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ORIGINAL PAPER

Alert-Grouping: Smart Personalization of Monitoring System Thresholds to Help Healthcare Teams Struggle with Alarm Fatigue in Intensive Care

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Abstract
In Intensive Care Units (ICUs), patients are monitored using various devices that generate alerts when specific metrics, such as heart rate and oxygen saturation, exceed predetermined thresholds. However, these alerts can be inaccurate and lead to alert fatigue, resulting in errors and inaccurate diagnoses. We propose Alert grouping, a "Smart Personalization of Monitoring System Thresholds to Help Healthcare Teams Struggle Alarm Fatigue in Intensive Care" model. The alert grouping looks at patients at the individual and cluster levels, and healthcare-related constraints to assist medical and nursing teams in setting personalized alert thresholds of vital parameters. By simulating the function of ICU patient bed devices, we demonstrate that the proposed alert grouping model effectively reduces the number of alarms overall, improving the alert system's validity and reducing alarm fatigue. Implementing this personalized alert model in ICUs boosts medical and nursing teams' confidence in the alert system, leading to better care for ICU patients by significantly reducing alarm fatigue, thereby improving the quality of care for ICU patients.

Keywords Alarm fatigue · Alert fatigue · Patient safety · Intensive care units · Personalized medicine · Quality of health care

Introduction

Work overload leads to fatigue and reduced attention [1]. The Internet of Medical Things (IoMT) has transformed healthcare by creating a precise patient monitoring network [2, 3]. Devices in IoMT collect real-time data for analyzing physiological patterns [4–9], facilitated by event processing (EP). EP consists of analyzing information about events to draw conclusions. EP is based on a set of real-time computational tools to extract valuable data [10, 11] following the "4D" framework. The 4D consists of "detect, derive, decide, do" [12, 13]. We utilized system dynamics (SD) to evaluate IoMT's impact, as SD helps understand complex systems [14–19].

In health sciences, SD and EP are widely used to model dynamic systems [20–23], particularly in acute-care departments and hospitals [18, 24]. However, the use of IoMT, creates a sheer volume of alarms from multiple devices often leads to a phenomenon known as "alert fatigue" [25], as alarms drown healthcare professionals with irrelevant information due to lack of time or cognitive resources [25–27].

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At hospitals, emergency departments (EDs) and intensive care units (ICUs), "alert fatigue" is a key issue [28–31]. Unfortunately, there is currently no internationally recognized standard measurement scale for "alert fatigue" [32]. Consequently, the prevailing strategy to alleviate this phenomenon is limited to reducing the overall number of alerts.

EDs and ICUs teams treat patients with complex clinical profiles and use IoMT devices to monitor and deliver treatment to each one by looking at their clinical needs. Most of these ICU monitoring devices, nowadays IoMT components, are endowed with automatic alarms aimed at calling the attention of the attending staff to supposed meaningful conditions such as respiratory distress. Each device's alarms are based on default factory-assigned thresholds as "turnkey systems". However, adjusting these thresholds to deliver personalized care is challenging due to inter-individual variability. IoMT devices employ default thresholds, challenging customization due to variability [33].

The task of multiple device combination alarm thresholds settings is handled at three levels according to the 4D paradigm perspective. The first level, single-level analysis, refers to monitoring, alerts, and control of a single device, such as blood pressure monitoring, which alerts in case of high or low pressure [34, 35]. The second level, multiple-level analysis, allows data aggregation across several devices, including device hierarchy and custom data queries like BP and blood saturation monitoring analysis [35–37]. Lastly, the third level, predictive analysis [38], enables data analysis [39] based on artificial intelligence techniques, specifically from machine learning [40, 41], to provide decision support outcomes such as classification of events, prediction of the following measurement value, and anomaly detection [42, 43]. This situation often leads to conscious and subconscious filtering of alarms as they occur too frequently and are conceived as "false alarms", that contributes and increases the "alert fatigue" [44–46].

To combat this, we propose "Alert-Grouping,“ a framework for personalizing monitoring thresholds [47–49], empowering healthcare providers to adapt the system to individual patient needs. "Alert-Grouping" is a smart personalization of monitoring system thresholds, based on an additional user layer, adjusted for non-technical users, that enables them to update devices, customize alerts, and optimize system usability. Furthermore, the "Alert-Grouping" allows combining multiple alarms together in a systematic way with threshold settings, which can address these sources differently.

Alert-Grouping brings forth two crucial components. The first requires users to define appropriate patient clusters within the system, tailoring monitoring parameters to specific clinical and personal parameters. The second component utilizes intelligent algorithms, bridging the gap between high-level concepts and implementable code [40, 43, 50]. The process of implementing the grouping definition, relies on rigors medical definition, based on medical, social and biological parameters [51], that should be defined, according to the specific EDs and ICUs domains.

To realize the full potential of Alert-Grouping, a "low code/no code" algorithm is needed. Low code/no code algorithms are approaches to software development that simplify and accelerate the process of creating applications without extensive coding [47–49, 52], by adding a user friendly layer, that provides "non-technical" users to build new system definitions [53]. The use of the low code/no code algorithm, in the EP and IoMT systems allowing fine tuning and highly responsive monitoring system, for the ED and ICU teams [54].

Throughout the upcoming sections, we evaluate the current status of ICU monitoring device systems and present a compelling argument for change, backed up by a powerful system dynamic simulation. Our analysis will demonstrate the invaluable contribution that Alert-Grouping can make in healthcare settings, as evidenced by the results and discussion. To conclude, we will provide a concise summary of our findings, firmly emphasizing the immense potential of Alert-Grouping in improving patient care and effectively reducing alert fatigue.

Materials and Methods

One way to reduce the number of alerts is by using a single integrating algorithm that combines multiple monitoring inputs. However, any update of the predetermined thresholds must be done on each sensor or monitor system [55, 56]. To tackle this challenge, Alert-Grouping incorporates user layers that enable non-technical users to easily include or modify thresholds and thresholds combinations for a group of devices.

This Alert-Grouping concept is materialized by the ability of the end-user (e.g., healthcare practitioners, intensivists) to define the suitable cluster, based on the patient's clinical and personal parameters. These rules can consist of threshold and multidevice alert combinations to create a tailored frequency of alarms that will respond to changes in clinical parameters of a specific patient or hospitalization facility (e.g., failure of a medical device). This behavior can become possible only if all factors that comprise the situation are given their appropriate representation in the tuning process. The architecture of the event-based systems consists of (a) sensors and devices, (b) gateway applications, (c) data storage, (d) domain algorithm, or analysis system, and (e) data visualization mechanism, as described in Fig. 1. The devices are the physical elements that collect the data, using

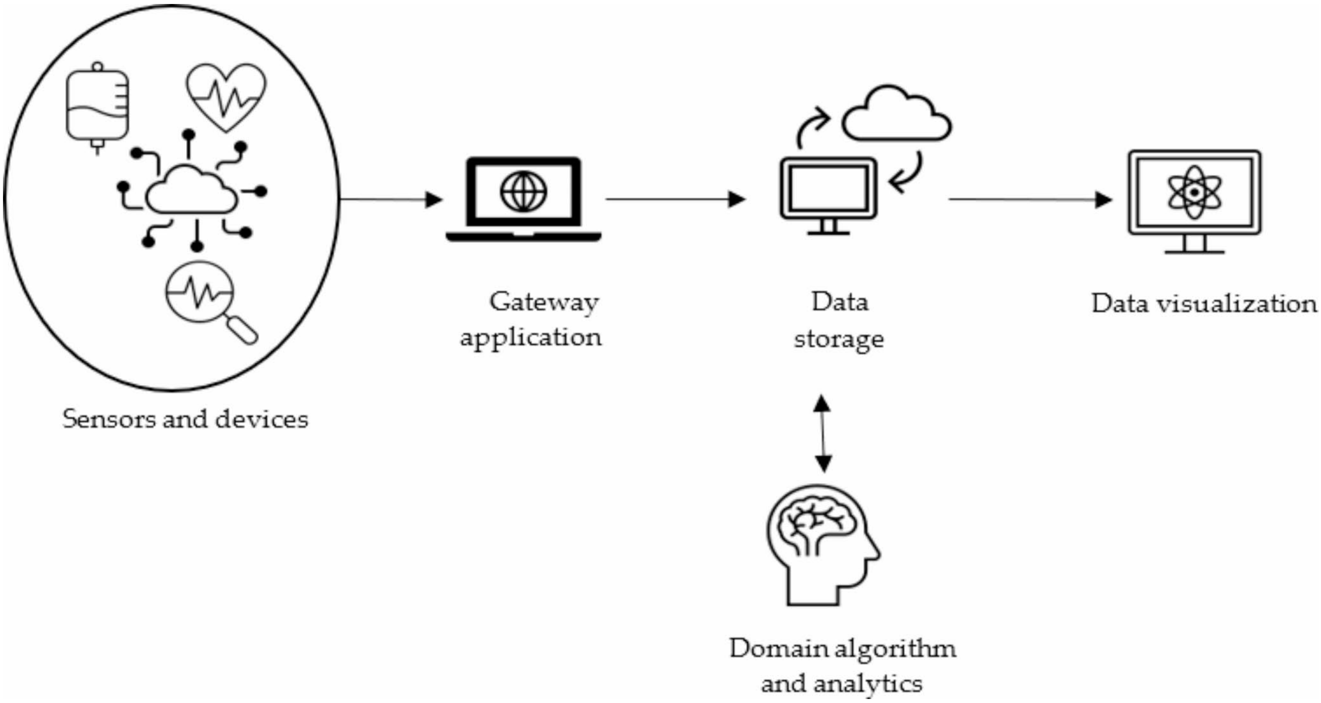

Fig. 1 IoMT common architecture

sensors and communication capabilities to submit the data to the system gateway.

Data is collected, processed, and transferred to a remote server for storage. The domain algorithm or analysis system identifies events or other required information. The data visualization enables the user to understand and use the analyzed results.

The event-based system developers focused on creating new capabilities using an integrated system. However, the user can change or influence each device's settings separately, with no integrated capabilities. This study focuses on developing a platform for the user side (i.e., medical and nursing staff), by implementing the cluster personalization of the event-based system, enabling the user to define cluster patient-specific conditions and health records. The intended platform, designated for users that lacks the technological know-how, can be connected to any existing or new sensors and devices, enabling users to configure notifications and alerts according to patients' clusters (with specific adaptations based on the patient's condition).

As of now, patients in ICUs are monitored using sensors, which are available in standard ICUs, and staff receive alerts on any sensor event. Multiple alerts are generated in the current state, resulting in enormous notification overload, even when the alerts are not related to significant events, causing the medical and nursing staff alert fatigue. Using Alert-Grouping enables the care providers to define the most suitable monitoring and event-based algorithm for a patient. Furthermore, the system will provide the ability to adjust the events and monitor each sensor for the specific patient. Therefore, staff alert fatigue can be reduced by reducing the total number of alerts.

We developed SD model, that serves as an exemplification of the ICU model, encompassing a comprehensive range of monitoring devices such as an invasive blood pressure monitor, saturation monitor, body temperature sensor, and respiratory monitor. The development of the SD model began with the initial stage of defining the ICU system in a 4D framework. Subsequently, utilizing this 4D model, we proceeded to establish the inputs, structure, and processes for the SD model. The final stage of development encompassed the validation of model outputs, conducted in collaboration with the ICU's medical and nursing staff. Figure 2 showcases the SD model, which specifically focuses on simulating a single-bed scenario. This model effectively integrates the patient's sensor attachments and the system's alerting processes, incorporated in the 4D model.

The model incorporates IoMT sensor alerts as its inputs, which are recorded in the detect repository represented by stock-Detect, as depicted in Fig. 2(I). It is vital to note that each sensor threshold can be defined by the caregivers, based on the manufacturer's settings. Given the substantial volume of alerts generated by the system, it is inevitable that some alerts do not indicate a medical intervention-worthy event.

All alerts generated by the system are directed to the main derive stock, as illustrated in Fig. 2(II). The main derive stock thoroughly analyzes these alerts, segregating them into nursing alerts (Fig. 2(IIa)) and medical alerts (Fig. 2(IIb)), subsequently forwarding them to the nursing or medical teams, respectively, to facilitate appropriate decision-making.

The medical team receives all medical issues reported by the system and performs an analysis. While some alerts may be disregarded due to their lack of relevance, others are subjected to a decision-making process, represented in Fig. 2 as decide phase, and depicted in Fig. 2(IIIb). These alerts serve as a basis for determining the available medical activity options, and subsequent measures are decided upon by the team. In certain instances, medical alerts may be redirected to the nursing team.

The nursing team receives nursing alerts routed from the main derive (Fig. 2(IIa)), as well as alerts redirected by the medical team's decisions. These alerts establish the range of medical activity options available to the team, guiding them in deciding the appropriate measures to be taken, represented in Fig. 2 as decide phase, and as shown in Fig. 2(IIIa).

Based on the medical options presented in Fig. 2(IIIb), decisions regarding medical aspects are made, leading to their execution (Fig. 2(IV)). Similarly, nursing decisions based on Fig. 2(IIIa) are implemented to address medical issues.

It is important to emphasize that the SD model reflects an accumulative status, whereby any stock (e.g., medical derive, nursing derive) collects an event rate stream and releases an output event stream that can be subsequently utilized as an input for another stock (e.g., medical decide, nursing decide). Consequently, in certain scenarios, the values of predecessor stocks might be lower than those of their successors.

Results

The SD model simulation was activated using current state definitions and proposed "Alert-Grouping" definitions. The results of the simulation are shown in Fig. 3. The red line represents the current state definitions, while the blue line represents the Alert-Grouping state. Both states have the same detection rate, as seen in the Detect box. However, in the Main Derive box, it can be observed that the current state definition has stabilized at approximately 20 alerts per hour, while the "Alert-Grouping" definition has stabilized at approximately 14 alerts per hour.

These outcomes were meticulously analyzed and verified by the medical and nursing teams.

During the Detect stage, which involves data collection from the entire sensor system, we determined the volume of data based on an analysis of the prevailing conditions in ICUs. In the current state, which is equivalent to the future state, an average of approximately 35–40 distinct alerts per patient bed per hour was recorded.

In the "Main Derive" stage of the current state, all alerts are processed, which includes an average of approximately 18–25 alerts per patient bed per hour. These alerts differentiate between nursing alerts and medical alerts, based on medical protocols. Approximately 11–15 alerts per patient per hour, derived from the total number of alerts, are received by the nursing teams, in the current state, the team then analyses and forwards some to the medical team to act. Among these, 3–4 medical alerts per patient per hour are forwarded to the medical team professionals, while an average of 8–12 nursing alerts per patient per hour (including

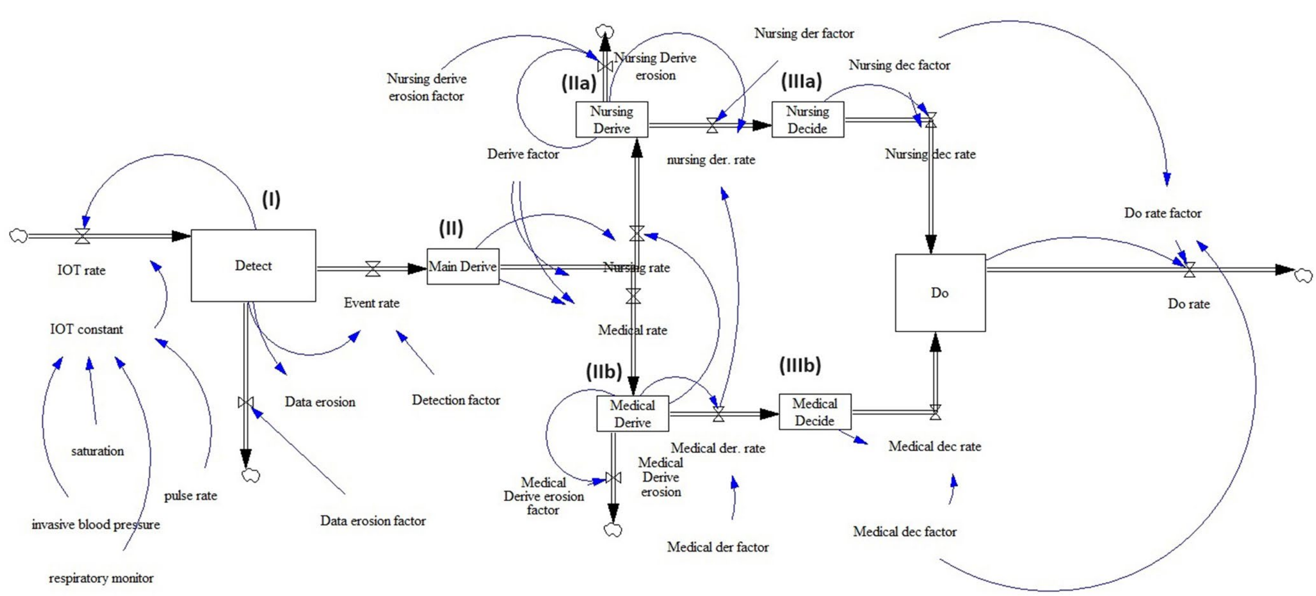

Fig. 2 ICU single-bed model

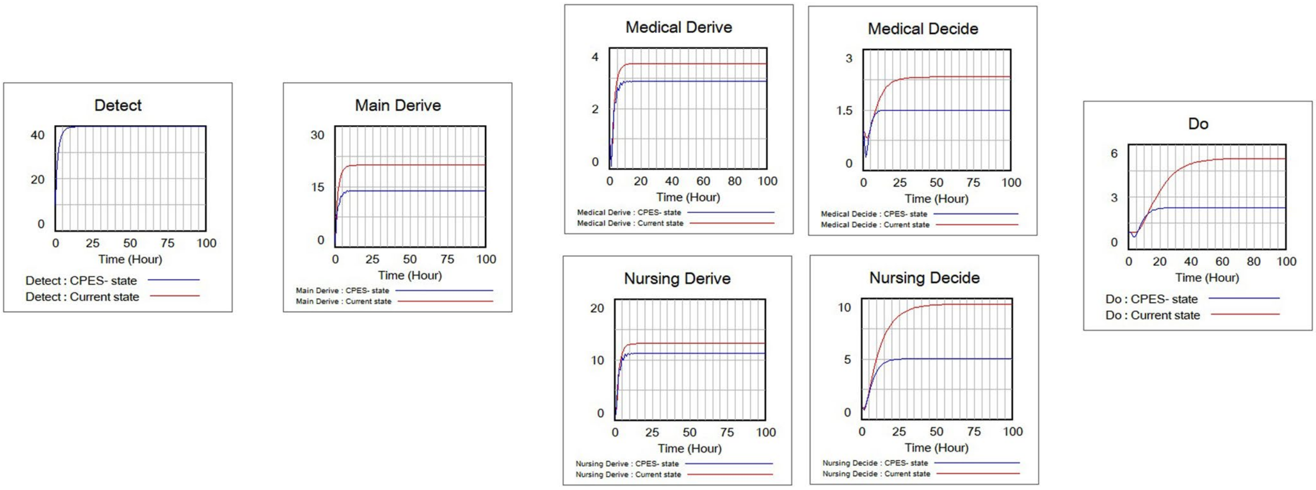

Fig. 3 Current state and Democratization state Patient-Based alarm report

both new and ongoing alerts) are managed by the medical and nursing staff.

In step 3, “Medical and Nursing Decisions”, relevant determinations are made based on the system’s status and the patient’s condition. In the current state, the medical team is responsible for making 2–3 decisions per hour per patient, some of which are transferred to the nursing staff. On the other hand, the nursing staff is required to make approximately 8–10 decisions per hour per patient.

During step 4, the decisions are implemented, with a majority of cases involving the “do nothing and continue to follow” approach. In the current state, approximately 4–6 active decisions per patient per hour are executed.

Through the implementation of the Alert-Grouping model a reduction of approximately 30–40% in the number of alerts from the current state is anticipated. The results were validated by the medical and nursing staff of the ICU, and should be rigorously tested, after implementing the suggested “Alert-Grouping” system.

By employing the concept of Alert-Grouping, the following outcomes have been observed:

During the Detect stage, which involves data collection from the entire sensor system, the total amount of alerts remains the at same volume.

In the Main Derive stage, the system, based on the new updated grouping thresholds, analyzes alerts related to the patient’s cluster event definitions, resulting in a reduction of approximately 25–30%, comparing to the default state. The system distinguishes between nursing alerts and medical alerts. The nursing alerts include nursing issues and technical issues. The number of nursing alerts analyzed in the Alert-Grouping state is approximately 8–11 alerts per patient per hour, derived from the total number of alerts, signifying a decrease compared to the current state.

During step 3, medical and nursing decisions, relevant determinations are made. The medical team is required to make approximately 1–2 decisions per patient per hour, while the nursing staff is responsible for deciding on approximately 4–5 medical events per patient per hour.

In step 4, the decisions are executed, with the majority of cases involving the “do nothing and continue to follow” approach. In the Alert-Grouping state, approximately 2–3 total active decisions per patient per hour are implemented.

Discussion

The SD simulation models include a current state model, based on ICU actual data, validated by the medical and nursing staff, and a simulation model of implemented “Alert-Grouping” future development. The results of the study, based on the SD model, using the “Alert-Grouping” methodology, demonstrate a significant decrease of approximately 30–40% in the overall number of actual activities or interventions performed per patient per hour. This reduction implies that fewer interventions were required to manage patients effectively within the given time frame, The results were validated by ICU medical experts, to ensure that the model reflects the current state.

Among the implications of this finding is the possibility of a reduction in false alarms, resulting in a reduction of alert fatigue.

As a result of considering these patient-specific factors, the system is able to generate more accurate and relevant alerts, increasing its ability to detect potential issues or changes in a patient’s condition. Overall, these results are promising and suggest that the model and system employed in the study have the potential to address two critical aspects of healthcare monitoring: immediate adjustment of the whole patient monitoring environment, based on patient group, and reducing alert fatigue by optimizing the alert system.

However, it is essential to emphasize that transitioning to this Alert-Grouping process requires careful consideration of staff education both prior to installation and during the initial operational phase. This undertaking entails the preparation of well-trained personnel who are capable of addressing familiar daily events in an alternative manner.

The limitation of the study stems from the limited validation, potential complexity and customization, and the requirements of staff education and adaptation. The implementation of Alert-Grouping may involve configuring patient groups and adjusting monitoring system settings based on expert-defined criteria. Depending on the complexity of the system and the customization required, there may be challenges in effectively implementing and maintaining the Alert-Grouping methodology in different healthcare settings. The other limitation could result from the implementation process in a complex environment.

Future research in this area could focus on several aspects to further enhance the understanding and application of the Alert-Grouping methodology. Firstly, conducting larger-scale studies across different healthcare settings and specialties would provide more comprehensive insights into the effectiveness and generalizability of this approach. Additionally, investigating the long-term impact of alert grouping on patient outcomes, including patient safety and quality of care, would be valuable. Moreover, exploring the optimal configurations and thresholds for patient groups, considering various patient populations and conditions, could lead to refinements in the methodology. Furthermore, studying the potential integration of machine learning or artificial intelligence techniques into the Alert-Grouping system could contribute to even more precise and dynamic alert management. Overall, future research in this field holds promise for advancing the understanding and practical implementation of Alert-Grouping, leading to improved healthcare monitoring and patient outcomes. Besides, the Acute Physiology and Chronic Health Evaluation (APACHE) IV model is used in ICUs to predict the length of stay of acute patients [57]. Combining the alert-grouping with APACHE scores can allows to facilitate the prioritization of the ICU team's attention and intervention [58].

Conclusions

This research highlights a notable disparity in perception between healthcare providers and IoMT sensor manufacturers concerning the interpretation of IoMT system alerts. IoMT sensor manufacturers strive to offer a universal solution that caters to a wide range of patients by establishing general thresholds for each sensor. However, this approach results in alerts being triggered for healthcare providers whenever any sensor threshold is violated, irrespective of the actual medical condition of the patient. Moreover, the implementation of patient-specific customization for each sensor, leveraging the current state capabilities, amplifies the workload for the medical and nursing teams. This approach does not necessarily lead to a reduction in the overall number of alerts, consequently intensifying the issue of alert fatigue.

To address this conflict, we have developed the Alert-Grouping methodology, presented by the SD model, that effectively illustrates and simulates a real case study based on a cluster patient condition. The model has undergone validation by medical experts, who have confirmed its representation of the patient base status in a given ICU. The process of cluster customizing alert settings for specific contexts will require careful and gradual implementation before yielding fruitful results.

The results obtained from the developed SD model demonstrate a substantial reduction in the required performance of medical activities (i.e., interventions) when employing the Alert-Grouping model as compared to the current static model. Although the Alert-Grouping model presented in this research pertains specifically to monitored patients in various types of ICUs, its methodology holds broader applicability. Future studies should explore the potential utilization of this method in other domains within the medical field, as well as in diverse applications such as agriculture, finance or manufacturing.

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Data Availability The data presented in this study are available on request from the corresponding author. The data are not publicly available due to institutional intellectual property rules.

Declarations

Conflict of Interest The authors declare no conflict of interest.

Competing Interests The authors declare no competing interests.

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