Pervasive Real-time Intelligent System for Tracking Critical Events in Intensive Care Patients

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Abstract

Nowadays it is fundamental in critical areas as is Intensive Medicine to have intelligent systems that are able to support the decision making process (DMP) giving important information in the right moment. Some of the biggest problems faced by such systems are related both to the number and the different types of data sources present in Intensive Care Units (ICU). Even though in such a setting the values for some variables are easy to collect, data collection is still performed manually for some others. In order to help the DMP in ICU, a Pervasive Intelligent Decision Support System, called INTCare was deployed in the ICU of Centro Hospitalar do Porto in Portugal. This system changed the way of the information is collected and presented. Taking advantage of the change of the environment and the data acquisition system, a system for critical events tracking was developed as the use of information regarding critical events to support decision making in Intensive Care Units is considered very useful.
The tracking system was deployed in a particular module of INTCare – Electronic Nursing Record (ENR) and it is accessible anywhere and anytime. The system allows for the calculation of the critical events regarding five variables that are usually monitored in an ICU. Moreover, this system is composed by a grid that shows the events by type and duration, a warning system to alert the doctors and intuitive graphics that allow them to follow the patient evolution. User acceptance was measured through a questionnaire designed in accordance with the Technology Acceptance Methodology (TAM). This paper presents the tracking system, its interface and the results achieved with TAM.

*Keywords***:** Critical Events; Adverse Events; Intensive Care Units; INTCare; Real-Time Data Processing; Pervasive Systems; Technology Acceptance Methodology; Tracking Systems; Decision Making Process

1. Introduction

Support for the decision making process in Intensive Care Units is still far from being enough. Even though ICUs are flooded by a wealth of situated devices that give much information about the patient it is sometimes still very difficult to make use of the collected

information due the high number of data sources. Patients have sensors connected to bedside monitors for monitoring a set of data as vital signs (eg. blood pressure, oxygen saturation, heart rate, temperature) ventilation (eg. ventilation type, PEEP) and others (Urine Output, Fluid Balance). Regularly they make a set of laboratory exams and other types of procedures. Some of that data is usually collected manually and even when it is registered in digital format that often done using proprietary applications that limit future data access. Some modifications were done in the environment and in the information system architecture in order to both change the way how the data are collected and to make these data accessible so as to be available to support the decision making process. These modifications in the environment were performed having in account the INTCare system features, i.e., the environment was prepared to allow applications such as INTCare to work (Filipe Portela et al., 2011; Portela, Santos, & Vilas-Boas, 2012).

INTCare is a pervasive intelligent decision support system developed in the Intensive Care Unit of Hospital Santo António, Centro Hospitalar do Porto in Portugal. This system uses an ensemble of classifiers in order to perform online-learning to predict both organ failure in the next 24 hours and the patient's hospital outcome (dead or alive).

Instead of a more traditional approach where a static dataset is used, INTCare is able to work with a number of data streams (Mador & Shaw, 2009). Indeed, for each monitored variable in the ICU one has a data stream and, to further complicate matters, it is often the case that data from different sources are gathered at different time intervals. Currently most patient data are automatically acquired and processed in real-time. Data thus collected and stored constitutes an important knowledge base that will be used to support the decision making process (DMP).

INTCare represents an important contribution to DMP. This system helps the doctors to have a better comprehension of patient condition. In this step the information provided by the IDSS are crucial. Indeed, given the huge number of variables to be considered and the rate at with they vary, automatic data processing is of paramount importance to highlight value changes that are potentially medically relevant. To a better comprehension of the patient's condition it is very important to understand how critical the values associated to some patient are. Until now this type of values weren't considered. In order to overcome this problem a Critical Events tracking system was developed and deployed in the Electronic Nursing Record (ENR).

Each patient has an ENR workstation at the bedside. The ENR contains information regarding several variables: vital signs, ventilation, medical scales, fluid balances. Simultaneously the data provided by them they are used to automatically calculate the number and the duration of an event. Having in account the settings of a real environment it was necessary to define a set of procedures to automatically compute critical events (CE) for five variables: Urine Output, Blood Pressure, Heart Rate, Respiratory and Temperature.

Furthermore an intuitive and user-friendly interface was designed. This interface is accessible anywhere and anytime and the number and duration of CE are disseminated

through situated ICU devices (touch monitors), one for each patient bed. During this work the CE system was also assessed in terms of usability and technology acceptance (Chooprayoon & Fung, 2010). Using the Technology Acceptance Methodology (TAM) (Chooprayoon & Fung, 2010) and a structured questionnaires, the INTCare system (Filipe Portela, Jorge Aguiar, Manuel Filipe Santos, Álvaro Silva, & Fernado Rua, 2013) was evaluated in four aspects: perceived usefulness (PU), perceived ease of use (PEOU), behavioural intention (BI) and use behaviour (UB). As part of INTCare the CE system also was evaluated. The results obtained show that the users are satisfied with the implementation of the critical events tracking system.

The paper is divided in seven sections, the first (this one) introduces the paper and the second section addresses the problem (INTCare, Intensive Care, Critical Events, Pervasive Health Cate and Technology Acceptance Methodology). The third and fourth sections, present the data acquisition process, the data analysis and the pervasive system. Section five introduces the CE tracking system and the sixth section presents the results obtained at level of interface and technology acceptance. Finally some concluding considerations are made and future work presented.

2. Background

2.1. INTCare

The development of a system for Critical Events tracking in Intensive Medicine is part of a research project called INTCare (Gago et al., 2006). The algorithms in use in INTCare's prediction module – ensemble data mining, require information regarding the critical events that have occurred during the stay of the patient in the ICU. In order to be able to use INTCare with real time data one must have some means of extracting the CE also in real time.

INTCare includes an automatic data acquisition module to acquire data in real-time and an Electronic Nursing Record (ENR) to collect some data that requires manual observation (Filipe Portela, Pedro Gago, et al., 2011) as is urine output. ENR maintains the patients hourly clinical records and other information relevant to the decision making process.

The data used by the INTCare system are collected from several different platforms and include the patient's vital signs, medical procedures, therapeutic plans, lab results, medical scores, information regarding ventilation and others. The ENR is a touch screen platform and it is deployed in a workstation near each ICU bed. Medical and nursing staff may use them to monitor the patient, i.e., record, validate and visualize all clinical information about each patient. INTCare (F. Portela et al., 2011; Portela, et al., 2012) is implemented in the Intensive Care Unit of Hospital Santo António, Centro Hospitalar do Porto.

2.2. Intensive Care

Intensive care is a critical area of medicine, where the patients are in too weak conditions and/or in serious life-risk (Bricon-Souf & Newman, 2007). Intensive Care units are the place where this type of medicine is applied. Usually, during the stay of these patients is possible to verify a set of adverse events. These events can influence the future outcome and can occur several times a day (Rothschild et al., 2005). The ability to calculate the events automatically and in real-time is an important support to the decision making process. In addition, the development of an Intelligent Decision Support System, like INTCare, which uses these variables to predict the patient condition, can help the doctors to maintain a pro-active action that will benefit the patients.

2.3. Critical Events

Studies done in the past reported that the most common adverse errors were due to wrong mechanical or human performance (Kaur, Pawar, Kohli, & Mishra, 2008). However, there are other issues that are difficult to analyze (eg. patient clinical events). This happens because it is very difficult to quantify the number of clinical errors due to a lack of automatic data acquisition systems in the ICUs. Normally, these results are collected by some alerts provided from bedside monitors ((Keegan, Gajic, & Afessa, 2011)). This paper will explain an approach to obtain the number and the duration of clinical adverse events for five variables (Heart Rate, Blood Pressure, Oxygen Saturation, Diuresis and Temperature).

The data needed to determine adverse events were continually recorded and processed by an electronic application. To understand if an event is critic or not, two main criteria were used (Silva, Cortez, Santos, Gomes, & Neves, 2008):

- occurrence and duration should be registered by physiological changes;
- related physiological variables should be routinely registered at regular intervals.

An event is considered critical when out of range values occur for a longer time or when the values are extremely out of range (Silva, et al., 2008).

In this project we used two different definitions: critical values and critical events. Critical values are values that are out of a normal range. Critical event are defined as labels to signal that a variable had critical values for more than the admissible time span, as defined in Table 1. Also, a critical event may signal that the critical value was so out of range that it is considered serious regardless of the duration of that observation. For example, a critical event happens whenever the patient's heart rate stays above 120 bpm for more than 1 hour. Also, a critical event happens every time the heart rate drops below 30 bpm or rises above 180 bpm.

Table 1. The protocol for the out of range physiologic measurements (adapted from (Silva, et al., 2008))

	BP (mmHg)	SpO2 (%)	HR (bpm)	UR (ml/h)	Temperature (ºC)
Normal range	90 to180	>= 90	60 to120	>= 30	35 to 37
Critical event [a]	>= 1h	>= 1h	>= 1h	>= 2h	>=1h
Critical event [b]	< 60	<80	<30 or >180	<= 10	<34 or >41

a Defined when continuously out of range.
b Defined anytime.

2.4. Pervasive health care

Pervasive health care derives from the concept of pervasive computing. Pervasive computing is characterized by Satyanarayanan (Satyanarayanan, 2002) as an evolutionary step resulting from two other steps: first distributed computing and then mobile computing. According to the own research it involves not only issues associated with the communication between the environments and their interaction with users, but also in supporting mobility of the users.

In this context Varshney (Varshney, 2009) defined pervasive health care as "conceptual system of providing healthcare to anyone, at any time, and anywhere by removing restraints of time and location while increasing both the coverage and the quality of healthcare".

The information returned by the applications should be stored and accessible from a website and includes some modifications to be able to access from small portable devices (Mikkonen, Va¨ yrynen, Ikonen, & Heikkila, 2002). As an example of applications that can be developed for this type of environments we have: universal systems of monitoring of clinical data, intelligent emergency management, universal access to clinical data and mobile and ubiquitous telemedicine (Varshney, 2007).

INTCare is categorized as a pervasive system because it is accessible anywhere and anytime through portable devices with access to the hospital network.

2.5. Technology Acceptance Methodology

Technology Acceptance Methodology(TAM) "is adapted from the Theory of Reasoned Action (TRA) model which describes human behaviours in a specific situation" (Fishbein & Ajzen, 1975). The main goal of TAM is study the effects of external variables towards people's internal beliefs, attitudes, and intentions (Chooprayoon & Fung, 2010).

TAM is supported by the use of questionnaires. In this case a questionnaire was prepared by a coordination team, composed by professionals of ICU and Information System, and sent to a set of participants (a group of experts from the ICU nurses team).

The questionnaire was prepared taking into account the constructs of TAM (Venkatesh

& Bala, 2008; Venkatesh & Davis, 2000): perceived usefulness (PU), perceived ease of use (PEOU), behavioural intention (BI) and use behaviour (UB).

3. Data Acquisition Process

The data acquisition process is the first step of the tracking system. In order to develop an automatic system the platform must be able to automatically gather the values for all variables continuously and in real-time. As previously reported, initially none of the variables was automatically acquired or/and in an electronic mode. Every hour the values were manually registered in a paper based nursing record. This reality lead the research team to implement some changes in the environment and in the data acquisition system (Filipe Portela, Pedro Gago, et al., 2011; F. Portela, et al., 2011; Portela, Santos, Silva, Machado, & Abelha, 2011). Currently, it is possible acquire to automatically, with the exception of the volume of urine output, the entire set of patient data associated with the critical events. In the case of urine output the value is manually entered by the nurses in the ENR.

For the critical events system, the following data sources are being used:

- **Bedside Monitor** (BM) - Vital signs (VS) – Temperature, Blood Pressure (BP), Heart Rate (HR), Oxygen Saturation (SpO2);
- **Electronic Nursing Record** (ENR) – Hourly values – Diuresis / Urine Output and the VS manually validated;

To perform the tasks associated to the data acquisition process, a set of intelligent agents has been implemented (Santos et al., 2011) to automatically acquire and process the data from the different ICU data sources.

Firstly, the data are extracted from the ICU data sources by the agents; during the extraction some automatic procedures are executed. Then, all process of interpretation of values is executed by the pre-processing agent and finally all data are loaded into a data warehouse that stores all critical values to be used by the Critical Events System.

Fig. 1 summarizes the process of the data acquisition system which has been developed in order to collect data from bedside monitors and ENR. These data are either automatic collected from the bedside monitors through the gateway agent or manually validated / inserted in the ENR by the ICU nurses. Afterwards, all the data is processed in order to obtain the critical events and the CE system is executed.

Afterwards the results attained are disseminated through the ENR. At same time the results are available to the INTCare prediction agent so that it may obtain the target probabilities. These results are available to consult by the doctors anywhere and anytime using a mobile device.

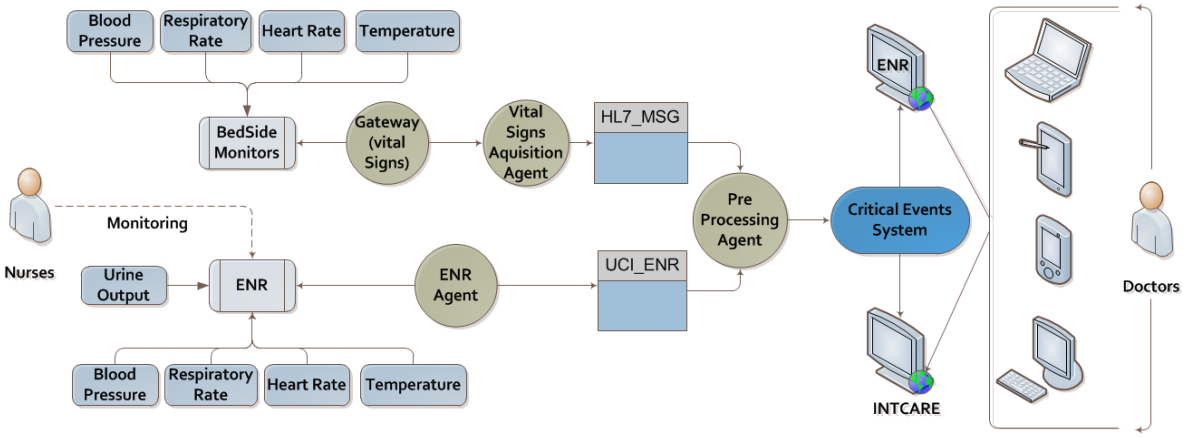

Fig. 1. ICU Critical Events – Data acquisition

Nowadays it is important to concentrate the efforts on detecting the critical events that are deemed most important by the doctors we are working with. Automated data acquisition without human intervention is already in place for most of them even though values can be manually inserted / validated by ICU staff. However, the urine output measurement isn't automated at the ICU and the respective values have to be manually entered by the nursing staff.

Table 2 shows which are the variables collected in real-time, the correspondent data source and if they are acquired in an automatic or manual way. In this case, only one of the variables requires human intervention, all the other are collected automatically and can be monitored manually.

Table 2. Critical variables data source and acquisition type

Variable	Data Source	Acquisition
Blood Pressure (BP)	BM	Automatic
Temperature (TEMP)	BM	Automatic
Hearth Rate (HR)	BM	Automatic
Oxygen Saturation (O2)	BM	Automatic
Urine Output (UR)	ENR	Manual (hour)

4. Data pre-processing

Data pre-processing is executed by the pre-processing agent. This agent is responsible for the automatic execution of all the tasks required to determine the number and the duration of critical events. This process is central to the entire system.

A first pass through the data allows for validation and for detection of values that may be part of CE. The data quality is fundamental to obtain the correct number of critical events. In this case, all values collected are being used, i.e., all values are necessary to be able to do a continuous calculation of events.

In order to streamline the process it is necessary to have an automatic validation procedure. This procedure is activated whenever a new value arrives. Each value is checked to see if it is inside the valid range of values for the respective variable and then it is flagged as potentially critical or non-critical. This task is executed according to the values defined in Table 3 (Filipe Portela, Pedro Gago, Manuel Filipe Santos, Álvaro Silva, & Rua, 2012). For example, a value of 10 for the urine output will be discarded as it is out of the valid range. A value of 190 (anytime) for the same variable will be flagged as critical and 70 as potentially critical (it will be confirmed as critical if the values stay out of range for at least 1 hour).

Table 3. Critical Events - Data Ranges (adapted from (Filipe Portela, et al., 2012))

EV_ID	DESCR	MIN_EC	MAX_EC	MIN_VAL_ICU	MAX_VAL_ICU	MIN_ANYTIME	MAX_ANYTIME
3510	TEMP	36	38	34	45	35	40
1011	BP	90	180	40	300	60	
3000	O2	90	100	0	100	80	
2009	HR	60	120	0	300	30	180
DIU	UR	30	1000	0	1000	10	

The procedure referred is applied only to the variables that are to be used in the calculation of the critical events. This procedure is executed through a trigger which is activated before that value is inserted in the table containing HL7 (Hooda, Dogdu, & Sunderraman, 2004) data.

Immediately after this procedure is executed another trigger, which is responsible to calculate the time of these events, is activated.

5. Critical Events Tracking System

The tracking system is executed in real-time using automatic data acquisition and data processing tasks. After collecting the critical values it is necessary to check if they originated a critical event. The rules for the calculation are in Table 1. In order to help ascertain if the event type collected is or is not the same which was before collected, a flag in the table will be used. The flag φ will identify the state of the event type collected, i.e., the flag value present in the table allows the system to know if there is some event in the table that has the same type and if that event is open (1) or not (0). An "open" event is still in progress while a "closed" one has already finished.

When a value is collected and, immediately after it is validated and inserted in the HL7 table, the trigger will verify if there is some "open" record for this event category. If it doesn't exist, a new row will be created. If there is a record for the same event type, nothing it is done, otherwise the event finish date will be defined according the collected date of the obtained value. For each event type (0, 1, 2) some operations will be done according to the respective event state (open or not). Finally and after the event start and event finish date is

filled, a procedure, which calculates the time of each event is executed. For each patient, event category and value collected (PEVID) and, after the values are correctly inserted in database, a trigger is executed to verify if the event is closed and if it is the same type in order to calculate the event duration and then classify the event as critic or normal.

After the value is correctly identified and inserted into the database, with total time filled, another trigger will be executed. This other trigger is designed to verify if an event is critic or not. To identify if a set of collected results is or not a critical event it is necessary to analyse the table which contains all values collected with the respective time interval. By computing the length of that time interval, the procedure identifies which set of values are critical.

6. Results

Our system is continually collecting and processing data and is continually providing us updated information regarding the number and duration of critical events for each patient. It is a two-step procedure: in the first step the value being analysed is flagged as critical or not critical and in a second step the systems calculates the Accumulated Critical Events (ACE) – to reflect the patients' clinical evolution/severity of illness by hour. The values obtained will be used to create some ratios (Filipe Portela, et al., 2012).

The procedures presented next are executed at regular intervals and have the objective to understand the number of events by type and hour, and their sum. The procedure is used to count the number of events and to sum the time; the values are grouped by type and hour.

In order to illustrate the functionality of the system, Fig. 2 presents the distribution of the values collected during the last six months. The values are grouped by variable, event type and hour. In the graph is possible to see the percentage of occurrence for three of the five variables (blood pressure (BP), SPo2, Heart Rate (HR) by hour (0-23) and event type (1 or 2). Analysing the figure 2 it is possible to retain some important conclusions (Filipe Portela, et al., 2012). The critical events of BP (59,85%) and HR (85,91%) are strongly associated to the events type 1 (less critical). In the case of SPo2 the critical events are mostly of the type 2 (68,22%). The vast majority of the events (almost 20%) occur between 9 and 11 am. This is most evident for the HR (critical event type 1) and SpO2 (critical event type 2). For the Blood Pressure, the 15th hour is the most critical (6,64% = 3,91% (1) + 2,73% (2) of the critical events occurred during this hour).

This sort of analysis can help the doctors understand when each the event type normally occurs. The information obtained about the critical events combined with other variables can be used to alert the doctors in order to avoid critical events.

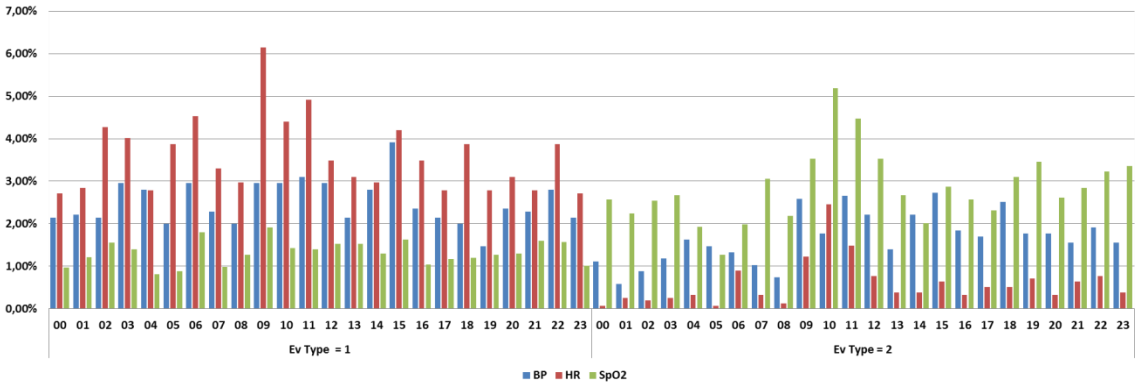

Fig. 2. ICU Critical Events – Data acquisition

6.1. Tracking System - Interface

The results obtained by the tracking system are presented inside the Electronic Nursing Record application. The results are presented in two different ways: a grid (table) and a chart. The table header is composed by 13 columns: the number, the duration of each CE and the total of events. The table also has 24 lines, one for each hour of the day.

The system fills the grid according to the patient values, i.e., if an event is critical or not and their duration.

Fig. 3 presents an overview of the CE grid. For example, in the tenth hour of the day the patient finished a Temperature critical event with the duration of 311 minutes.

This way of visualizing events also has a warning system to alert if current values are out of range, i.e., critical values. It is represented by a colour system to alert to the patient condition. For each variable, if some event is "open", the event type (1 or 2) is checked. Then, for the event type = 1, it calculates the time between the system date and the starting date. If the time in minutes is between 10 and 20 the label will be yellow. If this event is open more than 20 minutes the label will be red. In the cases of event type = 2 the label will be always red whatever the time it is started. In the other cases the label will be green.

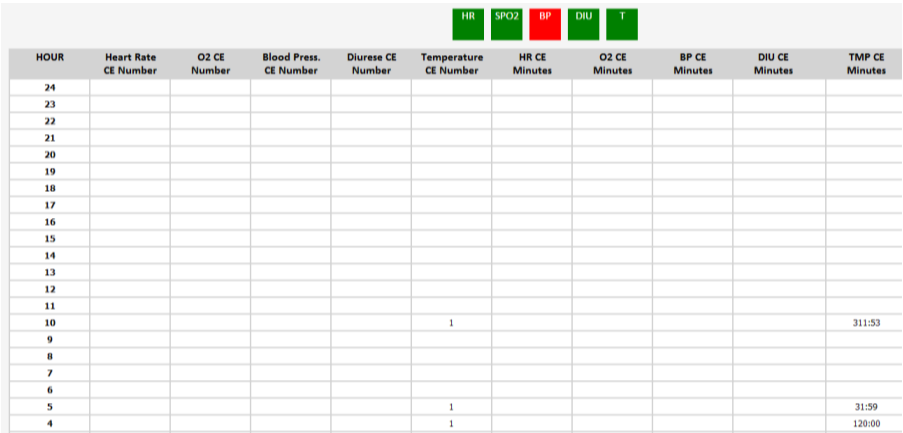

Fig. 3 Critical Events grid

The warning system is composed of five boxes, one for each category (z) and has three different colors. The box color is refreshed every minute and is defined according to the event type and duration. The following procedure shows the rule used:

```
IF EVENT(Z).TYPE = 2 THEN
      EVENT(Z).BOXCOLOR = RED
ELSE IF EVENT(Z).TYPE = 1 THEN
      IF EVENT_DURATION >= 30 THEN
            EVENT(Z).BOXCOLOR = RED
      ELSEIF EVENT_DURATION >= 10 THEN
            EVENT(Z).BOXCOLOR = YELLOW
      ELSE
            EVENT(Z).BOXCOLOR = GREEN
      END IF
ELSEIF EVENT(Z).TYPE = 0 THEN
      EVENT(Z).BOXCOLOR = GREEN
END IF
```

The charts present a new way of tracking the Critical Events. The user (doctor / nurse) can anywhere and anytime consult the evolution of a patient with regard to Critical Events. Users may view this information by minute, hour and day. When minutes are selected, it presents the evolution of the values in last 25 minutes using to the effect a continuous line graph. Figure 4 shows an overview of a chart for the minutes. In this figure it is possible to observe that the patient is having a critical event (SpO2) from 46 last minutes.

The second and third types of analyses are similar. In figure 5 is possible to observe that the information by hour aspect is presented in a different manner than information by minute. In this chart we use a bar chart that accumulates the minutes of the critical events during a day. Figure 5 shows a set of events (duration and type) verified from a patient in the last 12 hours. For example in the sixth hour the patient had a critical event (type 2) to

the temperature during 94 minutes. The third view (day) presents the sum of critical events by day. All the graphs are grouped by category (BP, SpO2, Temperature, Urine Output, Heart Rate) and event type (1 or 2).

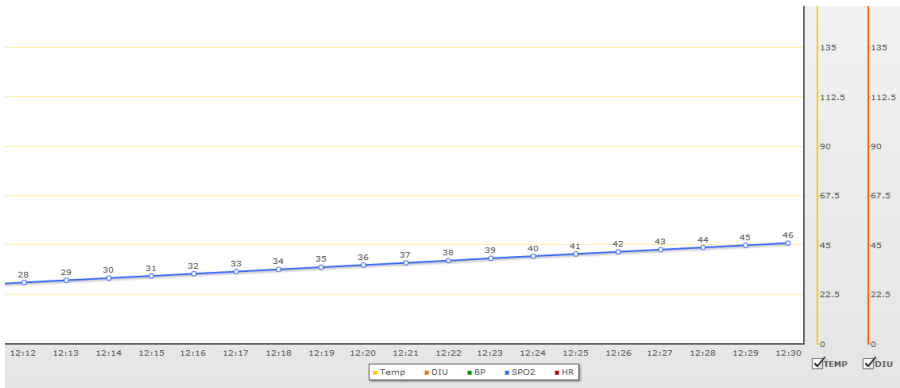

Fig. 4 Critical Events Chart by minute

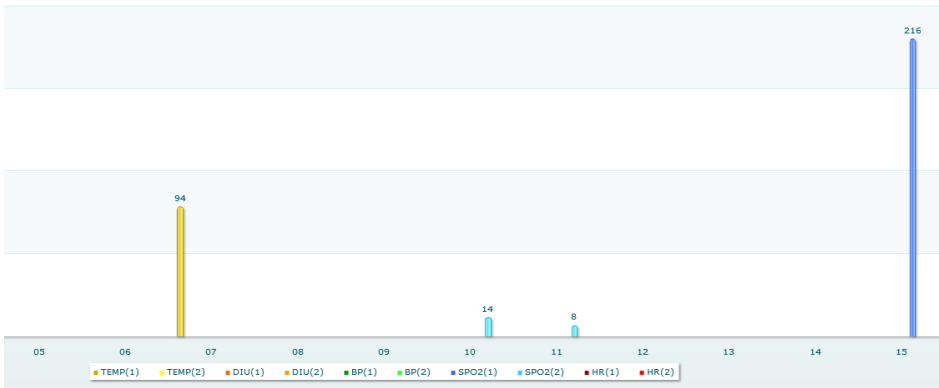

Fig. 5 Critical Events chart by hour.

6.2. Tracking system TAM assessment

The Critical Events tracking system was evaluated in questionnaire of INTCare system. Even though the questionnaire has 91 questions only six are concerned with CE System. This questionnaire was answered by 13 nurses (33% of ICU nursing staff). The questions were filled using Likert Scale (Johns, 2010). The considered levels were the following:

1) Not satisfies/in complete disagreement (< 20% of cases);

2) Satisfies a bit/in some level of disagreement (20-40%);
3) Satisfies/under some level of agreement (40-60%);
4) Satisfies a lot/strongly agreement (60-80%);
5) Satisfies completely/full agreement (> 80%).

Table 4 presents the question and respective construct of TAM: perceived usefulness (PU), perceived ease of use (PEOU), behavioural intention (BI) and use behaviour (UB).

Table 4 Answer VS TAM Construct

#	*Answer*	*PU*	*PEOU*	*BI*	*UB*
1	Potentiates a proactive action to the professionals	X	X	X	X
2	Allows the tasks to be performed with greater precision	X	X	-	-
3	Allow an easy operation through touch interface at the head of the beds	X	X	X	X
4	Critical Events - Utility of the System	X	-	X	X
5	Critical Events - Utility of warning system	X	X	-	X
6	Critical Events System - Interface	-	X	-	-

Having in account the answers received the results were grouped. Table 5 presents the average (avg), standard deviation (Stdev), minimum (min), maximum (max) and mode of the values collected by answer and TAM construct.

Table 5 Analysis of the results collected

#	*AVG*	*Stdev*	*MIN*	*MAX*	*MODE*
1	3,30769231	0,60569291	2	4	3
2	3,15384615	0,8634594	2	5	3
3	3,07692308	0,91664425	2	5	3
4	3,61538462	0,48650426	3	4	4
5	3,61538462	0,48650426	3	4	4
6	3,61538462	0,62492603	3	5	4

	AVG	*Stdev*	*Min*	*Max*	*Mode*
PU	3,35385	0,715169	2	5	3
PEOU	3,28846	0,753061	2	5	3
IC	3,19231	0,727952	2	5	3
CMPU	3,19231	0,686676	2	5	4

Analyzing Table 5 it is possible to observe that in general the results are satisfactory. All questions present positive results and the level of accordance by question / user it is high. The questions associated in particular to the CE system were which present better results, having an average of 3,65 and a mode of 4.

At level of the constructs it is obvious the importance that the CE tracking system has to

the decision making process, being the perceived usefulness the better construct. In all the cases the answers varies from two and five. This value signifies that nobody is totally in disagreement with the system.

7. Conclusions & Future Work

This new approach represents a set of innovations in the way of the data are collected and used to support the decision making process. It is now possible to acquire, process, and present knowledge automatically and in real-time using online-learning, anywhere and anytime.

Aiming at promoting proactive actions with the patient this Pervasive Intelligent System is able to determinate and evaluate the number and duration of critical events patients. The doctors in ICU of Centro Hospital do Porto now have some new information that helps them to have a better understanding of the patient's condition.

The doctors can see, for each patient and in real time the number of events by hour and the time in which the patient was in a critical event. In addition, they possess a traffic light system (green, yellow, red) to alert / show the present situation for each event.

The system presents its results in three different ways: the first one presents all events in a based the second shows the evolution of the events in a chart and the third presents results from the prediction models for organ failure and final outcome and also shows the number of critical events. In order to assess the tracking system, a questionnaire based in the TAM methodology was performed. The results attained were very satisfactory and motivate futures developments in this area. The tracking system interface is the aspect which reaps greater acceptance by the ICU users. At the same time they recognize the importance of this type of system to help the decision.

Due to the success of this implementation, in the future, further adverse events types will be explored and added to the system. A set of new data mining models will be addressed in order to explore other targets.

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