoMT systems, by helping provide healthcare professionals with a clear understanding of the patient's health status [33]. Various visualization techniques have been proposed for IoMT systems, including dashboards, charts, graphs, and maps [34–37].

Ref. [38] presents a system that visualizes data collected from distributed sensors for different patients being treated at the same place. The system uses a dashboard that allows healthcare providers to monitor and analyze real-time data for multiple patients simultaneously. The study highlights the importance of data visualization in healthcare. Furthermore, the proposed system is claimed to have high efficiency and effectiveness for remote patient monitoring. The authors describe the technical details related to the system, including the Data Acquisition, Data Pre-Processing, and Data Visualization Dashboard. However, the usability and user satisfaction of the suggested solution **was** not evaluated in the study. This article offers a useful tool for healthcare workers to monitor and manage the health of several patients, making it a significant contribution to healthcare monitoring and visualization.

The authors in [39] proposed a wearable sensor patch based on rigid-flex for IoMT. The sensor patch is designed to be worn on the chest to monitor three vital signs, including heart, respiratory, and body temperature. The patch is designed considering the ergonomics of patients, making it flexible and comfortable, and thus allowing them to wear it for an extended period. The article discusses the design of the patch, including the materials used and the manufacturing process. The patch is connected to an IoT platform, which allows healthcare providers to access patient data in real-time. One of the key contributions is the design and implementation of a flexible wearable sensor patch that can be used for health monitoring applications. The patch is easy to wear, comfortable, and provides accurate measurements of vital signs. However, it was noted that it had not been tested in a clinical setting, and thus clarification is needed with regard to how accurate the patch is under real-world conditions. Moreover, a website based on a cloud server for remote health monitoring displaying Heart-Rate and Patient Temperature metrics was proposed but needed to be tested for usability. In [40], the authors present a healthcare system for ECG monitoring via IoT and Blynk application. In the study, the authors have claimed to develop a cost-effective, easy-to-use, and accessible healthcare system to improve healthcare services. It comprises a wearable ECG sensor, a microcontroller, and an IoT platform. The authors used the Blynk application to create a user-friendly and interactive user interface that allows patients to monitor their ECG data on their mobile devices. Moreover, the system uploads ECG data storage to the cloud. After authenticating their identity, healthcare experts can access the data available in the cloud for remote diagnosis and monitoring. Its main advantages are the system's inexpensive cost, simplicity of use, and real-time tracking. There was little insight indicating that the system had undergone a thorough evaluation; therefore, it is uncertain whether it can reliably identify and classify cardiac abnormalities. An IoT framework based on the cloud was proposed in [41] for automated health analysis and management. The system is made up of four key parts: sensor-based data collecting, mobile device data transfer, cloud-based data processing and analysis, and mobile application feedback to the user. Applications of the suggested framework in healthcare include managing chronic diseases, monitoring health and wellness, and remotely monitoring patients. The report emphasizes the advantages of storing and processing data on the cloud, which allows for real-time monitoring, effective data analysis, and customized healthcare services. Figure 2 shows the interface to examine the patient's health condition, sensor data graphs, and the patient's severity score. Nevertheless, neither the specific algorithms utilized for data processing and analysis nor the sensors used for data gathering are covered in detail in the study. The authors contend that this method has the potential to raise patient engagement, lower healthcare expenditures, and improve healthcare outcomes.

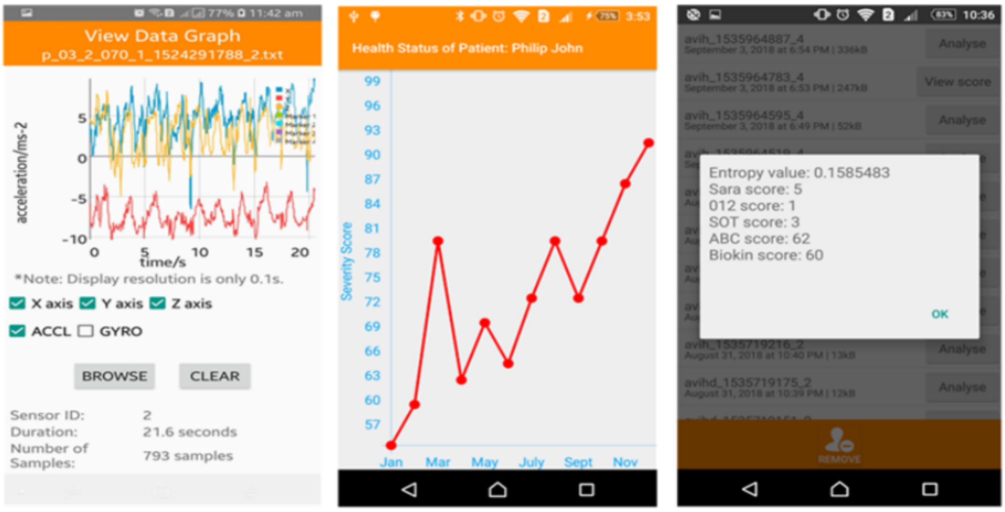


Figure 2. Dashboard including a preview of symptoms and medical records, as proposed in [41].

A user-friendly, intuitive interface for visualising a patient's electronic medical record (EMR), which contains patient demographics, laboratory test results, and clinical notes, is proposed in [42]. The user interface makes it simple and quick for clinicians to monitor a patient's progress over time. To help clinicians make better judgments, the authors also created a machine learning method to extract useful insights from the EMR data. The invention of an efficient EMR visualization technique that can enhance patient care and outcomes is one of the study's major accomplishments. Unfortunately, the efficiency of the suggested solution is not thoroughly discussed in the study, and neither is the system's scalability or interoperability. This article makes a significant contribution to the field of medical informatics and paves the way for additional research on EMR visualization in the future.

The authors of [43] propose a graph-based visualization approach for sensitive medical data that overcomes the limitations of traditional visualization techniques. The suggested approach makes use of graph theory to more fully and clearly describe medical data, making it simpler to identify significant patterns and trends. The authors' case study further demonstrates the efficiency of the suggested approach in finding patterns and trends in a huge dataset of heart rate variability recordings. This paper's key contribution is the introduction of a novel method for visualizing medical data that can increase the precision and effectiveness of medical data analysis. However, a limitation of this study is that it only presents a case study in the context of heart rate variability measurements. It is unclear how the proposed approach would perform on other types of medical data. Ref. [27] presents a health monitoring system developed for IoMT to provide patients with personalized health monitoring and disease management services. The system uses various medical sensors, including ECG, blood pressure, temperature, and glucose sensors. These sensors monitor the patient's health in real-time and transmit the data to the cloud for analysis. The analysis is carried out while providing insights regarding the health status of the patient using a variety of machine-learning techniques. Patients can view their health records and receive timely reminders for appointments and medication using a mobile application built on the Android operating system as part of the system. However, the article does not provide details on the system's accuracy or any other limitations related to sensors. The reliability and effectiveness of the system in real-world scenarios need further evaluation and testing to ensure its safe and efficient deployment in healthcare settings.

In [44], the authors propose an IoT-based patient monitoring system called Smart-monitor that leverages deep learning algorithms for more efficient and accurate health monitoring. The scheme aims to provide real-time patient data analysis, remote access to medical professionals, and automated health status updates to patients and their caregivers. The authors describe the system architecture and the different components of the system, including the wearable sensor device, data acquisition, and data analysis modules. The proposed system utilizes deep learning algorithms to identify and classify different health conditions, making it more accurate and efficient than traditional patient monitoring systems. The authors also offer a thorough analysis of the system's effectiveness, with encouraging results for accuracy and response time. The system's key drawbacks are the wearable sensor device's price and the requirement for a reliable internet connection. Every user interface presented in their work must be specifically mentioned in the study. However, the study does not share any information regarding an interface or dashboard to display the data and help remote patient monitoring process.

3. Motivation and Proposed Solution

In recent years, there has been a substantial increase in the importance of remote patient monitoring (RPM), due to the compelling need for persistent patient care and the rising prevalence of chronic diseases. Providing healthcare workers with the ability to manage and monitor patient health remotely represents one of the most important duties of an RPM system. This helps patients avoid going to the hospital physically and accelerates their rehabilitation. RPM has improved its effectiveness and efficiency in supplying real-time data and information to healthcare professionals as IoMT solutions have become more widely available. However, the volume and complexity of data created by these sensors and devices can be overwhelming, and analyzing or managing such a vast amount of data can be challenging.

To address this challenge, we propose a visualization system that helps healthcare providers better visualize the data collected from IoMT devices in real-time or retrieved from already stored medical records. The proposed approach employs an Android-based mobile application that allows healthcare providers to monitor patient health status and identify any anomalies in the data. A dashboard is designed into the application to visually represent the data, making it easier to analyze and interpret. The proposed visualization system can improve the efficiency and effectiveness of remote patient monitoring by providing a user-friendly interface that displays accurate and reliable information. Furthermore, the system can reduce the burden on healthcare providers and lower healthcare costs, leading to better patient outcomes.

RPM has appeared and has been adopted as a critical solution for managing the health of patients with chronic diseases, particularly in situations where frequent hospital visits may not be practical or safe. However, the large volume and complexity of the data being created by the IoMT devices can make it challenging for healthcare professionals and doctors to monitor and analyze patient data effectively. We suggest a solution to this problem that entails data collection from body sensors and interface creation at the RPM server.

An Android-based mobile application is part of the proposed solution, which enables healthcare professionals to track patients' health status and identify any data irregularities. The system collects data from sensing devices, processes it at the local RPM server, and then presents it on a dashboard with a user-friendly visual representation of the information. The efficiency and effectiveness of remote patient monitoring can be increased with the use of this visualization system, which can assist healthcare professionals in successfully monitoring and analyzing patient data.

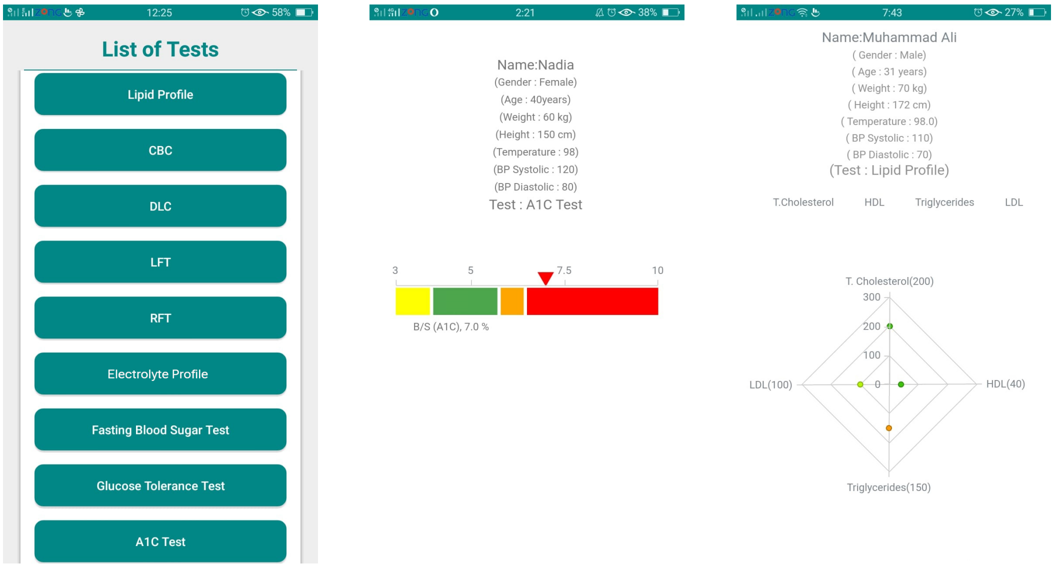
Compared to conventional RPM systems, the suggested method offers a number of benefits. The first benefit is that it provides a user-friendly interface with reliable information that makes it simpler yet useful for healthcare professionals to monitor and assess patient data successfully. Second, the system can reduce the burden on healthcare providers by automating many of the routine tasks involved in patient monitoring. Finally, the system can lower healthcare costs by reducing the need for hospital visits and providing more efficient and effective care to patients.

4. Materials and Methods

To implement the proposed solution, an Android-based mobile application was developed that allows healthcare providers to monitor patient health status and identify any anomalies in the data. The application was designed to display the collected data in a visually appealing and easy-to-understand dashboard. AnyChart library was utilized to create an interface for various health data [45]. The data acquisition process involved retrieving real-time data using functions that imitate IoT sensors providing data streams. This allowed us to create the required data while ensuring patient privacy and security. In some cases, data were also acquired from existing records which were taken from various sources, including Kaggle https://www.kaggle.com/datasets accessed on 30 March 2023. The results of diagnostic tests, including Lipid Profile Test, Complete Blood Count (CBC), Differential Leukocyte Count (DLC), Liver Function Test (LFT), Renal Function Test (RFT), Blood sugar, etc., were used to provide visualization as listed in the interface snapshot shown in Figure 3a.

For the purpose of data visualization, the following four charts were used:

- Linear Color Scale is another type of color scale that creates a linear gradient of colors between two endpoints to represent continuous and numerical data, such as temperature or precipitation. (Preview available in Figure 3b)
- Radar Chart is an interactive graphical preview mechanism for displaying multivariate data. The data are given in two dimensions comprising some quantitative variables in such a preview. (Preview available in Figures 3c and 4c)
- Tree Map Chart is a visualisation method showing hierarchical data using nested rectangles. They are useful for visualizing large amounts of hierarchical data in a way where comparisons can be built between different data groups. (Preview available in Figure 4a)
- Circular Gauge is used to display a single value on a circular scale in the shape of progress or completion, where the progress is represented by different colors. (Preview available in Figure 4b)



(**a**) (**b**) (**c**)

Figure 3. Interface previews of the proposed scheme. (**a**) List of Medical Diagnostic Tests. (**b**) Linear Color Scale using [45] for A1C Test. (**c**) Radar Chart using [45] for Lipid Profile Test.

(**a**) (**b**) (**c**)

Figure 4. Interface previews of the proposed scheme (contd.). (**a**) Tree map using [45] for CBC Test. (**b**) Circular Gauge using [45] for Electrolytes Profile. (**c**) Radar Chart using [45] for CBC Test.

A post-test-only research design was adopted to evaluate the system's usability, where control and treatment groups were created. The control group used traditional methods, including looking at data from screens displays or printouts. The treatment group utilized our designed application to visualize the results and access patients. The Post-Study System Usability Questionnaire (PSSUQ) [46,47] and the System Usability Scale (SUS) [48] evaluation measures were used to access both the systems for usability, information quality, interface quality and system quality. PSSUQ is a validated and widely used questionnaire that assesses the overall quality of a system that provides results on a Likert scale of 1 to 7, where 1 represents "strongly agree" and 7 represents "strongly disagree". To make the results easily understandable by the stakeholders of the respective domain, we have inverted the scale by applying the formulae i-e 7 minus the Likert scale score plus 1. After inverting, 1 represents "strongly disagree" while 7 represents "strongly agree". The System Usability Scale (SUS) is also a global evaluation standard for measuring the usability of a system or product. It consists of a ten-item questionnaire with five response options ranging from 1 representing "strongly disagree" to 5 representing "strongly agree". A sample of 20 practising doctors from private and public sector hospitals in Haripur, Pakistan, were selected. The sample selection was based on convenience and accessibility to participate in the evaluation, whereas 10 participants were randomly divided into the control and treatment groups. Participants were tasked to interact with the health records using the given system and visualize them to extract information. After performing tasks related to the interaction with health records, both group members filled out PSSUQ and SUS questionnaires.

A statistically independent sample *t*-test [49] was used to determine whether the results of a user-centered survey were significant. We aimed to assess whether the means of both the control and treatment groups were different or not. Additionally, we wanted to generalize the results beyond the sample size and draw conclusions about the entire population. In this respect, the following alternate and null hypotheses were developed:

4.1. Null Hypotheses

- $H_0 1$: Our proposed visualization system and traditional visualization system used for visualizing health records has no significant difference in their population means regarding overall quality.
- $H_0 2$: Our proposed visualization system and traditional visualization system used for visualizing health records has no significant difference in their population means regarding system quality.
- $H_0 3$: Our proposed visualization system and traditional visualization system used for visualizing health records has no significant difference in their population means regarding information quality.
- $H_0 4$: Our proposed visualization system and traditional visualization system used for visualizing health records have no significant difference in their population regarding interface quality.
- $H_0 5$: Our proposed visualization system and traditional visualization system used for visualizing health records has no significant difference in their population means regarding usability.

4.2. Alternate Hypotheses

- $H_a 1$: Our proposed visualization system and traditional visualization system used for visualizing health records are significantly different in terms of overall quality.
- $H_a 2$: Our proposed visualization system and traditional visualization systems used for visualizing health records significantly differ regarding system quality.
- $H_a 3$: Our proposed visualization system and traditional visualization system used for visualizing health records significantly differ regarding information quality.
- $H_a 4$: Our proposed visualization system and traditional visualization system used for visualizing health records significantly differ regarding interface quality.
- $H_a 5$: Our proposed visualization system and traditional visualization system used for visualizing health records are significantly different in terms of usability.

5. Results and Discussion

The following sections contain an extensive compilation and analysis of results obtained through PSSUQ and SUS.

5.1. Results Obtained Using PSSUQ

The overall quality computed by the participants' response for the treatment group was 5.93, while the control group was 4.51. Similarly, the system quality of the treatment group's visualization system was 6.55, whereas, for the control group, it was 5.42. Moreover, the information quality of the proposed visualization system was 5.15, while that of the traditional visualization system was 3.38. Lastly, the interface quality of the proposed visualization system turns out to be 6.27 compared to the traditional visualization system, which has an interface quality of 4.77. Figure 5 provides a graphical representation of the results.

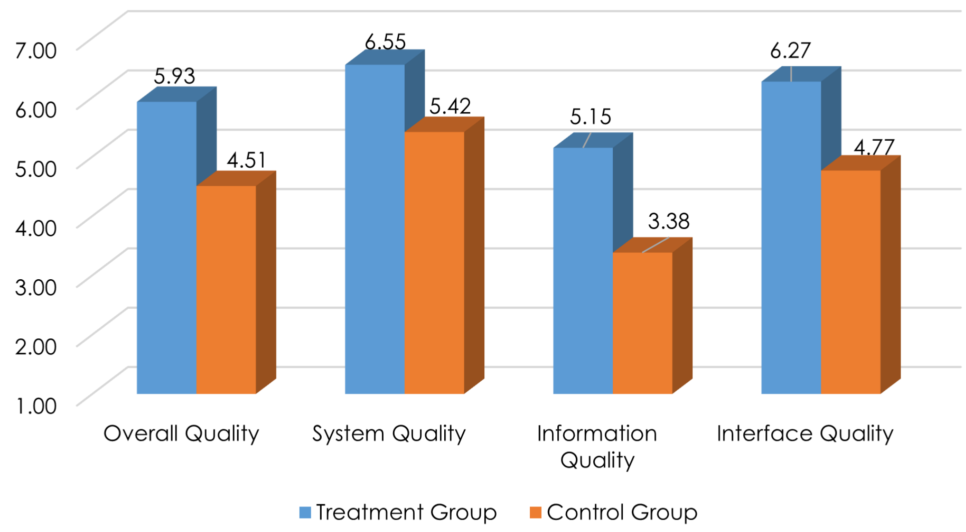


Figure 5. The findings of PSSUQ, whereas the X-axis represents the sub-measures of PSSUQ, and Y-axis represents the computed scores of those sub-measures.

In a more detailed analysis of the results as presented in Table 1, we found that 60% of participants in the control group and 91.43% of the group members of the treatment group reported being satisfied with the usability of the visualization system. Moreover, 97.14% of the treatment group participants while 81.43% of the control group participants proclaimed the system's simplicity in use. Regarding tasks and scenario completion, 95.71% of the treatment group participants and 78.57% of the control group performed them promptly. 97.14% treatment group participants and 81.43% control group participants were comfortable using the system. Similarly, learning the relevant visualization system was easy for 97.14% participants of the treatment group and 87.14% participants of the control group. The opinion of 82.86% of participants who used our proposed visualization system was that they could become productive in no time using the system. In contrast, 75.71% of the participants who used the traditional visualization system thought the same.

Furthermore, 55.71% members of the treatment group and 34.29% members of the control group mentioned that the system's error messages clearly stated the solution to the problem. Recovery from a mistake while using the system was easy and swift for 72.86% of the group members from the treatment group and 40% of the group members from the control group. Furthermore, 30% individuals in the treatment group and 28.57% individuals in the control group were satisfied with the clarity of information provided to them with the system. Similarly, finding the required information was easy for 97.14% treatment group participants and 75.71% control group participants. Additionally, this information was helpful for 94.29% members of the treatment group and 72.86% members of the control group in completing the tasks and scenarios. According to 91.42% of the treatment group, the information was clearly organised on the system screen and 38.57% control group participants.

Regarding opinions about the interface of the visualization system, 94.29% participants in the treatment group and 61.43% participants in the control group found it to be pleasant. Moreover, 97.14% treatment group participants and 70.00% control group participants liked using the interface of the visualization system. In addition, 77.14% participants of the treatment group and 72.86% participants of the control group stated that the visualization system being used possesses all the expected functionalities. To conclude the entire evaluation, the tests showed that 82.86% and 71.43% members of the treatment and control groups were overall satisfied with the visualization system.

Table 1. Statement-wise comparison of the entire PSSU-Questionnaire, $\bar{x}$: Average, $\tilde{X}$: Median, M_o: Mode, σ: Standard Deviation, S1–S16: Statement 1 to Statement 16 of the PSSUQ

	Control Group		Treatment Group	
	% Score	$\bar{x}, \tilde{X}, M_o, \sigma$	**% Score**	$\bar{x}, \tilde{X}, M_o, \sigma$
S1	60.00	4.2 (4.0, 3, 1.317)	91.43	6.4 (6.0, 6, 0.516)
S2	81.43	5.7 (5.5, 5, 0.823)	97.14	6.8 (7.0, 7, 0.422)
S3	78.57	5.5 (6.0, 6, 0.850)	95.71	6.7 (7.0, 7, 0.483)
S4	81.43	5.7 (6.0, 6, 1.059)	97.14	6.8 (7.0, 7, 0.422)
S5	87.14	6.1 (6.0, 6, 0.738)	97.14	6.8 (7.0, 7, 0.422)
S6	75.71	5.3 (5.5, 6, 0.823)	82.86	5.8 (6.0, 6, 0.422)
S7	34.29	2.4 (2.0, 2, 0.516)	55.71	3.9 (4.0, 4, 1.101)
S8	40.00	2.8 (2.0, 2, 1.033)	72.86	5.1 (5.5, 6, 1.197)
S9	28.57	2.0 (2.0, 2, 0.000)	30.00	2.1 (2.0, 2, 0.316)
S10	75.71	5.3 (6.0, 6, 0.949)	97.14	6.8 (7.0, 7, 0.422)
S11	72.86	5.1 (5.0, 5, 0.738)	94.29	6.6 (7.0, 7, 0.516)
S12	38.57	2.7 (3.0, 3, 0.483)	91.42	6.4 (6.0, 6, 0.516)
S13	61.43	4.3 (4.5, 5, 0.823)	94.29	6.6 (7.0, 7, 0.516)
S14	70.00	4.9 (5.0, 6, 1.197)	97.14	6.8 (7.0, 7, 0.422)
S15	72.86	5.1 (5.0, 6, 0.876)	77.14	5.4 (5.0, 5, 0.516)
S16	71.43	5.0 (5.0, 5, 0.816)	82.26	5.8 (6.0, 6, 0.422)

5.2. Results Obtained Using SUS

The computed SUS score for the group treated with the proposed visualization system was 75, while for the control group treated with the traditional visualization system, it was 43.5, as shown in Figure 6.

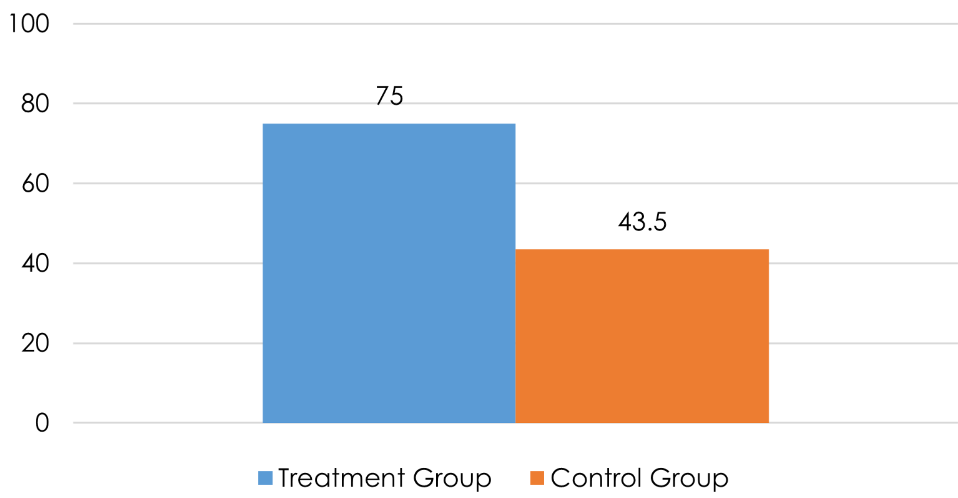


Figure 6. SUS Score obtained by both control and treatment groups. X-axis represents the treatment and control groups, whereas Y-axis represents the SUS score.

For further details, in response to the statement concerning the user's likeliness to use the visualization system frequently, 6 out of 10 treatment group participants rated it 5 and 4 participants rated it 3 (Average score = 3.2) while 6 and 4 participants of control group rated it 3 and 4 (Average score = 1), respectively. The complexity of the visualization system was rated 1, 2, 3 by 4, 2 and 4 participants of the treatment group (Average score = 3) and 3, 4 by 8 and 2 participants of the control group (Average score = 1.8), respectively. Ease of use while using the system was rated 5, 3, 2 by 8, 1 and 1 participant of the treatment group (Average score = 3.5) and 2, 4 by 6 and 4 participants of the control group (Average score = 1.8), respectively. In addition, the need for technical person support in order to use the system was rated 1, 2, 3 by 2 1 and 6 participants of the treatment group (Average score = 2.7) and 2, 3, 4 by 4, 3 and 3 participants of the control group (Average score = 2.1), respectively. Well-integration of various functions in the visualization system was rated 3, 4, 5 by 6, 1 & 3 participants of the treatment group (Average score = 2.4) and 2,3 by 4 & 6 participants of the control group (Average score = 1.6), respectively. Inconsistency in the system was rated 3, 4 by 6 & 4 participants of the treatment group (Average score = 2.4) and 2, 3 by 4 & 6 participants of the control group (Average score = 2.4), respectively. Statement regarding prompt and easy learning to use the visualization system was rated 3, 4 and 5 by 2, 2 and 6 treatment group participants (Average score = 3.4) and 2 and 3 by 8 and 2 control group participants (Average score = 1.2), respectively. Similarly, a statement regarding the system being cumbersome was rated 1 and 3 by 4 and 6 participants of the treatment group (Average score = 2.8) and 2 and 3 by 4 and 6 participants of the control group (Average score = 2.4), respectively, while using the system, the confidence of the user was rated 3 and 5 by 3 and 7 participants of the treatment group (Average score = 3.4) and 2 and 3 by 7 and 3 participants of the control group (Average score = 1.3), respectively. Lastly, the need to learn a lot before getting going with the system was rated 1, 2 and 3 by 4, 1 and 5 participants of the treatment group (Average score = 2.9) and 3 and 4 by 8 and 2 participants of the control group (Average score = 1.8). The average score computed with these rating scores with SUS formulas against each statement is depicted in Figure 7.

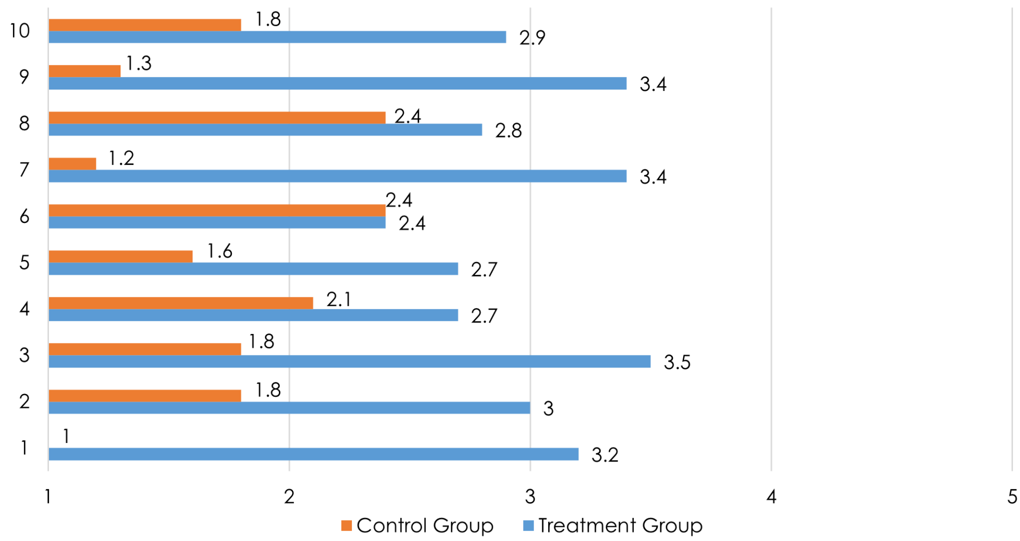


Figure 7. Description of SUS average score computed against the individual statements. X-axis represents the average score from 1 to 5, and Y-axis represents SUS question statements from 1 to 10.

Independent sample *t*-test results for all the measures depict that the change in means of control and treatment group does not occur by chance. Furthermore, on the basis of the statistics obtained, the null hypotheses can be declined, and we can consider alternate hypotheses for all measures. The findings of the test can be interpreted as:

- A prominent difference exists between the usability of the proposed visualization system and the traditional approach used to visualize the remote patient record t(18) = 4.9, p = 0.000.
- A significant difference is found between the overall quality of the proposed visualization system and the traditional visualization system used to visualize the remote patient record t(9) = 6.19, p = 0.000.
- With respect to the system quality, a significant difference was identified between the treatment and control system, which was used to visualize the remote patient record t(9) = 4.12, p = 0.002.
- In terms of information quality of the proposed visualization system and the traditional visualization system, a major difference is witnessed between the used to visualize the remote patient record t(16) = 9.14, p = 0.000.
- For the interface quality of the proposed visualization system and the traditional visualization system used to visualize the remote patient record, a difference in significant value exists, t(10) = 4.97, p = 0.001.

Based on these interpretations, we can conclude that the proposed visualization system demonstrates enhanced usability calculated using SUS. The proposed approach is better than the traditional visualization system for remote patient health records for all the sub-measures of PSSUQ, including the Overall Quality, Quality of System, Quality of Information and Interface. The statistical evaluation for the *t*-test is presented in Table 2.

Table 2. Findings of the Independent Sample *t*-test.

Measures	Value of t	Value of df	2-Tailed, *p* Value	Cohen's d
Usability	4.9	18	0	6.9
Overall Quality	6.19	9	0	8.8
System Quality	4.12	9	0.002	5.9
Information Quality	9.14	16	0	12.9
Interface Quality	4.97	10	0.001	7.07

6. Conclusions

Across the globe, the healthcare domain has witnessed a significant paradigm shift due to the inclusion of IoT in the provision of various healthcare services. This study proposes a visualization system that helps healthcare providers monitor patient health status and identify anomalies in real-time data collected from IoMT devices and health data acquired from other sources. The proposed visualization system is tested for usability and user satisfaction using a System Usability Scale and Post-Study System Usability Questionnaire, respectively. A subsequent qualitative and statistical analysis of the results reflect that the proposed visualization system received significantly better results regarding Usability, Overall Quality, Quality of System, Quality of Information and Quality of Interface in comparison to traditional mechanisms utilized for previewing health records. This indicates that the system is user-friendly, provides accurate and reliable information, and has a well-designed interface that is easy to use. It can be deduced that the proposed visualization system has the potential to improve the efficiency and effectiveness of remote patient monitoring, ultimately leading to better patient outcomes.

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