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Modified Early Warning Score (MEWS) Visualization and Pattern Matching Imputation in Remote Patient Monitoring

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ABSTRACT Remote Patient Monitoring (RPM), which leverages the Internet of Medical Things (IoMT) and autonomous systems, has grown in popularity recently. In RPM, the IoMT sense a patient's biophysical data and transmits it in real time while the autonomous system processes the data for clinical notifications and storage. However, RPM deployments face two diverse challenges: how to present continuous data so that healthcare professionals can quickly interpret data streams and how to manage a great deal of missing data that occurs in RPM. Several studies suggested techniques for imputing missing data in static databases, which are unsuitable for RPM. A method for constantly streaming healthcare data to medical experts involves summarizing vital signs information into a numerical score, such as the Modified Early Warning Score (MEWS), which may be visually displayed to highlight MEWS patterns over a certain period. However, a MEWS chart is simplistic and more sophisticated ways to present data visually for straightforward interpretation are needed. This research proposes a solution for the visualization and missing data challenges by identifying patterns in the RPM data. First, a pattern-matching technique is proposed to address the missing data by considering the correlation and variability of the vital signs, resulting in a comparable correct match rate. Second, we transform the observed raw physiological vital signs data into concepts we call trust, frequency, trend, and slope parameters for visualization and automated alerts. The proposed approach can better support clinical decision-making than the MEWS. Comprehensive visualization approaches and missing data solutions can improve the quality and dependability of patient risk assessments.

INDEX TERMS Pattern Imputation, Data Integrity, Visualized Remote patient monitoring (VRPM), Clinical Decision Support, Wearable technology.

I. INTRODUCTION

The Internet of Things (IoT) has revolutionized how we interact with the environment by integrating into various sectors. The healthcare sector is seeing a promising paradigm change with the introduction of the IoT into RPM. IoT makes monitoring patients in RPM with real-time data collection, processing and transfer possible. IoT enables seamless communication across various wearable sensors and medical equipment.

RPM enables ongoing patient monitoring and remote patient data access, improves patient outcomes, encourages patient participation, and adds more effective and personalized healthcare management [1]. RPM comprises three primary components: a wireless body area network (WBAN), a wide area network (WAN), and remote access. WBAN comprises wireless sensors to track physiological indicators, edge devices on wide area networks (WAN) mediate data transfer to the cloud, and real-time cloud process provides remote access.

As shown in Figure (1), the proposed cloud-based RPM system will enable the physician to monitor patients and automatically rank alarms using data mining on long-term health data. This system has significant data acquisition, pre-processing, and visualization components. For data acquisition, the patient is equipped with wearable sensors capable of monitoring physiological signs such as heart rate (HR), oxygen saturation (SpO_2), blood pressure (BP), respiratory rate (R), and temperature (T) [2]. After gathering the patient's health data, sensors send the health data via Bluetooth or ZigBee to the iPad/tablet or smartphone. The health data is pre-processed on the smartphone/tablet and in the cloud using algorithms to raise alarms for significant medical conditions. Healthcare professionals with remote cloud access to health applications can access data analytics, visualization, and other helpful information [3, 4].

In conventional hospital wards, vital signs such as BP, SpO2, T, HR, and R are typically taken every 4-6 hours to check for patient deterioration [5]. In numerous healthcare settings worldwide, nurses routinely use Modified Early Warning Scores (MEWS) to trigger warnings for patient deterioration [6]. Individual parameters receive scores ranging from 0 to 3 based on a pre-defined threshold in raw data, illustrated in Table (1) [7, 8]. The Modified Early Warning Score (MEWS) is calculated by adding these scores. For patients with various illnesses, these default threshold general values could change [6]. Clinically, MEWS helps identify patient deterioration [8, 9].

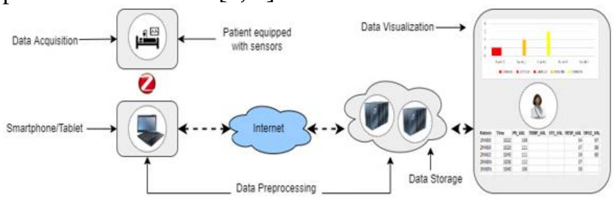

FIGURE 1. RPM System Architecture

TABLE 1: MODIFIED EARLY WARNING SCORE [3, 7, 10]

Vital Sign	3	2	1	0	1	2	3
Blood Pressure (BP) (mmHg)	<70	71-80	81-100	101-199	-	>=200	-
Heart Rate (HR)(bpm)	-	<40	41-50	51-100	101-110	111-129	>=130
Respiratory Rate(R) (bpm)	-	<9	-	9-14	15-20	21-29	>=30
Temperature (T) (degree C)	-	<35	-	35-38.4	-	>=38.5	-
Oxygen Saturation (SpO_2)	<85	85-89	90-93	>94	-	-	-

MEWS risk assessment procedures are used to analyze the possibility of the patient's health decline. These solutions include various track and trigger systems [11], including a multi-parameter approach to detect one or more abnormal changes in vital signs. One of the criteria implemented in this scenario is the "Patient at-risk team." (PART). In contrast, the aggregate scoring system attributes scores to vital signs. The early warning score (EWS) metric is used for this. MEWS is one of the variations of EWS [11]. The combination system combines single and multiple parameters with the aggregation system [11].

The wearable sensors used in remote monitoring allow for continuous surveillance of vital signs, providing a greater frequency of data beyond the traditional 4-6 hour intervals. Consistent monitoring of vital signs is critical for early diagnosis of patient deterioration, contributing to higher survival rates [12]. However, difficulties such as patient mobility, sensor failures, low battery levels, and electromagnetic interference might cause inconsistencies in the gathered data [13]. A few challenges of aberrant data are a problematic interpretation of MEWS and missing data, which causes reliability issues in clinical decisions. MEWS scores are often displayed in tabular format, making fast analysis of the information a time-consuming and effort-intensive task. Missing data leads to biased and unreliable results, affecting the accuracy of medical diagnoses and delaying treatment decisions [14]. There are three types of missing data [15, 16]:

- Missing Completely at Random (MCAR) is a condition where the likelihood of missing data is unrelated to observable and unseen factors. This type of missing data is avoidable. An example is when sensors have no power or low power while monitoring, no data gets recorded.
- Missing at Random (MAR) data signifies that the observable factors impact the likelihood of data missing. This type of data is recoverable. An example is monitoring the patient's vitals for heart monitoring after surgery but without assessing the patient's heart or respiratory rate.
- Missing not at Random (MNAR) occurs when the likelihood of missing data depends on the missing data's attributes. This type of data is not easily recoverable.

A. MOTIVATION AND CONTRIBUTION

Extensive work exists on analyzing clinical abnormalities [17] and missing data in the literature [15, 18]. Understanding the cause and pattern of missing or erroneous data is critical for selecting a practical analytics approach, especially when the degree of missing data is unknown. Analyzing data in Remote Patient Monitoring (RPM) becomes difficult due to variations in the recorded data, as machine learning algorithms require a large quantity of data for proper training [19]. Using data-mining methods can significantly reduce false alarms [20-22]. However, in the context of vital signs under RPM, most techniques do not prioritize pre-processing, correlation, and data transformations. In this research, we report on our attempt to impute the missing vital values by finding co-relationships among the vitals. The suggested technique in this research utilizes the principles of MAR and MCAR to represent the ratios of aberrant data. The accuracy of our missing pattern-match data method is validated against actual data without reduction using a matching strategy for comparable patterns. Another notable addition is the visualization of vital signs in RPM using MEWS. Visualization is accomplished by adding data modifications known as trend, trust, slope, and frequency. For our visualization, our output is compared against the MEWS tabular format.

The following are some of the study's main contributions:

- Missing Data Imputation: We suggested an approach for dealing with missing data that considers the co-relationships between vital signs and patterns obtained from MEWS values. We demonstrated the effectiveness of the suggested matching of similar patterns by independently verifying the accuracy of the missing pattern-

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match data method's accuracy against actual data without any reduction.

- Visualization of Vital Signs in RPM: We suggested novel data transformations (trend, frequency, trust, and slope) for RPM vital sign data visualization. These transformations were implemented with the MEWS to improve data representation in RPM settings. We demonstrated the method's effectiveness in enhancing data interpretation by contrasting the visualization output with the traditional MEWS tabular format.

This paper is structured as follows: We discuss related work in Section 2, our data analysis in Section 3, and our suggested pattern-matching strategy for handling missing values in Section 4. Section 5 investigates the semantic aspects of vital indicators, Section 6 describes pattern prioritization, Section 7 summarizes our findings, and Section 8 provides the paper's conclusion.

II. Related Work

Analyzing patients' vital signs and additional health records enables physicians to provide decision and knowledge-based support. In several investigations, MEWS has been a helpful method in predicting in-hospital mortality [23, 24]. MEWS may not be reliable for forecasting in-hospital mortality or health decline based on studies from diverse demographics or fields [25, 26]. For COVID-19 patients, MEWS forecasts intensive care unit admission and mortality incorrectly [23]. Data must also be synchronized, formatted, and normalized [21]. Finding the relationships between the various vitals has been the subject of several investigations [25, 26]. Normalizing the variables in the obtained data is critical due to the varied frequency with which multiple scoring systems, including MEWS and the Sequential Organ Failure Assessment (SOFA), were recorded [27].

The research [28] established the Mayo Clinical Early Warning Score (MC-EWS), which combines gradient-boosting techniques with feature engineering methodologies. The MC-EWS showed a 73% sensitivity. Notably, the MC-EWS generated 0.7 daily warnings per 10 patients at this sensitivity level, representing a 45% decrease in alert frequency compared to the National Early Warning Score. Another study [29] presented the MEWS++ model, which included three machine learning algorithms: RF, Linear Support Vector Machine, and Logistic Regression. These models were compared to the traditional MEWS in terms of performance. The MEWS++ model demonstrates predictive skills by correctly forecasting clinical deterioration or fatality using clinical data collected 6 hours before the occurrence. Many early warning scores focus solely on a patient's vital signs and ignore how these vital signs change over time. However, the vital signs trend increased the accuracy of these scores in predicting severe disease in hospital patients [30].

New algorithms for patient monitoring extract many aspects of physiological information. Five hospitals in three European nations have installed remote wireless vital sign monitoring systems in their medical and surgical wards. This case series demonstrates how such a new method might shorten the time required to identify patients at risk of deterioration, enhancing timely intervention and improving outcomes [31]. A new study describes a unique method for anticipating patient deterioration using Long Short-Term Memory Recurrent Neural Networks in critical care units. The programme outperforms traditional approaches EWS by reliably forecasting patient deterioration up to one hour in advance [32].

A study has shown that their developed Artificial Intelligence (AI) model performs better in foretelling cardiac arrest and respiratory failure [33]. Clinical abnormalities and accompanying symptoms have been identified using various Machine Learning (ML) methods [17], such as Support Vector Machine (SVM) [34], Artificial Neural Networks (ANN) [35, 36] and the Hidden Markov Model [37] [38]. These ML models, including ANN and SVM, are classified as black-box models. This implies they can't explain their predictions or prove cause-and-effect links between input factors and projected outcomes [39]. AI and ML models can only be useful in healthcare if they produce interpretable structures and outcomes that healthcare workers can comprehend and apply successfully [40].

One disadvantage of using machine learning methods is the possible loss of interpretability compared to linear models, making identifying and contributing to positive outcomes challenging [41]. Implementing the MEWS in RPM presents issues due to big data [42], demanding visualization for better decision-making. Monitoring continuous interval visual trends of vital signs without alarms proved feasible within the general ward environment [43]. Research [44] found that basic statistical learning approaches paired with feature engineering, particularly those requiring considerable human learning through data visualization and exploration, outperformed more complex methods.

To address this research gap, techniques for healthcare applications must be accessible and interpretable. These EWS systems may be effectively used by emphasizing the development of models that provide insights into the decision-making process. These activities are critical for closing the gap between cutting-edge technology solutions and the actual deployment of MEWS in RPM.

A systematic review of EWS has advised that each study should detail the methods employed for managing missing data [45]. To substitute missing data values, imputation techniques such as single mean imputation, last observation carried forward (LOCF), conditional mean imputation, full information maximum likelihood (FIML), and multiple imputations (MI) are used [46]. Missing data are commonly imputed using mean, median, last observation imputation, or multiple imputations. These imputation algorithms, however, may need to be revised when dealing with missing data classed as MNAR. In the literature for clinical research, a few straightforward and numerous imputation techniques are included in Table 2 [47]. Iterative imputation is performed using the random forest-based method Miss Forest. Random Forest, as an intrinsically multiple imputation approach, computes the mean of the data by examining numerous untrimmed classes or regression trees in the Miss Forest framework [48]. The probability distribution is used in constructing linear regression for missing data management, allowing a self-acting procedure to be included via Bayesian ridge regression [49]. The hot/cold deck imputes the missing values using the mean or mode of the cluster's variable [50]. By substituting missing data using comparable values, the K-nearest neighbour approach assesses the similarity between two variables using Euclidean distance [50]. The literature explores several machine learning strategies for dealing with missing data, including but not limited to ANN, SVM, Long Short-Term Memory (LSTM), and generic algorithms. [51]. Long processing times, single-parameter imputation, and biased results are some downsides of these machine-learning techniques.

TABLE 2: MULTIPLE AND SINGLE IMPUTATION APPROACHES.

Single Imputation	Multiple Imputation
Mean/Median	Predictive Mean Matching
Combination of Imputations	Miss Forest
Regression	Bayesian Ridge Regression
Last Observation Carries Forward	
Hot/Cold Deck	
K-Nearest-Neighbours	

The RPM collected data is extensive, and handling missing values for continuous data in real time is challenging. Existing methods have good imputation accuracy, but they could be more efficient due to complexity, computational time, and parameter correlation, among other things. Our suggested pattern-matching imputation technique considers elements like the correlation of the parameters, which reduces biased imputation. Additionally, computational time may be regulated utilizing the sliding window.

The conventional MEWS method is susceptible to corruption due to unforeseen occurrences like patient movement and noise as a single score at one moment. To make various MEWS computations in an ongoing RPM scenario easier, we introduce characteristics for data mining, which we refer to as trust, trend, slope and frequency. These functions will aid in handling noise, pointless spikes, and missing values in pre-processing the physiological vitals data. The suggested cloud-based approach also enables medical professionals to see the patient's critical conditions in ranked priority order. The identified illnesses of the patient are prioritized by employing a majority voting rule.

The following section discusses the analysis of RPM data using the suggested modifications, known as the Patterned Modified Early Warning Score (PMEWS).

III. Analysis of RPM Data

Data pre-processing is a critical phase in our technique. Data pre-processing involves the utilization of the MEWS [26]. The relevance of pre-processing data stems from potential noise, motion, vibrations, and sensor mistakes during patient observation. Pre-processing of collected data allows for an accurate evaluation. The crucial pre-processing step includes removing duplicated data, incorrect information, and high-frequency noises [52]. The data for the current study was collected from a trial conducted in India involving patients in a general ward at a private hospital [53]. Their vital signs were measured using wearable sensors for five vitals (BP, T, SpO2, R, and HR) and captured data discretely at regular intervals. The snippets of our dataset are shown in Table (3). Table (3) includes the following variables: time, PR (pulse rate), T, BP, R, and SpO2. Our data collection has been cleaned of erroneous values produced by sensor errors, motion artefacts, and noise. Temperature and blood pressure were recorded less often than the other vital indicators. The frequency of vital sign data collected, including missing values, varied from minute to minute during our pre-processing. To maintain the authenticity of the simulated data and avoid any evaluation, we deliberately refrained from using publicly accessible datasets.

TABLE 3: RAW DATA SUMMARY FOR 10 MINUTES

Time	PR	T	BP	R	SpO_2
1122	108	-	-	34	97
1123	111	-	-	37	98
1124	106	-	-	33	99
1125	106	-	-	25	99
1126	108	-	-	25	99
1127	113	-	-	41	97
1128	113	-	-	38	97
1129	113	-	-	40	98
1130	114	-	-	38	97
1131	109	-	-	39	98
1132	110	-	-	29	98

Our suggested method accepts sliding window as a pre-defined parameter. The sliding window is used to evaluate each data point individually and predict the values of the missing data points using the values inside the frame. The observed vitals are combined in a sliding window for data analysis. A sliding window is a helpful method for forecasting a specific data segment [54, 55]. As with RPM, the sliding window may be continually applied to new inbound data. Prompt diagnosis of alterations in the patient's state is crucial for effective medical intervention. The overall observation duration during RPM is the set length of the process window. When analyzing a subset of data within the processing window, a sliding window with a minimum overlap of one point is used. The alteration is dependent on the window increment time inside the processing window. The imputation approach considers the data's temporal context, which uses a sliding window to forecast the missing values more precisely.

According to equation (1), the sliding window sw_{δ}^{i} comprises various time slots $t_{(\delta+n)}^{i}$. The physician's discretion determines the process window length (L) and sliding window increment (δ). According to the literature, a six-hour forecast window for clinical decline is best [29]. The illustration of the overlap in the process window and sliding window increment is shown in Figure 2 with respective time points. Equation (1) specifies the sw_{δ}^{i}, which comprises various time slots $t_{(\delta+n)}^{i}$.

For computation throughout the remainder of the article, the notation $(t_{(\delta+n)}^{i})$ will be written as TS, as seen in equation (2).

$$sw_{\delta}^{i} = (t_{(\delta+0)}^{i}, t_{(\delta+1),}^{i} t_{(\delta+2)}^{i} \dots \dots \dots \dots \dots t_{(\delta+n)}^{i}) \quad (1)$$

$$(t_{(\delta+n)}^{i}) = \text{TS} \quad (2)$$

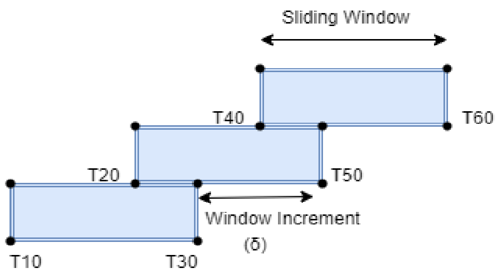

FIGURE 2. Sliding window.

Following the sliding window process, the organization of MEWS scores for each parameter gives rise to the Patterned Modified Early Warning Score (PMEWS), discussed in the subsequent section. The PMEWS architecture is the foundation for our proposed pattern-matching approach and semantic features (trend, trust, slope, and frequency).

B. *Patterned MEWS*

Many algorithms that lower false alarms fail to improve patient condition forecasting because they ignore distinguishing patterns in the data. Research [56] claimed that the temporal relationship among alert warning patterns switching categories might be utilized to lessen alarms. Our approach to addressing the missing values in our data set is to recreate the pattern from the observed patient data by substituting characters or symbols. Another advantage of using patterns with characters is that no reliance on thresholds or previously documented values is required, which might alter the forecast of the patient's state. Our approach allows for the recording of patterns in any format. Table (3) displays our snippet's dataset, and Table 4 shows the formation of patterns from raw vital sign values in a sliding window.

TABLE 4. PATTERN IDENTIFIED

	HR	BP	SpO_2	R	T	Pattern
Vitals	99	-	96	22	-	
MEWS	0	N	0	2	N	0N02N

An arranged sequence of MEWS values that shape the pattern is saved and specified as PMEWS, as shown in Table (4). The pattern array $P[TS]$, which consists of time slots TS, is compatible with handling differences in sensor signals due to null values (N) and the distinct time for data compilation from various sensors seen in Equation (3).

$$P[TS] = [\text{MHR}, \text{MR}, \text{MBP}, \text{MSPO2}, \text{MT}] \quad (3)$$

Possible unique patterns (P^V) Where P = 5, and V = (0, 1, 2,3, null). Our algorithm performance investigation found that the computational complexity is $O(n^2)$. This quadratic complexity is caused by the algorithm's nested iterative operations over the input data set, demonstrating that processing time increases quadratically with input data size.

Despite its $O(n^2)$ complexity, the suggested approach has significant advantages for Remote Patient Monitoring (RPM). One significant benefit is using a sliding window and pattern recognition technique. The system uses these approaches to effectively record temporal patterns and fluctuations in patient data, allowing for early detection of abnormalities and potential health problems. The pattern-matching algorithm for missing vital values is described in the next section.

IV. Pattern-Matching for Missing Vital Values

The fundamental goal of this approach is to compare the pattern to the closest matching pattern observed within the sliding window. Once a match is found, the approach replaces the missing value with the found matching values. The snippets of raw data (Table 5) show HR, T, BP, SpO_2, R and patterns. At minute four, HR is missing. At minute one, the pattern will be matched and imputed to match the maximum number of characters.

TABLE 5: PATTERN FORMATION AND CHARACTER MATCH UP

Time (minutes)	HR	T	BP	R	SpO_2	Pattern	Character match up
1	99	-	-	22	96	0NN20	4
2	97	-	141	25	99	0N020	3
3	102	-	-	34	99	1NN30	2
4	*	-	-	28	99	NNN20	

The first step (line 1) for the pattern-matching algorithm is to set start time (T), L, number of vitals recorded (T_{MV}), δ, sliding window time (t), where sliding window and time slots are as shown in equations (1) and (2). A loop is started until

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(TS) is less than (L) for pattern-matching (line 2). Pattern P[TS] is recorded for raw, vital values. Then, recorded patterns (lines 3-5) are copied into the string pattern array S_P[ ], and the loop to transverse the S_P[ ] is set (line 6). For no null values, the counter is increased by one (line 7). The inner loop ensures that every pattern is considered. str1 and str2 are allocated to SP[j] and SP[i+1] (line 8). The count function (line 9 and lines 17-20) checks if the str1 matches str2, and then the character count is stored in CS_P[k] (lines 10-12). The CS_P[k] is checked for the patterns with the highest match of characters, and then the relative pattern is displayed as the closest match (lines 13-15). Timeslot (TS) and window increments (δ) are updated to transverse the whole window (line 16). The pattern-matching algorithm is shown next:

1 *Input variables start time (T), (TMV), (δ), sliding window time (t)*
2 *While (TS<=L) do*
3 *Record vitals (HR, T, BP, R, and SpO2)*
4 *Set MEWS for vitals and save in pattern at time TS. P[TS] =["MHR","MR","MBP"," MSPO2","MT"]*
5 *Copy recorded patterns in SP[ ]*
6 *for each pattern P[TS] in SP[ ] from i=T to i<=TS do*
7 *Check if the values at [i+1] index In the string pattern array is 'N' then check the next index.*
8 *Else*
for each pattern in SP[ ] from j=T to j<=I do
assign str1 to SP[j] and str2 to SP[i+1]
9 *Call count (str1, str2)*
10 *for each count c for pattern in array CSP[k] from j = T to TS do*
11 *Assign CSP[k]= c, end for*
12 *for each count in CSP[k] from j = T to TS do*
13 *If (CSP[k] is the highest match parameter count) then*
14 *print relevant pattern P[TS] and count from CSP[k]*
15 *Else print no suitable match found.*
16 *Increment time slot TS = t + δ,*
17 *function count (string str1, string str2)*
18 *Initialize counter c = 0, index j = 0*
19 *For each i in str1.length( ) do*
20 *If str1 matches str2, then for each matching character, increment c, j and return c.*

The following section explores the semantic features of vital indicators used for data visualization.

V. SEMANTIC FEATURES OF VITAL SIGNS

The feature extraction process significantly reduces the volume of sensor data input. Given the timely monitoring of patient's vital signs, the majority of the attributes under consideration for this study are connected with time domain characteristics [57]. This study considers both spectral and temporal domains for feature extraction from data. Details regarding features are provided in the following section.

A. Trust

Trust signifies the certainty level that the PMEWS provides. The proportion of vitals participating in the PMEWS is operationalized as trust. Trust is at its lowest if all crucial indications are negative. In a medical environment, four to six vital signs can be monitored. Every necessity is treated equally by us.

The Trust percentage is computed according to equation (4). For each non-null value in the observed pattern, the counter of the pattern $C_{P[TS]}$ is increased by one.

$$\theta_{P[TS]} = \frac{(C_{P[TS]})}{T_{MV}} \tag{4}$$

B. Frequency

Frequency aids in locating spikes resulting from movement, vibration, improper gadget handling, etc. According to equation (5), the percentage frequency $F_{P[TS]}$ is determined. The frequency counter is represented as $FC_{P[TS]}$ and is increased by one each time.

$$F_{P[TS]} = \frac{(FC_{P[TS]})}{L} \tag{5}$$

C. Trend

The trend offers data on the typical time a specific pattern appears in L. When a pattern match is discovered by linear search [58] in sw_{δ}^{i}, record the index number for the first appearance in the P^F variable and P^L for the last appearance .

Equation (6) calculates the trend $T_{P[49]}$. Where the number of unique pattern occurrences is denoted by (n).

$$T_{P[TS]} = \frac{P^L - P^F}{(n)} \tag{6}$$

D. Slope

Slope measurement aids in predicting how the pattern will change throughout the process window. The dispersed chart sw_{δ}^{i} with TS is produced by the count of patterns, which varies with time. Linear regression calculates the slope of the dispersed chart [59]. To observe the behaviour of the pattern's emergence sw_{δ}^{i} partitioned into M parts. The slope $bP_{[TS]}$ is represented in Equation (7). Where the frequency counter is $FC_{P[TS]}$.

$$(bP_{[TS]}) = \frac{\Sigma\left(\left(\frac{TS}{M} - \frac{\overline{TS}}{M}\right)(FC_{P[TS]} - FC_{p[\overline{TS}]})\right)}{\Sigma\left(\frac{TS}{M} - \frac{\overline{TS}}{M}\right)^2} \tag{7}$$

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VI. Prioritization of Patterns

Understanding the patient's urgent medical condition requires the prioritization of patterns. Deciding priority patterns employs the majority voting rule [60], if each semantic feature holds equal significance. In Table 2, for n number of patterns, the semantic characteristics are displayed together with the prioritization criteria based on mean values.

According to the criterion for prioritizing the semantic characteristics of trust, trend, and slope, the rank $R_{P[TS]}$ the feature's calculated value will increase if it is more significant than their mean values. The slope simultaneously receives values of zero, positive and negative. Therefore, the slope's prioritization guideline considers patterns with positive values, which indicates that the number of patterns is growing with time. Then, the patterns' rank $R_{P[TS]}$ values are ranked. Emphasizing prioritization directs the doctor's attention to ranked patterns, leading to an earlier cure for the patient and preserving valuable time.

TABLE 6: PRIORITIZATION LAWS

Semantic traits	Mean	Prioritization LAWS
Frequency	$\boldsymbol{FM_{P[TS]}} = \frac{\sum F_{P[TS]}}{n}$	$(\boldsymbol{F_{P[TS]}} \geq \boldsymbol{FM_{P[TS]}})$
Trust	$\theta M_{P[TS]} = \frac{\sum \theta_{P[TS]}}{n}$	$(\boldsymbol{\theta_{P[TS]}} \geq \boldsymbol{\theta M_{P[TS]}})$
Trend	$\boldsymbol{TM_{P[TS]}} = \frac{\sum T_{P[TS]}}{n}$	$(\boldsymbol{T_{P[TS]}} \leq \boldsymbol{TM_{P[TS]}})$
Slope	-	$\boldsymbol{bP_{[TS]}} \geq \boldsymbol{0}$

The algorithm for data visualization using the semantic features of data is shown below. This algorithm first calculates the semantic features of data for various recorded unique patterns and applies the prioritization rule to determine the rank of the different patterns. First, input the variables (line 1). Then, start a loop until the length of the process window (line 2). Retrieve the vitals and record the patterns and corresponding MEWS values according to equations (4-7) (lines 3-5). Calculate the trust, frequency, trend, slope, and mean values (lines 6-8). If the calculated MEWS value for the pattern is greater than four, then apply the prioritization rule provided in Table 6, increment the rank, and print the relevant pattern and its rank (lines 6-12). Increment the time slot TS and reset the rank value (lines 13-14).

1 *Input (T), (L), (TMV), (δ), (t)*
2 *While (L) do*
3 *Retrieve vitals (HR, T, BP, R, and Spo2)*
4 *Retrieve unique patterns P[TS]*
5 *Record the MEWS sum for every pattern in MP[TS] = [MHR+MBP+MT+MSPO2 +MR]*
6 *Compute trust, frequency, trend and slope according to equations (4 -7).*
7 *For each T in TS, do*
8 *Compute the mean value of trust, frequency and slope according to equations presented in Table (6)*
9 *If MEWS sum (MP[TS]) is bigger than four, then*
10 *Increment rank* $R_{P[TS]}$
If the trust and frequency values are greater than mean, trust and frequency values.
and if the slope is positive, Table (6).
11 *Increment rank* $R_{P[TS]}$ *If the trend value is less than the mean value of the trend Table (6).*
12 *Print the relevant rank and pattern*
13 *Increment time slot TS for δ*
14 *Reset the rank to zero.*

VII. Results

Data requested from the trial [53] is used for experimental findings, and Table 3 shows a snippet of data. Table (7) displays the results of implementing the missing pattern-match (PM) algorithm from four distinct datasets using various imputation techniques and the root mean square error (RMSE) to determine the precision. Tables (7) and (8) list the HR and SpO_2 values observed for imputation in the four datasets. The dataset was divided into additional sets with different record durations. Our suggested technique is contrasted with MI and Expectation Maximization (EM)[61], two extensively used methods to impute missing data. Normalization is a crucial stage in our approach since it scales the records and improves their suitability for analysis by minimizing biased results. The MEWS is used for normalization. To check the accuracy of our method, we started with the whole set of measurements and subtracted various percentages from the SpO_2 and HR. Subsequently, MI and EM are applied to impute the values of the missing parameter. Our method chooses the parameter imputation that has the best match. The RMSE for imputed values was calculated by comparing them to the initial values throughout the full dataset.

Figures 3 and 4 display the variance in RMSE for the SpO_2 and HR, two of the measures we used. Both the sliding window method and the PMEWS have shown to be quite helpful when dealing with missing data. Every pattern that appears is considered in the algorithm, which then utilizes these patterns to look for a close match. When all the patterns that arose within that time have been covered, the window is moved across the process window.

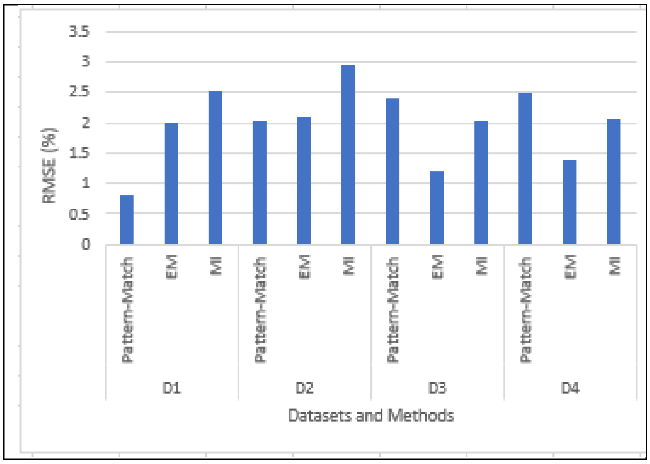

FIGURE 3. RMSE for SpO_2

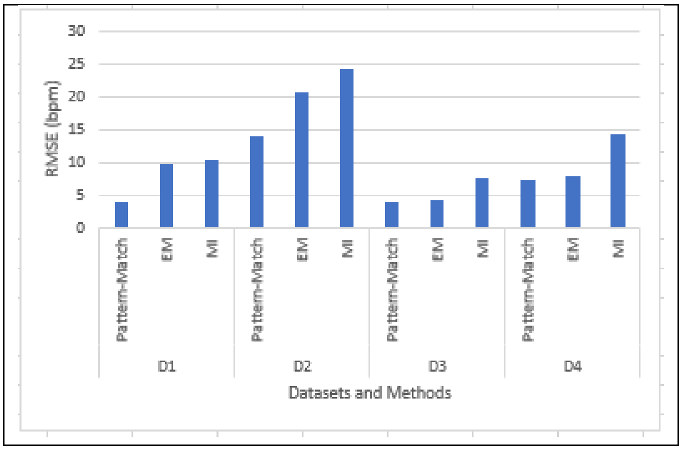

FIGURE 4. RMSE for HR

TABLE 9: MEWS COMPUTATION

Time	PR_ Val	Temp_ Val	Sys_ Val	Resp_ Val	SpO_2	MEWS
1122	108	-	-	34	97	4
1123	111	-	-	37	98	5
1124	106	-	-	33	99	4
1125	106	-	-	25	99	3
1126	108	-	-	25	99	3

Understanding the pattern or the correlation among the numerous vital sign data that have been recorded may be done through data visualization. In contrast to a graphical report, which emphasizes spatial information, MEWS provides tabular information that emphasizes symbolic information, as shown in Table (9). A significant amount of data is generated while monitoring the patients; tabular, unrefined information is not an excellent match for the RPM. Enormous volumes of data are challenging to examine and may influence clinical judgment.

TABLE 7: RMES(%) FOR SpO_2

DataSet	Records	Observed Records	Approach	RMSE(%)
DS1	756	45	PM	0.82
			EM	2.01
			MI	2.52
DS2	1000	88	PM	2.03
			EM	2.1
			MI	2.94
DS3	490	25	PM	2.4
			EM	1.2
			MI	2.04
DS4	932	84	PM	2.5
			EM	1.39
			MI	2.06

TABLE 8: RMES(BPM) FOR HR

Dataset	Records	Observed Records	Approach	RMSE(bpm)
DS1	756	27	PM	3.9
			EM	9.6
			MI	10.2
DS2	1000	26	PM	13.9
			EM	20.6
			MI	24.3
DS3	490	HR	20	PM
			EM	EM
			MI	MI
DS4	932	HR	28	PM
			EM	EM
			MI	MI

The rank of various prioritized patterns at the 30th minute is shown in the column graph in Figure (5) and tabular format in Table (10). Discovered patterns are displayed along the x-axis, and the importance of the pattern is displayed as rank one to four on the y-axis. The visualization shows the degree of risk associated with each pattern, which ranges from extremely high to extremely low. Because the semantic traits comply with the majority vote norm, rank 1 signifies the highest relevance. Information about the conditions that need urgent attention will be easy to observe in the visual form for the clinician and will be helpful in decision-making.

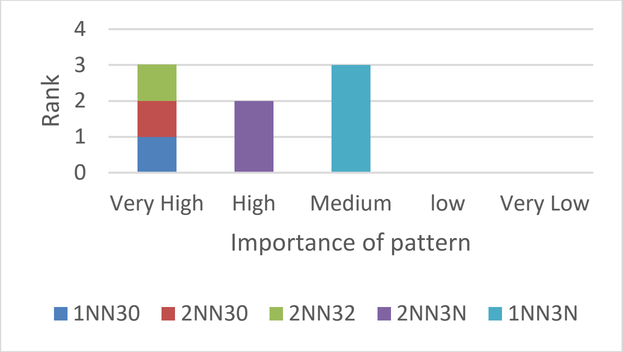

FIGURE 5. Pattern Rank at 30th minute

TABLE 10: PATTERN RANK (TABULAR FORMAT)

Pattern	Very High	High	Medium	Low	Very Low
1NN30	1	-	-	-	-
2NN30	1	-	-	-	-
2NN32	1	-	-	-	-
2NN3N	-	2	-	-	-
1NN3N	-	-	3	-	-

The conventional MEWS is inappropriate in RPM due to a large amount of continuous and missing data. This problem results in inadequate clinical decision-making regarding the significant conditions of the patient. It is essential to prioritize the patient's condition from those that arise due to various deviations of the surroundings, such as noise, vibration, and motion. Pattern-specific algorithms can be used for these deviations to handle the issues of missing values and to provide visualization. The suggested approach addresses the missing data issues in RPM using a sliding window and pattern match algorithm with PMEWS, considering the temporal context of the missing data, leading to a more accurate medical data analysis and decision-making. The proposed method also uses the semantic features of the vital signs and introduces a new parameter, PMEWS, to prioritize patterns based on their clinical significance. The result shows that the proposed method provides better visualization and a practical imputation approach than the traditional MEWS. The proposed method can lead to more competent healthcare by transforming RPM data management and examination.

VIII. Conclusion and Future Research

In conclusion, this study fills in essential gaps in the healthcare field, particularly in evaluating the MEWS and RPM. The study offers creative solutions by recognizing and addressing missing values and inadequate data visualization. The pattern-matching strategy in patient monitoring effectively handles missing data. The proposed data-mining visualization method improves the interpretation of MEWS and presents a thorough brief of patient information to support well-informed decision-making.

Despite these advancements, we must consider the complexity of healthcare facilities, which can incorporate various systems and procedures. To achieve seamless integration in such situations, several aspects must be carefully considered, including interoperability standards, data protection requirements, and the varying demands of healthcare professionals and patients. Furthermore, the effective deployment of our algorithm depends not only on its technical capabilities but also on its usability and acceptability by end users. As a result, user acceptability testing and stakeholder input are critical elements in fine-tuning our solution to suit healthcare practitioners' and patients' requirements and expectations. Furthermore, as the healthcare landscape develops, it becomes increasingly important to remain current on emerging technology, regulatory changes, and best practices. To maintain our algorithm's relevance and efficacy in tackling emerging healthcare concerns, we must analyze and update it continuously. By recognizing and proactively addressing these limits, obstacles, and continuing considerations, we may boost our algorithm's robustness and efficacy, eventually increasing its ability to improve patient care and healthcare outcomes.

Looking forward, we may pursue various fascinating areas for future study. One such potential is understanding how patterns change in response to illness progression or therapy treatments. By closely studying these changes, we can get significant insights into how health issues evolve and optimize treatment tactics accordingly. Including contextual data in visualizations can improve our knowledge of health trends and patterns. We may develop complete and meaningful representations of population health dynamics by including demographic data, environmental variables, and socioeconomic indicators. Healthcare constantly evolves; we must be informed about new technology, policies, and best practices. We must continue to ensure that our algorithm functions appropriately and make improvements as necessary.

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