Journal of the Brazilian Computer Society, 2024, 30:1, doi: 10.5753/jbcs.2024.3201

IoT Peritoneal Dialysis: an approach exploring remote patient monitoring

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Received: 28 February 2023 • **Accepted:** 25 March 2024 • **Published:** 16 August 2024

Abstract It is estimated that 5.4 million people will undergo Renal Replacement Therapy by 2030. Peritoneal dialysis seems to be the most widespread form of home treatment for these patients, but it faces problems related to its adherence. Remote monitoring has the potential to increase treatment adherence. This work aims to design an approach that integrates: (i) a platform for the acquisition of vital signs and other parameters of a patient on peritoneal dialysis; (ii) an environment where customizable rules build Situation Science and, when necessary, send notifications to the medical team; and (iii) a signal and image visualization interface that can be accessed remotely.

Keywords: Internet of Things, Vital Signs, Peritoneal Dialysis, Remote Patient Management

1 Introduction

Societies around the world are facing the problem of managing the increasing number of patients with End-Stage Kidney Disease (ESKD), driven by population growth, advancing average age, obesity, diabetes and hypertension. The Global Burden of Disease (Global Burden of Disease, 2020) estimates that chronic kidney disease will become the 5th leading cause of death by 2040, well above the current 16th position (Foreman *et al.*, 2018).

When Chronic Kidney Disease (CKD) progresses to ESKD, Renal Replacement Therapy (RRT) is required. RRT includes dialysis (hemodialysis or peritoneal dialysis) and kidney transplantation Levin *et al.* (2017) - procedures that can add many significant years to patient's lives.

It is estimated that at least 5.4 million people will undergo RRT by 2030, mainly in low-middle-income countries. However, the number of people without access to RRT will remain substantial because dialysis is one of the most expensive therapies for individuals and governments. These data show a pressing need to develop innovative and cost-effective approaches so that RRT can be made available to the most people with the potential to benefit from it.

These data show a pressing need to develop innovative and cost-effective approaches so that RRT can be made available to the majority of people with the potential to benefit from it.

Peritoneal Dialysis (PD) currently appears to be the most widespread form of home treatment for patients requiring RRT, but it faces several problems with concerning adherence. The necessary care is complex and requires significant staff involvement to integrate medication adherence, lifestyle modification and nutritional adaptation into the daily routine (Diamantidis and Becker, 2014). In addition, PD patients are often not satisfied with the communication with health care providers (Nunes *et al.*, 2011) when dealing with treatments of this nature, which can happen without a presence in specialized clinics.

Remote Patient Management (RPM) for people with PD is an emerging technology in which patients' biometric information (including pulse, blood pressure and other parameters) can be remotely monitored, along with important information about PD treatment. As part of an evolving field of telemedicine, RPM has the potential to improve clinical outcomes for patients who practice PD, reduce resource utilization and improve adherence to the PD procedure, as well as positively impact the patient experience. Reports on RPM are encouraging Wallace *et al.* (2017).

The premise pursued in this work is to explore Internet of Things (IoT) resources, both for acquiring information about patients in PD, and for interoperating with the medical community whenever necessary. This interoperation will be coordinated by automated procedures, governed by mechanisms for Situation Awareness.

Situation Science refers to a model in which the computational system is capable of verifying the aspects in which it is interested and, when necessary, reacting to changes in it by triggering relevant procedures. This approach materializes IoT premises, in which there is an autonomous communication between intelligent objects, used by health professionals, cooperating for the advancement of their different activities with patients (Perera *et al.*, 2014).

According to Sezer *et al.* (2018), for the construction of situation-aware systems in distributed environments, as is the case of the present proposal, some challenges must be addressed: (i) context acquisition from heterogeneous and distributed sources; (ii) processing of acquired contextual data; and (iii) the respective actions directed to the devices and people involved.

Considering this scenario, the main objective of this work is to design an approach, called IoT Peritoneal Dialysis: An Approach Exploring Remote Patient Monitoring (IoT PD-RPM), which integrates: (i) a platform for the acquisition of vital signs and other parameters of a patient undergoing PD, as well as images of the effluent bag; (ii) an environment for contextual processing, which, through customizable rules, builds the Situation Awareness of patients and, when necessary, sends notifications to the health professionals involved; and (iii) an interface for textual and graphic visualization of signals and images that can be accessed remotely.

Therefore, in the design of the IoT PD-RPM approach, the software architecture of the EXEHDA middleware will be explored, particularly its subsystem dedicated to contextual processing, which will be used in the inference of the situation of patients.

The expectation with the IoT PD-RPM is to allow physicians to remotely anticipate diagnoses and the consequent prescription of procedures. In addition, reassure the patient about the fact that his treatment, despite being done far from a clinic, is being followed up and monitored.

It is understood that the research associated with the development of the IoT PD-RPM has the potential to increase the likelihood of acceptance of the treatment, as part of an often complex daily routine, contributing to adherence to the option for treatment with PD.

This article is organized into seven sections. The second Section presents concepts considered interesting when reviewing the literature in relation to the proposal. In the third Section, related works are discussed. In the fourth Section, the EXEHDA middleware is introduced, highlighting its main functionalities involved in obtaining Situation Awareness. The fifth Section presents the IoT PD-RPM approach addressing its main characteristics. The sixth Section discusses the prototyping and tests performed of the IoT PD-RPM approach. Finally, the seventh and last Section presents final considerations and future work.

2 Scope of the Developed Approach

In this section, concepts considered relevant when reviewing the literature in relation to the developed proposal are presented.

2.1 Remote Patient Management (RPM)

New methods for managing end-stage renal disease at home have been available for several years, however, acceptance of PD at home has been below expectation for several reasons. Non-adherence is an important factor that determines the results of PD, since patients on home dialysis are likely to feel isolated and may feel anxious due to the lack of routine clinical supervision. When patients feel disconnected from their healthcare professionals, compliance with medical advice as well as confidence in self-care decreases Liu *et al.* (2017). Monitoring PD patients enhances adherence to therapy and is essential to allow troubleshooting when clinical outcomes appear to be outside the predicted range based on the therapy prescription Rosner and Ronco (2012). RPM allows clinicians to closely monitor and detect early problems and initiate immediate interventions to prevent hospitalizations John and Jha (2019). In this way, RPM offers an opportunity to increase uptake and technical survival of home dialysis modalities, improving patient satisfaction and outcomes, and may lead to cost savings Wallace *et al.* (2017).

2.2 Peritoneal Dialysis Effluent Color

Peritoneal dialysis effluent is usually clear. A change in appearance indicates a complication of the technique and requires quick and accurate handling. It may also reveal a problem not directly related to the dialysis technique itself, but to another pathological situation that would go unnoticed in patients who are not undergoing peritoneal dialysis exchanges (Dossin and Goffin, 2019).

Vital signs

Vital signs are medical signs that indicate the status of the vital (life-sustaining) functions of the human body. These measurements are taken to help assess a person's overall physical health, provide clues to possible illnesses, and show progress toward recovery. Among the vital signs we can highlight: Pulse, Blood Pressure and Pulse Oximetry.

Medical Information Mart for Intensive Care (MIMIC)

MIMIC, currently in version-III, is a relational database containing data referring to patients who remained inside the intensive care units of Beth Israel Deaconess Medical Center (Boston, Massachusetts, United States) comprising more than 58,000 hospital admissions out of 38,645 adults and 7,875 newborns Johnson *et al.* (2016).

Data spans from June 2001 to October 2012, including vital signs, medications, laboratory measurements, observations, and notes taken by caregivers, fluid balance, procedural codes, diagnostic codes, imaging reports, length of hospital stay, survival data, etc.

2.3 Database auditing in IoT

Database auditing has become a very relevant aspect when preserving sensitive information, as the Database Management System (DBMS) is considered the main asset that stores, maintains and monitors information. In the IoT environment focused on healthcare, the patient data stored falls exactly into this sensitive category, according to the main world data protection laws (Rapôso *et al.*, 2019) (Li *et al.*, 2019).

The use of Computer-Assisted Audit Tool (CAATs) (Serpeninova *et al.*, 2020) can facilitate the completion of the audit by auditors. In this approach, we will propose a CAAT module for the EXEHDA middleware, with the objective of automating the performance of audits in its database, in the category of logon/off audit, usage audit, security attribute audit (privileges, user/login and password changes). The audit in this approach starts with the creation of triggers that will supply the tables responsible for obtaining data that will be used in the audit process. The resulting reports include suspicious access, inactive users, access outside operating hours, data of vital signs outside the expected range and/or outside normal standards.

Association Rule and Apriori Algorithm

Association rule learning is a rule-based machine learning method for discovering interesting relationships between variables in large databases. It is intended to identify strong rules discovered in databases using some measures of interest. In any transaction with a variety of items, association rules are intended to discover the rules that determine how or why certain items are connected

The basic premise of Association Rules is to find elements that imply the presence of other elements in the same transaction, that is, to find relationships or frequent patterns between sets of data (Agrawal *et al*., 1993).

Several algorithms stand out in the challenge of frequent pattern mining, among them can be mentioned:

Apriori Algorithm: It is a classic method for frequent pattern mining. It iteratively generates candidate itemsets and then checks their support in the database. However, its efficiency is compromised by the need for repeated database scans, especially in large datasets (Dhinakaran and Prathap, 2022);

Reduced Association Rule Mining (RARM): It is an algorithm designed to reduce the number of association rules generated during the mining process. It aims to filter out redundant rules and focus on generating only the most relevant ones, thereby improving efficiency (Varol Altay and Alatas, 2020);

Equivalence Class Transformation (ECLAT): It is a popular algorithm that avoids candidate generation by using a depth-first search strategy to directly find frequent itemsets. It uses a vertical database format to efficiently count support for itemsets (Mohapatra *et al*., 2021);

Frequent Pattern Growth (FP-Growth): It is a highly efficient algorithm that addresses the problem of repeated database scans by employing a divide-and-conquer strategy. It builds a compact data structure called FP-tree to represent the dataset and extracts frequent patterns recursively from this structure (Shawkat *et al*., 2022).

The strengths and weaknesses of each of these algorithms are reflected in the choice of algorithm, which is influenced by factors such as the size and characteristics of the data set, the available computing resources, and the specific requirements of the mining task.

This is a preliminary work, and at this stage, we are considering the use of the Apriori algorithm. As the work progresses, all listed algorithms will be analyzed with the aim of determining which one best suits data mining for auditing purposes.

Apriori (Agrawal *et al*., 1994) is an algorithm for mining frequent itemsets and learning association rules in relational databases. It identifies frequent individual items in the database and extends them to ever-larger sets of items, provided those sets of items appear frequently enough in the database. The sets of frequent items determined by Apriori can be used to determine association rules that highlight general trends in the database.

The Apriori is an iterative two-step process consisting of join and prune operations. At each iteration, the join step generates a set of candidate itemsets from the frequent itemsets found at the previous iteration. Then the prune step is performed to filter out only the potential candidate itemsets from the candidate itemsets generated in join step using apriori property. Finally, the input dataset is scanned to count the support of these candidate itemsets. If the support of a candidate itemset is more than the user-defined threshold value, that candidate itemset is called a frequent itemset.

Here, support value represents the occurrence frequency of an itemset, i.e., the number of transactions that contain that itemset. Apriori property says that an itemset is frequent only if all its non-empty subsets are also frequent. As the name Apriori suggests, it uses prior knowledge. It finds the k-frequent itemsets based on previously found (k-1) itemsets where k represents the iteration number and also the length of the itemset.

Algorithm 1 depicts the pseudo-code of the Apriori algorithm. In the first iteration, the input dataset is scanned to find the support of each item. 1-frequent itemsets are determined by filtering only those items whose support count is equal or more than a user-specified threshold value called minimum support (line 1). Then k-frequent itemsets (for k > 1) were found using (k-1) frequent itemsets (line 2). The join step produces all the possible k-candidate itemsets by joining (k-1)-frequent itemsets with itself (line 3). The prune step uses apriori property to reduce the number of candidate itemsets (line 4–5) by filtering out the promising candidates only. Then the input dataset is scanned again to find the frequency of these promising candidate itemsets to filter out the k-frequent itemsets (line 6–10). The set of all the k-frequent itemsets (k >= 1) are then returned as the final output Raj *et al*. (2021).

Algorithm 1 Apriori Algorithm

Input D: Input Dataset
minSup: minimum support threshold
Output All 2 to k-frequent itemsets

1: $L_1 = \{\textit{1-frequent itemset}\}$
2: **for** (k=2; $L_{k-1} \neq \varphi$; $k{+}{+}$) **do**
3: $C_k = apriori\_gen(L_{k-1})$
4: **for each** *transaction t in D* **do**
5: $C_t = subset(C_k, t)$
6: **for each** C in C_t **do**
7: $c.count{+}{+}$
8: **end for**
9: **end for**
10: $L_k = \{c \in C_k \mid c.count \geq minSup\}$
11: **end for**
return $U_k L_k$

3 Related Works

During the research effort, several approaches related to the remote monitoring of patients were identified, among which five works were selected. For its selection, the work should include the following aspects: (i) monitoring vital signs; (ii) support remote sensing and actuation operations (sending alerts, etc.); and (iii) consider employing Situation Awareness.

The work of Jaiswal *et al*. (2018) presents a model that automates the collection, delivery and processing of vital patient data with the help of an edge device and the Docker container Turnbull (2014). According to the author, health monitoring and IoT-based emergency response applications require lower latency and delay when exchanging information. Information is exchanged between the edge server, the cloud, and the user's device, which directly affects performance. To achieve the objective proposed in the work, the Raspberry PI is used as an edge device to optimize the process of analyzing sensor data.

In the article by Dridi *et al*. (2017), the SM-IoT platform is proposed, an IoT-based platform for smart and personalized healthcare, dedicated to patients as well as caregivers. The purpose of this platform is to improve remote patient monitoring and promote healthcare services. The SM-IoT platform is able to collect data from heterogeneous information sources, integrate it using a flexible semantic web, store it in the cloud for further analysis, visualize this data with user-friendly interfaces and facilitate its sharing taking into account its appearance privacy.

The proposal of Ahmed (2017) presents a generic Health-IoT framework that contains a Clinical Decision Support Systems-CDSS, to provide a self-adapted and personalized health monitoring system for the elderly in a home environment. The framework is primarily focused on supporting sensors, media, secure and reliable data communication, cloud-based storage and remote access of the data.

In Maia *et al*. (2015) EcoHealth (Ecosystem of Health Care Devices) is presented, a middleware platform that integrates heterogeneous body sensors to allow remote monitoring of patients and the improvement of medical diagnoses. Its main objective is to integrate information obtained from such heterogeneous sensors for the purposes of monitoring, processing, viewing and storing this data, as well as reporting and acting on the current conditions of patients and their vital signs.

Among the main differences of the IoT PD-RPM we have the use of the Medical Individual Rules Pattern (MIRP), which is a set of rules defined by the doctor, individualized for each patient, not being considered in the related works.

Another differential of the IoT PD-RPM concerns the use of a middleware, which is only used by the related work Maia *et al*. (2015). To address the challenge of providing support for Situation Awareness to IoT applications, the use of middlewares has been highlighted, which are inserted between computational infrastructures and applications [20]. Middlewares, through high-level interfaces, allow the interoperability of different IoT devices, providing, among other functionalities, a standardized way to access the resources available in them.

4 Middleware EXEHDA

EXEHDA consists of a service-based middleware, which aims to create and manage a widely distributed computing environment, as well as promote the execution of situation-aware applications on top of it. This middleware has been explored in research fronts that address IoT challenges Souza *et al*. (2018).

EXEHDA has an organization composed of a set of execution cells, be seen in Figure 1. Each cell, with concerning to the provision of Situation Awareness, is composed of a Context Server (SC), and several Edge Servers (SB) and/or Gateways.

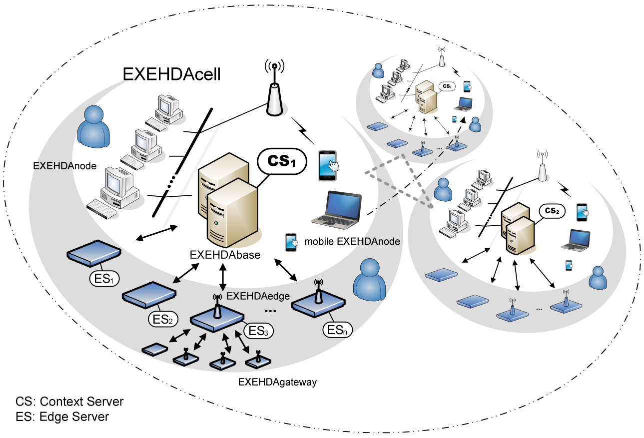

Figure 1. Environment for IoT managed by EXEHDA

Gateways collect contextual information from physical or logical sensors and with deal with the heterogeneity of different types of sensors, in terms of both hardware and protocol, transferring this collected information in a normalized way to the Edge Servers. In EXEHDA, Gateways are implemented on specific embedded hardware for the purpose of interoperating with sensors and actuators.

In EXEHDA, the processing of contextual information is distributed, leaving a part with the Edge Server, and another with the Context Server (see Figure 1).

The data received by the various Edge Servers are transmitted to the Context Server, which manages them and performs the storage and contextual processing steps. The Context Server can combine data from the Edge Servers with historical information, which is recorded in the Context Information Repository. A broader discussion of the different functionalities of both the Gateway and the Edge Servers is available in (Souza *et al*., 2018). In turn, an assessment of the with various capabilities of the Context Server can be found in (Lopes *et al*., 2014).

5 IoT PD-RPM : Design and Features

The software architecture designed for the IoT PD-RPM approach is shown in Figure 1. This section describes the different modules, funcionalities and discusses their operational profiles.

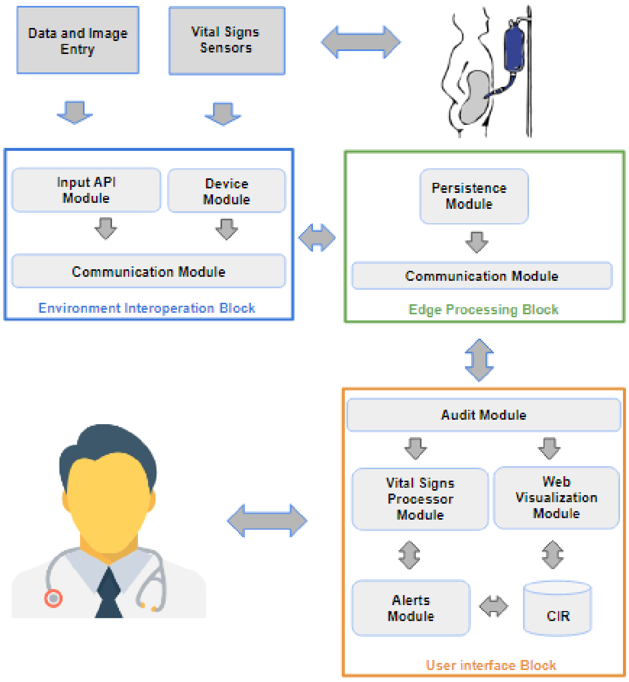

Figure 2. IoT PD-RPM Architecture

5.1 Block of Interoperation with the Environment

The Environment Interoperation Block consists of the API-MQTT Module. This IoT PD-RPM block operates on a Native Gateway of the EXEHDA middleware.

The API-MQTT Module includes a RESTful API that allows the entry of parameters from a web interface and/or mobile application and from images generated from the ESP32-CAM System-on-a-chip (SOC).

The Devices Module is responsible for receiving information from vital signs sensors, through the General Purpose Input/Output (GPIOS) of an ESP32-CAM SOC, having a program in MicroPython (Gaspar *et al.*, 2020) that collects the data coming from the sensors. In turn, the Communication Module is responsible for transferring/receiving information and commands from the Persistence Block.

5.2 Edge Processing Block

Two modules form the Edge Processing Block, which is instantiated on top of the EXEHDA Edge Server. Insert The Communication Module responsible for interoperating with the User Interface Block is instantiated in the Interoperation Module of the Edge Server of EXEHDA. The Persistence Module, on the other hand, aims to perform a temporary persistence in case the Internet connection with the User Interface Block is lost. This functionality is instantiated on top of EXEHDA's Edge Server Local Persistence Module.

5.3 User Interface Block

The User Interface Block comprises the Audit Module, the Vital Signs Processing Module, the Web Visualization Module, the Alerts Module and the Contextual Information Repository, operating on a Context Server of the EXEHDA middleware.

5.4 Audit Module

The auditing of the EXEHDA Contextual Information Repository takes place in the Audit Module. Its function is to maintain the integrity of the IoT PD-RPM database, comparing it with previously established standards based on association rules, using the Apriori algorithm.

The Audit Module was divided into smaller components, as shown in figure 3: Audit Agent, Patterns Database and Data Analysis.

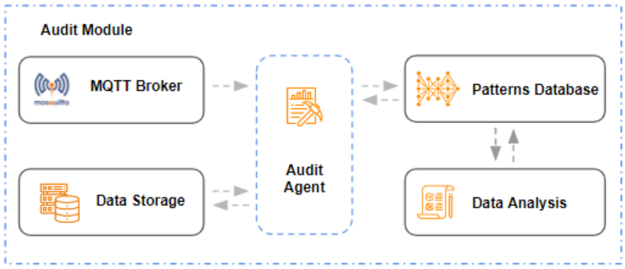

Figure 3. Audit Module Architecture

Audit Agent:

This component is responsible for saving all transactions performed by users and sensors of the IoT PD-RPM. This process is done through database triggers (Kromann and Kromann, 2018) that save transactions in JSON (Bourhis *et al.*, 2020) formatin a table modeled particularly for the audit task, as described in Listing 1.

Patterns Database:

The data mined in the EXEHDA middleware database, by the Audit Agent, and written to the audit tables are used to generate Association Rules. The basic premise of Association Rules is to find elements that imply the presence of other elements in the same transaction - to find relationships or frequent patterns between sets of data. In IoT PD-RPM, the Audit Module, at this moment, seeks to assemble association rules between: (i) Users and login times; (ii) Wrong passwords and users; (iii) Sensors and published values and (iv) Sensors and publication time intervals.

Database auditing is useful in detecting unconventional behaviors of users and/or sensors. Association rules will identify these behaviors. For example, if a user who frequently logs into IoT PD-RPM during business hours and eventually logs in at a different time, the audit module must create an alert to check whether it was an occasional access or an intrusion.

The Apriori algorithm is the most popular algorithm for association rules. It finds the most frequent combinations in a database and identifies the association rules between elements, based on three important factors:

- Support: the probability that item sets X and Y will meet;
- Confidence: the conditional probability that Y knows X. In other words, how often Y occurs when X comes first;

- Lift: the relationship between support and trust. An increase of 2 means that the probability of X and Y together is twice as likely as the probability of Y simply existing.

The rules generated using the Apriori Algorithm are saved in the IoT PD-RPM pattern tables in order to establish user and sensor behavior patterns.

Listing 1: JSON Audit Column


```
{
"audit": {
    "id":"349d00f7-ac8b-11ed-8a09-12df67a99bbf",
    "database":"exehda",
    "table":"exd_sensor_data",
    "user_app": "simone.silva",
    "dml": {
      "action":"INSERT",
      "timestamp":"2023-02-14 14:15:40",
      "user":"albandes@%",
      "ip":"172.31.73.30"
    },
    "row": {
      "new_row": [{
         "sensor_data_id": 62561,
         "sensor_id": 52,
         "collected_date":"2023-02-14 14:15:40",
         "published_date":"2023-02-14 14:15:39",
         "collected_value":22.562500
      }]
    }
  }
}
```


Data Analysis:

In Internet of Things applications, aimed at the health area (IoT-Health), personal data considered sensitive are transmitted and analyzed. This data processing is the subject of great attention in both the LGPD and the GDPR. The Data Analysis component is responsible for auditing the data processed by the IoT PD-RPM, comparing the patterns generated by the Association Rules that are defined in the Patterns Database component, with the data that transit through the approach. When data deviates from the behavior pattern established in the Patterns Database, alerts are generated to the middleware administrator, using the IoT PD-RPM Alerts Module. It is also possible to generate reports and statistics to be viewed on the dashboard of the EXEHDA interface.

5.5 Vital Signs Processing Module

The processing takes place in the Vital Signs Processing Module, where the data is received and standardized according to the internal standard of the IoT PD-RPM. After standardized, these data will go through the set of rules that will define the status of each signal. Afterward, the Medical Individual Rules Pattern (MIRP) is processed, which is a set of rules defined by the physician, individualized for each patient.

This module deals with all the rules regarding triggering alerts, based on collected vital signs. The set of rules includes: (i) rules defined by the physicians, which will meet their specificities based on their professional experience or particularities of their specialty; (ii) rules based on international standards.

The physician, a user of the IoT PD-RPM, can configure his rule templates using his definitions, the rules of established standards or even a hybrid set of rules - which makes the configuration of his personalized alerts flexible. Custom rules configuration has an intuitive interface called Template Registration, where the physician defines which vital signs will be used, their values, relational operators (equal, different, greater, lesser, greater or equal, lesser or equal) and the logical operators (and or) to concatenate the different vital signs. With this, the doctor creates a template for each situation of his/her specialty. This template receives a name and will be stored for later use in any patient.

5.6 Alerts Module

In the IoT PD-RPM approach, the role of alerts is preponderant, considering the characteristics of the activity of health professionals regarding mobility and prolonged periods without the possibility of answering phone calls. Alerts will be issued to the team responsible for the patient following rules established by them and/or internationally accepted indicators. The proposal explores two messaging services that use the Internet as a medium: Pushover and Telegram; and another called SMSGateway, which uses the Short Message Service (SMS) service of the GSM (Global System for Mobile Communications) cellular telephony network.

5.7 Web View Module

The Web Visualization Module is responsible for the entire visual interface of the IoT PD-RPM. Its functions range from login routines to patient dashboard views and screens that show important data.

The Web Visualization Module was divided into smaller components, as shown in Figure 4: Authentication, Logs, Storage, Web Front-end, Cloud Connector, Administration and Configuration, and CIR.

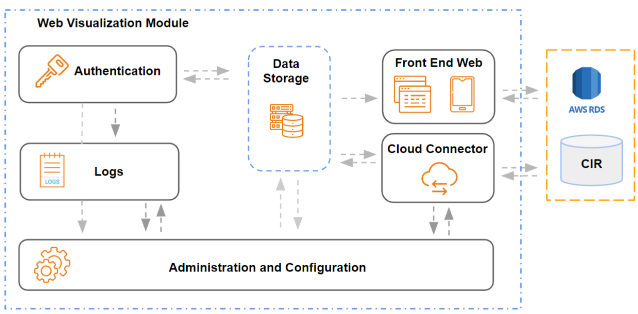

Figure 4. Architecture of the Web Visualization Module

Authentication: This component is responsible for authenticating IoT PD-RPM users. Access to the system takes place in three ways: (i) Using a password stored in the database; (ii) via the SMTP protocol of an email server; and (iii) using the Lightweight Directory Access Protocol (LDAP) to obtain credentials from an Active Directory domain.

Logs: In the Log component, the logs of all events that occurred in the IoT PD-RPM are recorded. Since the IoT PD-RPM stores sensitive data, involving human beings Kruse *et al*. (2001), a method is needed to track user activities for audit purposes, if necessary.

Cloud Connector: The Cloud Connector module connects to the Amazon cloud service called AWS IOT [1]. AWS IOT is a suite of cloud services aimed at IoT applications. IoT PD-RPM publishes the data coming from the "Environment Interoperation Block" on AWS IOT. The Cloud Connector component uses several AWS services to process data, perform analysis and generate charts for dashboards used for better visualization by the user.

Web Front-end: The Web Front-end component is responsible for the user interface. In this component are all the screens that will make the interaction between the end users and the IoT PD-RPM. It contains a dashboard with updated patient information, graphics and a photo of the effluent bags. In addition, it includes the template registration screen, the patient registration screen, the vital signs history screen, etc.

Administration and Configuration: In the Administration and Configuration component, all the parameters necessary for the operation of the IoT PD-RPM are inserted. In this component, users' credentials and their access levels are established.

CIR: It is the module responsible for the persistence of the data that are used in the Web Visualization Module. Contextual user data, their templates, images, visualization interfaces and alerts service are stored, as well as configuration parameters.

6 IoT PD-RPM: Assessment

In the MIMIC-III database, collections are performed every 15 min. In order to adapt the database to the reality of the proposal, only a daily measurement was considered.

In order to evaluate the functioning of the Vital Signs Processing Module, the MIMIC-III was used, already adapted to the reality of the approach, with the following alerts being configured: (i) Values of vital signs outside normal standards and (ii) Alert configured by the doctor, based on MIRPS. Data from 1,000 patients were processed, generating 38 alerts corresponding to non-normal vital signs and 16 alerts with parameters configured by the physician.

In turn, for evaluation with health professionals, the Technology Acceptance Model (TAM) was used, a model that has the advantage of being specific to information technology and has a strong theoretical basis, in addition to broad empirical support Okoli (2015).

The model suggests that when users are introduced to a new technology, several factors influence their decision on how and when they will use it, notably: (i) Perceived Usefulness (PU) - the degree to which a person believes that using a certain system would increase your work performance; and (ii) Perceived Ease of Use (PEOU) - the degree to which a person believes that using a certain system would be effortless Davis *et al*. (1989). Thus, a questionnaire was prepared whose questions are shown with table 1, using the Likert scale Likert (1932): I totally disagree; I partially disagree; Indifferent; I partially agree; and I totally agree.

[1]https://aws.amazon.com/pt/iot/

In this stage of designing the IoT PD-RPM, the evaluation questionnaire developed was applied to 10 doctors from three hospitals in the city of Pelotas-RS, being presented to them a demonstration of the IoT PD-RPM, and the alerts, generated at from MIMIC-III, which brought them closer to the actual functioning of the proposal.

It is essential to assess whether the questionnaire used in the research can infer or measure what it really proposes, precisely, to give relevance to the research. Cronbach's Alpha Coefficient is a widely used measure of reliability (assessment of the internal consistency of questionnaires) for a set of construct indicators. Cronbach's Alpha Coefficient measures the correlation between the answers in a questionnaire, considering the analysis of the profile of the answers given. It is calculated from the sum of the variance of the individual items and the sum of the variance of each evaluator Taber (2018).

In the literature it is found that acceptable alpha values range from 0.70 to 0.95. A low alpha value may be due to a low number of questions, low interrelation between items or heterogeneous constructions. If alpha is too high, it may suggest that some items are redundant as they are testing the same question but with a different look and feel. A maximum alpha value of 0.90 is recommended Streiner (2003). Considering the data obtained in the questionnaire, the Cronbach's Alpha value was equal to 0.876.

Based on the value obtained for Cronbach's Alpha, greater than 0.7, we can consider that the assessment made by health professionals, following the methodology of the TAM proposal, has considerable reliability, and can be understood as a representative instrument of medical opinion.

The physicians, objects of the research, were fully satisfied with the functioning of the IoT PD-RPM, not only in its functional aspects, but also with the possibility of earlier diagnosis and improved adherence to treatment.

7 Conclusion and Future Work

IoT PD-RPM acquires vital signs data, images and other significant parameters for peritoneal dialysis at the patient's home under treatment, through sensors with an IoT profile.

The acquired data are processed both by pre-defined rules that will assess whether the vital signs are in a normal range, as well as by rules specified by the medical team of the patient in question. Based on the processing of these rules, alerts are generated so that doctors are notified of events that have occurred with their patients.

Based on the processing of these rules, alerts are generated so that physicians are notified of events that occur with their patients

With the IoT PD-RPM, it is possible to anticipate diagnoses and procedures by the medical team, as well as providing greater patient safety, which enhances their adherence to treatment, as well as reducing the number of visits to clinics and offices.

The current phase of the research involves a clinical study with 12 patients, all on home peritoneal dialysis. However, due to the preliminary nature of this study and its recent implementation in the user community, there is not enough

Table 1. TAM Questionnaire Answered By Evaluating Physicians

Construct	Affirmative
Perceived ease of use	1 - I consider using the clear and objective .
	2 - Interacting with this proposal does not require much mental effort.
	3 - I consider the proposal easy to use.
Perceived usefulness	4 - Using would improve my day-to-day performance.
	5 - Using this technology would increase my productivity.
	6 - Using this technology would make me more efficient.

data for a comprehensive evaluation of the IoT PD-RPM approach with real patients. Despite this, considering the importance of the evaluation, it is already part of the research group's agenda and will be carried out as study and research efforts progress.

Partial results obtained with physicians regarding the assessment of perceived Usefulness and Ease of Use (TAM) are promising and point to the continuation of research on the IoT PD-RPM, while an approach that employs the EXEHDA middleware in the provision of approaches to health.

Among the foreseen future works is the development of a native application for smartphones. Also the digital processing of the images of the effluent bag with the objective of analysis from the color and the use of IoT with machine learning, considering that the prediction of the value of biomarkers using the approach of IoT sensors is very promising.

Declarations

Acknowledgements

This work is supported by the *Coordenação de Aperfeiçoamento de Pessoal de Nível Superior* (CAPES) (88887.941768/2024-00).

Funding

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) - Finance Code 001

Authors' Contributions

All authors contributed to the writing of this article, read and approved the final manuscript.

Competing interests

The authors declare that they have no competing interests

Availability of data and materials

The source code for creating triggers in the database used in this approach is available at: https://github.com/albandes/audit-mysql.

References

Agrawal, R., Imieliński, T., and Swami, A. (1993). Mining association rules between sets of items in large databases. In *Proceedings of the 1993 ACM SIGMOD international conference on Management of data*, pages 207–216. DOI: 10.1145/170035.170072.

Agrawal, R., Srikant, R., *et al*. (1994). Fast algorithms for mining association rules. In *Proc. of the 20th VLDB Conference*, volume 487, page 499. Available at: https://www2.it.uu.se/edu/course/homepage/infoutv/ht08/vldb94_rj.pdf.

Ahmed, M. U. (2017). An intelligent healthcare service to monitor vital signs in daily life–a case study on health-iot. *Int. J. Eng. Res. Appl.(IJERA)*, 7(3):43–55. Available at: https://www.researchgate.net/publication/314474269_An_Intelligent_Healthcare_Service_to_Monitor_Vital_Signs_in_Daily_Life_-_A_Case_Study_on_Health-IoT.

Bourhis, P., Reutter, J. L., and Vrgoč, D. (2020). Json: Data model and query languages. *Information Systems*, 89:101478. DOI: 10.1016/j.is.2019.101478.

Davis, F. D., Bagozzi, R. P., and Warshaw, P. R. (1989). User acceptance of computer technology: a comparison of two theoretical models. *Management science*, 35(8):982–1003. DOI: 10.1287/mnsc.35.8.982.

Dhinakaran, D. and Prathap, P. J. (2022). Protection of data privacy from vulnerability using two-fish technique with apriori algorithm in data mining. *The Journal of Supercomputing*, 78(16):17559–17593. DOI: 10.1007/s11227-022-04517-0.

Diamantidis, C. J. and Becker, S. (2014). Health information technology (it) to improve the care of patients with chronic kidney disease (ckd). *BMC nephrology*, 15(1):7. DOI: 10.1186/1471-2369-15-7.

Dossin, T. and Goffin, E. (2019). When the color of peritoneal dialysis effluent can be used as a diagnostic tool. In *Seminars in dialysis*, volume 32, pages 72–79. Wiley Online Library. DOI: 10.1111/sdi.12740.

Dridi, A., Sassi, S., and Faiz, S. (2017). A smart iot platform for personalized healthcare monitoring using semantic technologies. In *Tools with Artificial Intelligence (ICTAI), 2017 IEEE 29th International Conference on*, pages 1198–1203. IEEE. DOI: 10.1109/ICTAI.2017.00182.

Foreman, K. J., Marquez, *et al*. (2018). Forecasting life expectancy, years of life lost, and all-cause and cause-specific mortality for 250 causes of death: reference and alternative scenarios for 2016–40 for 195 countries and territories. *The Lancet*, 392(10159):2052–2090. DOI: 10.1016/S0140-6736(18)31694-5.

Gaspar, G., Fabo, P., Kuba, M., Dudak, J., and Nemlaha, E. (2020). Micropython as a development platform for iot applications. *Intelligent Algorithms in Software Engineering: Proceedings of the 9th Computer Science On-line Conference 2020, Volume 1 9*, 1(9):388–394. DOI: 10.1007/978-3-030-51965-$0_3$4.

Global Burden of Disease (2020). Global burden of disease. Available at: http://www.healthdata.org/gbd.

Jaiswal, K., Sobhanayak, *et al*. (2018). An iot-cloud based smart healthcare monitoring system using container based virtual environment in edge device. In *2018 International Conference on Emerging Trends and Innovations In Engineering And Technological Research (ICETIETR)*, pages 1–7. IEEE. DOI: 10.1109/ICETIETR.2018.8529141.

John, O. and Jha, V. (2019). Remote patient management in peritoneal dialysis: An answer to an unmet clinical need. In *Remote Patient Management in Peritoneal Dialysis*, volume 197, pages 99–112. Karger Publishers. DOI: 10.1159/000496305.

Johnson, A. E., Pollard, T. J., Shen, L., Li-wei, H. L., Feng, M., Ghassemi, M., Moody, B., Szolovits, P., Celi, L. A., and Mark, R. G. (2016). Mimic-iii, a freely accessible critical care database. *Scientific data*, 3:160035. DOI: 10.1038/sdata.2016.35.

Kromann, F. M. and Kromann, F. M. (2018). Mysql triggers. *Beginning PHP and MySQL: From Novice to Professional*, pages 717–731. DOI: 10.1007/978-1-4302-6044-$8_3$0.

Kruse, R. L., Ewigman, B. G., and Tremblay, G. C. (2001). The zipper: a method for using personal identifiers to link data while preserving confidentiality. *Child abuse & neglect*, 25(9):1241–1248. DOI: 10.1016/S0145-2134(01)00265-4.

Levin, A., Tonelli, *et al*. (2017). Global kidney health 2017 and beyond: a roadmap for closing gaps in care, research, and policy. *The Lancet*, 390(10105):1888–1917. DOI: 10.1016/S0140-6736(17)30788-2.

Li, H., Yu, L., and He, W. (2019). The impact of gdpr on global technology development.

Likert, R. (1932). A technique for the measurement of attitudes. *Archives of psychology*. Available at: https://psycnet.apa.org/record/1933-01885-001.

Liu, N., Kim, J., Jung, Y., Arisy, A., Nicdao, M. A., Mikaheal, M., Baldacchino, T., Khadra, M., and Sud, K. (2017). Remote monitoring systems for chronic patients on home hemodialysis: field test of a copresence-enhanced design. *JMIR human factors*, 4(3):e21. DOI: 10.2196/humanfactors.7078.

Lopes, J. L., de Souza, R. S., Geyer, C., da Costa, C., Barbosa, J., Pernas, A. M., and Yamin, A. (2014). A middleware architecture for dynamic adaptation in ubiquitous computing. *Journal of Universal Compuerter Science*, 20(9):1327–1351. Available at: https://www.jucs.org/jucs_20_9/a_middleware_architecture_for/jucs_20_09_1327_1351_lopes.pdf.

Maia, P., Baffa, A., Cavalcante, E., Delicato, F. C., Batista, T., and Pires, P. F. (2015). Uma plataforma de middleware para integraçao de dispositivos e desenvolvimento de aplicaç oes em e-health. *Anais do XXXIII SBRC*, pages 361–374. Available at: https://www.researchgate.net/publication/276411607_Uma_Plataforma_de_Middleware_para_Integracao_de_Dispositivos_e_Desenvolvimento_de_Aplicacoes_em_e-health.

Mohapatra, D., Tripathy, J., Mohanty, K. K., and Nayak, D. S. K. (2021). Interpretation of optimized hyper parameters in associative rule learning using eclat and apriori. In *2021 5th International Conference on Computing Methodologies and Communication (ICCMC)*, pages 879–882. IEEE. DOI: 10.1109/ICCMC51019.2021.9418049.

Nunes, J. A. W., Wallston, *et al*. (2011). Associations among perceived and objective disease knowledge and satisfaction with physician communication in patients with chronic kidney disease. *Kidney international*, 80(12):1344–1351. DOI: 10.1038/ki.2011.240.

Okoli, C. (2015). A guide to conducting a standalone systematic literature review. *Communications of the Association for Information Systems*, 37(1):43. Available at: https://hal.science/hal-01574600/.

Perera, C., Zaslavsky, A., Christen, P., and Georgakopoulos, D. (2014). Context aware computing for the internet of things: A survey. *Communications Surveys Tutorials, IEEE*, 16(1):414–454. DOI: 0.1109/SURV.2013.042313.00197.

Raj, S., Ramesh, D., and Sethi, K. K. (2021). A Spark-based Apriori algorithm with reduced shuffle overhead. *Journal of Supercomputing*, 77(1):133–151. DOI: 10.1007/s11227-020-03253-7.

Rapôso, C. F. L., de Lima, H. M., de Oliveira Junior, W. F., Silva, P. A. F., and de Souza Barros, E. E. (2019). Lgpd-lei geral de proteção de dados pessoais em tecnologia da informação: Revisão sistemática. *RACE-Revista de Administração do Cesmac*, 4:58–67. DOI: 10.3131/race.v4i0.1035.

Rosner, M. H. and Ronco, C. (2012). Remote monitoring for continuous peritoneal dialysis. In *Peritoneal Dialysis-State-of-the-Art 2012*, volume 178, pages 68–73. Karger Publishers. DOI: 10.1159/000337812.

Serpeninova, Y., Makarenko, S., and Litvinova, M. (2020). Computer-assisted audit techniques: Classification and implementation by auditor. *Public Policy and Accounting*, (1 (1)):44–49. DOI: 10.26642/ppa-2020-1(1)-44-49.

Sezer, O. B., Dogdu, E., and Ozbayoglu, A. M. (2018). Context-aware computing, learning, and big data in internet of things: a survey. *IEEE Internet of Things Journal*, 5(1):1–27. DOI: 10.1109/JIOT.2017.2773600.

Shawkat, M., Badawi, M., El-ghamrawy, S., Arnous, R., and El-desoky, A. (2022). An optimized fp-growth algorithm for discovery of association rules. *The Journal of Supercomputing*, pages 1–28. DOI: 10.1007/s11227-021-04066-y.

Souza, R., Lopes, J., Geyer, C., Cardozo, A., Yamin, A., and Barbosa, J. (2018). An architecture for iot management targeted to context awareness of ubiquitous applications. *Journal of Universal Computer Science*, 24(10):1452–1471. DOI: 10.3217/jucs-024-10-1452.

Streiner, D. L. (2003). Starting at the beginning: an introduction to coefficient alpha and internal consistency. *Journal of personality assessment*, 80(1):99–103. DOI: 10.1207/S15327752JPA$8001_1$8.

Taber, K. S. (2018). The use of cronbach's alpha when developing and reporting research instruments in science education. *Research in Science Education*, 48(6):1273–1296. DOI: 10.1007/s11165-016-9602-2.

Turnbull, J. (2014). *The Docker Book: Containerization is the new virtualization*. James Turnbull. Book.

Varol Altay, E. and Alatas, B. (2020). Performance analysis of multi-objective artificial intelligence optimization algorithms in numerical association rule mining. *Journal of Ambient Intelligence and Humanized Computing*, 11:3449–3469. DOI: 10.1007/s12652-019-01540-7.

Wallace, E. L., Rosner, *et al*. (2017). Remote patient management for home dialysis patients. *Kidney international reports*, 2(6):1009–1017. DOI: 10.1016/j.ekir.2017.07.010.