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Integration of temporal data visualization techniques in a KDD-based DSS
Application in the medical field

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***Abstract*: This paper addresses the interactive temporal Decision Support System (DSS) based on Knowledge discovery in Databases (KDD). Our goal is to propose an approach to improve decision-making process by integrating visualization techniques in the different KDD stages for producing visual interpretations in order to combine potential computational capabilities of the machine with the human judgment. Our application context is the fight against the Nosocomial infections.**

Keywords: Temporal Decision Support Systems, Knowledge Discovery in Databases, Visualization, Nosocomial Infections

I. Introduction

Given the diversity and the complexity of temporal data, it is essential to have methods and tools for structuring these data, analyzing them and establishing meaningful relationships between their elements identified to support decision-makers about their choices [20] [23]. The Knowledge discovery in Databases has proven itself in the complex fixed and temporal data analysis used for decision-making issues [24] [25].

This paper is proposed as a reflection on the knowledge-based DSS. This knowledge can be extracted using data mining techniques in the form of new patterns to be interpreted and evaluated in order to propose it as a valid element of decision support.

The KDD-based DSS produce decisions on the basis of a high number of intelligent results or models: decision tree, grid scores, rule-based regression model, neural network, etc. The form of these results depends on the used data mining technique. Since the ability of the data mining techniques to acquire and generate data exceeds its ability to interpret them, we propose to support them by specific visualization tools to provide users synthetic information representations and interactive visualization interfaces [25] [10].

The KDD process is carried out according to three main stages: (1) data preparation, (2) data mining for automatic generation of intelligent patterns and (3) evaluation and patterns' interpretation. The researchers in the KDD field have indicated that the use of interactive graphical methods can increase the Human-Computer Interaction in the KDD process (HCI) [16] [21] [22] [17]. HCI plays a fundamental role in the DSS [7].

In this context, integrating interactive data representations in a KDD-based DSS enhance cognition, and facilitate the interaction with the system [8]. These representations can be generated by data visualization techniques [24]. For this reason, the objective of our research work is to involve the users in the KDD process by applying a set of combined visualization techniques of temporal data in the three KDD phases of data preparation, mining and interpretation [5].

To choose the appropriate temporal visualization techniques, it seems important to be based on the visualization techniques classification proposed in the literature.

We developed and validated our proposed approach with the help of physicians in the Intensive Care Unit (ICU) of Habib Bourguiba Teaching Hospital of Sfax, Tunisia. In fact, these physicians need a temporal clinical DSS to help them to predict and prevent nosocomial infections, called also hospital infections. These infections are caught by some patients; a few days after their admission in the hospital. Some of these patients may die because of nosocomial infections.

This article continues with a theoretical background about temporal DSS and their techniques (analytic and visual) in section 2. Section 3 presents our proposed approach. Section 4 provides a case study of its implementation in the healthcare domain. In section 5 we provide an evaluation, the research and practice implications of this work. This article ends with our conclusions and the perspectives for future research in section 6.

II. Theoretical Background

The decision support is the activity that provides answers to questions asked by actors involved in a decision process. Interactive decision support systems (DSS) are tools which use data and models to solve problems. Decision-makers are frequently faced with temporal data.

Temporal data are defined by two dimensions: temporal values dimension (date) and structural dimension (value of data) [12]. The exploitation of these temporal data allows the dynamic acquisition of temporal patterns that are essential for temporal decision-making. Decision makers are brought to create and analyze great quantities of temporal data [2]. Among the significant challenges relating to these data, we can mention their analysis, their storage, their sharing and their visualization [27]. We particularly concentrate on the temporal data analysis and visualization.

A. *Temporal data analysis: KDD based DSS*

In literature, the purpose of DSS is mainly of a practical nature by assisting decision makers to resolve complex problems. Their development requires real knowledge on the application domain, which refers to an approach of Knowledge Discovery in Databases (KDD). This approach allows extraction of interesting, non-trivial, implicit, previously unknown and potentially useful information from large databases containing fixed and temporal data.

A link between the decision support systems and knowledge discovery systems can be established (KDD based DSS). This kind of systems allows the user to explore a large amount of data to discover new patterns useful for decision-making. It is an interactive and iterative process [16].

The three main phases that form the KDD process are: (1) the data preparation phase which consists in selecting, cleaning and transforming data in a format compatible for the next phase; (2) data mining at the heart of the KDD process, it allows to extract relevant and interesting patterns (non trivial, implicit, previously unknown and potentially useful) from large quantities of data by applying intelligent methods; (3) The evaluation and interpretation phase during which generated patterns are interpreted and evaluated for the knowledge integration in the decision making stage.

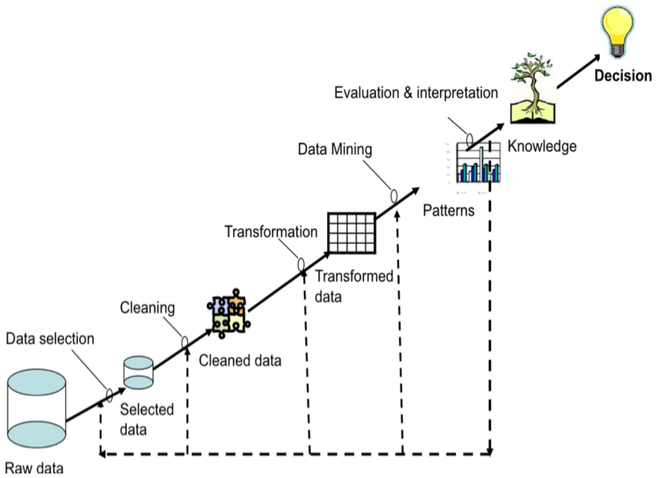

Figure 1. The KDD process (inspired from [15])

The majority of the research works in the field of KDD are focused on developing efficient automatic algorithms. Currently, the role of the user gradually becomes a major concern [24]. Then it seems necessary to include the user in the intelligent temporal decision making process in order to combine human judgment with potential computational capabilities of the machine. In this context, the field of HCI is highlighted and must be integrated in the KDD-based DSS stages. Especially in the data preparation, mining and interpretation in order to improve the human confidence in the knowledge discovered and then the decisional solutions generated by the DSS.

In this paper, we are interested in the interactive visualization techniques. Since most of the data treated by this kind of system are temporal, we are particularly concerned by the temporal data visualization techniques.

B. *Temporal data visualization*

Temporal data represent a state in time. They are collected to analyze environmental variables and study changes over time. These data come from different sources, whether manual entry of data or information collected using sensors or generated by simulation models.

Temporal data visualization consists in translating, transcribing or encoding temporal data displayed in an appropriate visual form. It aims to help user to browse and visualize data in time and observe patterns or trends emerging over time.

A review of the literature shows that temporal data visualization techniques help the user to "make sense" to data [19] [12] [9] to better understand them by using the human capacities in their interpretation. This visual representation allows the spatial and temporal visualization with an aim of assisting the users to extract temporal knowledge useful for better understanding, predicting, preventing the future and thus making better dynamic decisions.

C. *Motivation: visual KDD-based DSS*

The most significant aspect of KDD-based DSS is not the temporal data storage, but the capacity to exploit and analyze them for decision support. KDD and visualization are related and their commonalities for the decision-making are presented in the table 1.

KDD approach	Interactive visualization approach
Basic principles: - Apply a temporal data mining technique. - Present knowledge to the users in form of models to be validated. ***Relevance:*** Generation, analysis and development of the possible solutions to the decision problem in a given time basing on the knowledge made in form of patterns and discovered by the data mining process. ***Weaknesses:*** - It is difficult for the user to build a mental representation of the evolution of the data in time. - The discovered patterns are not easily understood by a human.	***Basic principles:*** - Use of temporal visualization techniques to generate temporal visual representations. - Reduce the cognitive load provided by the user to follow, analyze the evolution of the relevant data in time, compare and interpret the various evolutions. ***Relevance:*** Visual representations allow materializing the results according to: (1) different levels of details and (2) the user needs and views (e.g. selecting a time interval and then a spatial area). This tool features an ergonomic component associated with the visual perception to better differentiate the information displayed, and to improve its interpretation. ***Weaknesses:*** Visualization technique presents data not solutions to the decision problem. It allows only interpreting data

KDD approach	Interactive visualization approach
An approach that improve decision making process by generating a decisional solution based on computational capacities of data mining algorithms	*An approach that improve decision making process by generating interpretations based on the human cognitive capacities*

Table 1. The complementarity of the KDD and the visualization approaches

In our opinion, these two approaches are complementary. Table 1 presents the different elements that can justify this choice. As the table shows, both approaches have elements that are relevant for the decision-making process. The temporal decision support approach that we propose must make it possible to take the user into account (the contribution of visualization) by emphasizing the use of interactive temporal visualization technique and the intelligent temporal data analysis (the contribution of KDD).

Hence visualization integration in the KDD is required. Our goal is to combine human judgment with the computing processing of the machine using visualization techniques. Our proposal is to provide interactive representations of the temporal data as shown in the following figure (cf. figure 2).

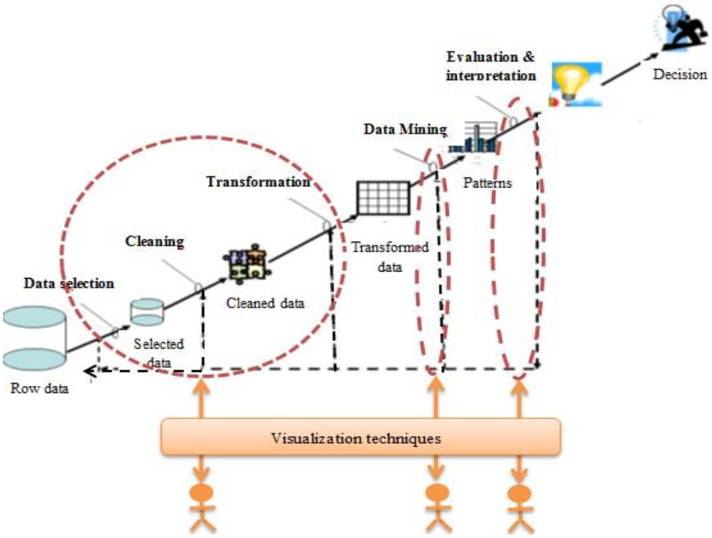

Figure 2. Visualization techniques integration in the KDD process

The temporal visualization techniques can present data and knowledge in a visual form by giving the user a role in the data interpretation and in drawing conclusions. To transform them from its raw format to visual elements, Daassi [12] proposed to use temporal data visualization techniques according to their dimensions: (1) temporal Dimension (the date) and the Structural Dimension (the value).

But the question is: *what are the appropriate temporal data visualization techniques to be used in each KDD stage?*

III. Proposed approach

A. What visualization techniques of temporal data to use?

Different research works on the visualization techniques classification of temporal data exist. In our context, we are interested in the classification proposed by Daassi et al. [12]. According to [12], the choice of the visualization technique of temporal data is influenced by the step "point of view on time" of Daassi visualization process visible in figure 3.

This visualization process is an extension of Ed Chi data state model [9] that is composed of four steps described as follows:

1. Data: data to be displayed.
2. Point of view on data: transformation of the data onto an analytical representation.
3. Visualization space: transformation of the analytical representation onto values ready to be displayed.
4. Point of view on the visualization space: Transformation of the displayable values onto a graphical representation.

The Daassi et al. extension defines the visualization process as an association between two visualization processes devoted to the two temporal data dimensions. It consists in applying the Chi' s visualization process to the temporal dimension (cf. Fig. 3 (b)) and to the structural dimension (cf. Fig. 3 (c)).

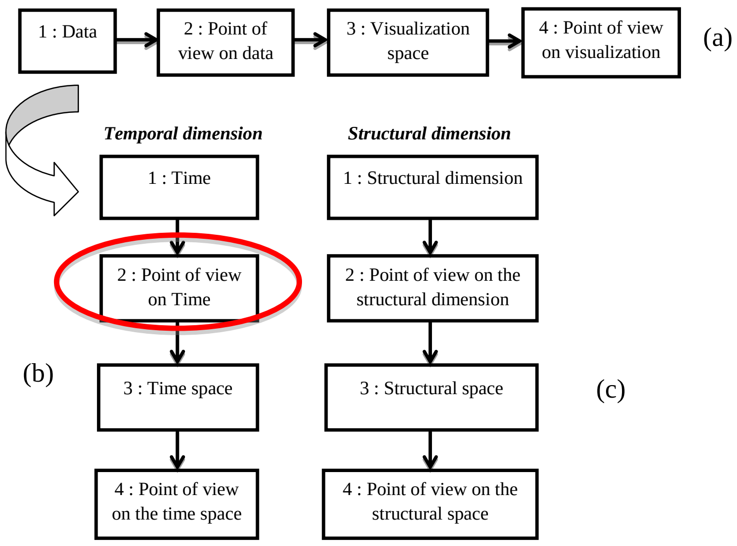

Figure 3. (a) The Chi visualization process [9]; (b) and (c) Daassi et al. visualization process [12]

The point of view on time is the critical step (cf. Fig. 3 (b)) on which is based our approach. It allows identifying the characteristics of the temporal values to be represented: **linear or periodic**. Basing on this idea, we generate the table 1 presenting the classification of a set of temporal data visualization techniques according to Daassi [12]:

Point of view on time	Temporal visual representation	Temporal visualization techniques
Linear	Linear representation of time	1. Perpective wall technique (PWT) 2. Tabular representation technique (TRT) 3. Pixel representation technique (PxRT) 4. Superposed Diagram technique (SDT) 5. Diagram representation technique (DT)
Periodic	Time representation in a cyclic form	1. Star Representation Technique (SRT) 2. Spiral Representation Technique (SpRT) 3. Concentric circles technique (CCT) 4. Graph Representation technique (GRT)

Table 2. Visualization techniques classification according to point of view on time

The proposition of Daassi [12] [13] classifies the visualization techniques taking into account the temporal data but not the user task, which is a critical factor in Human-Computer Interaction.
In this context, we examine the latest classification made by Adjanor et al. [1]. It extends existing taxonomies basing on the three factors: Time, Data and user Task. For this reason, we propose to classify the visualization techniques presented by table 2 according to [1] (cf. table 3)

User tasks	Temporal visualization techniques	
Overview	*instantaneous*	SDT
	on interval	TRT, PWT
	Total	SRT
Search	*Time criterion*	TRT, PWT, SRT,SpRT, GRT
	Data criteion	TRT, PWT, SDT, SRT, SpRT, GRT
Relationship	*Temporal*	TRT, PWT, SDT, DT, SRT, SpRT, GRT
	Semantic	SRT, SpRT
Comparison	SDT, DT, SRT, SpRT, GRT	
Trend	TRT, PWT, SRT, SpRT, GRT	
Repetitive patterns	SRT, SpRT	

Table 3. Visualization techniques classification *according to user tasks [1]*

According to table 2, only the following techniques (classified by [12] and then by [1]) will be considered in our context:

- **Tabular Representation Technique (TRT)**: allows a visualization of data sets in tabular form [29]
- **Perspective wall Technique (PWT)**: allows data to be presented chronologically on several panels (walls) [26]
- **Diagram Representation Technique (DT)**: allows representing quantitative data values compared to the corresponding temporal moments [11].
- **Superposed Diagrams Technique (SDT)**: allows representing each structural value compared to two values of two regular temporal units [11].
- **Star Representation Technique (SRT)**: allows representing data in the form of a star [11]. Because that the spiral and the star techniques are quite similar in terms of periods' treatment and visual interpretation, we propose to keep the star representation technique in our classification.
- **Graph Representation Technique (GRT)**: It is a tool for visualizing graphs. It presents nodes and links between these nodes [4].

To ensure the navigation mode in these visualization techniques, we propose to combine them with the timeline technique. It allows visualizing data according to a chronological order. [18]
The time line uses a simple and linear distribution of time values. The time navigation is carried out by the navigation buttons. It can be used as a reusable component to view the time dimension of temporal data.

B. Visualization techniques integration process

In this section, we tend to define what temporal visualization techniques can be integrated in each phase of the KDD process basing on the Daassi et al. [12] and Adjanor et al. [1] classifications.
To achieve this, we must examine the technical specificities of each KDD phase.

1) Data preparation stage: in this stage, it is question of:

- Selecting relevant data,
- Formatting data often different in nature. It is about access to data in order to build of a specific data corpus. Missing values are handled by the complete elimination of the line or by interpolation.
- Changing the data structure to facilitate the data mining.

These preprocessing operations handle large amounts of complex fixed and especially temporal data. These data can be linear or periodic. Thus, Depending on the type of temporal data that the user has to select, clean or transform, it should be given the appropriate visualization technique to achieve his/her goal.
According to our classification, tabular representation, superposed diagrams or star representation techniques can be used by referring to the point of view on time (table 1) [5]. A temporal data global view can be carried out by using the perspective wall technique (cf. Fig. 4)

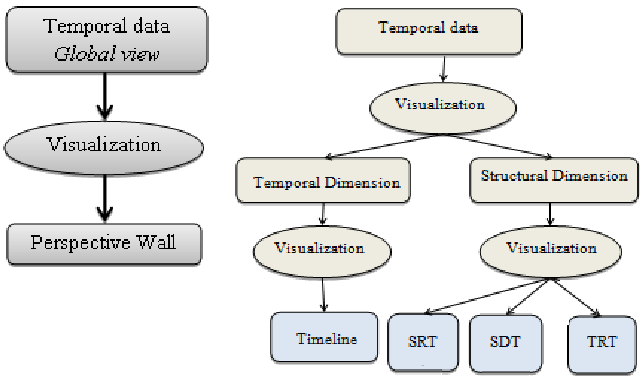

Figure 4. Used visualization techniques in the preparation phase

2) Data Mining Stage

Whatever the data mining technique to apply (classification or clustering); it uses input variables to extract new patterns. The number of variables to handle can be very important. Thus, the appropriate visualization technique to use to visualize structural dimension of temporal data is the tabular representation technique allowing visualizing large data sets [5].
In the case of a data mining technique based on the graph such as the Bayesian Networks, the visualization of this graph can be represented by the GRT.
The tabular and the graph representations techniques have to be combined with the timeline technique to represent temporal dimension.

3) Patterns evaluation and interpretation stage

This stage consists in interpreting and evaluating discovered information by an expert in the form of textual or encoded lists.

Visualization tools offer the analyst a synthetic view of the represented information that is a pattern (eg. probability) in most cases, changed over time.

We can note that the amount of data to be displayed in this stage is not large. For this reason, we propose to use the diagram representation technique in order to facilitate the evaluation and interpretation of the discovered pattern. The navigation task is carried out by the timeline technique [5].

IV. Medical application

Decision support is a vital element in improving healthcare quality; especially in the intensive care units where Nosocomial Infections represent a critical problem. An infection is considered as nosocomial if it develops in a patient during his/her hospitalization [6].

Our applicative context is the design and development of interactive visualization techniques to represent temporal data in the intensive care unit of the Teaching Hospital Habib Bourguiba Sfax. These techniques must be integrated in the different modules of an existing KDD-based DSS for the fight against nosocomial infections [26].

The ICU data of the Habib Bourguiba hospital are classified into two categories (see fig. 5): fixed and temporal data. The amount of temporal data is the largest in the ICU database (almost 80%).

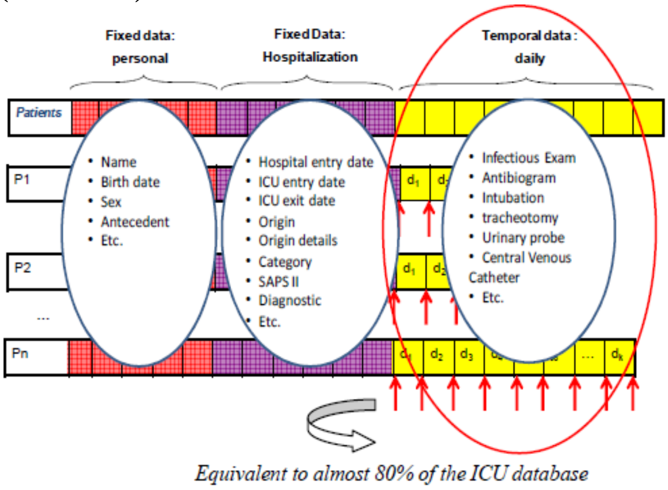

Figure 5. Explored database in ICU

A. Data preparation stage

In this stage, we are interested in presenting the patient fixed and temporal data.

Fixed data concerns the patient personal and hospitalization admission data.

Four relevant temporal data are daily taken: (1) the acts which are the facts carried out on the patient; (2) the infectious exams which describe the sensibility or the resistance of the germs to antibiotics in different locations of the body; (3) the antibiotics prescription which describes the history of antibiotics and the doses taken every 10 days of hospitalization; (4) the biological parameters which show the results of the biological analyzes.

Respecting the classification previously described:

1. An overview on the patient data can be represented by the perspective wall technique. Indeed in figure 6, we have implemented a central wall that has two edges extended by two other walls. The central wall displays global patient information; the two adjacent walls incorporate other visualization techniques to display temporal data.

Figure 6. Perspective wall technique for visualizing patient fixed and temporal data

2. The antibiotics are periodic data; consequently they can be representing using the star representation technique (cf. Fig. 7).

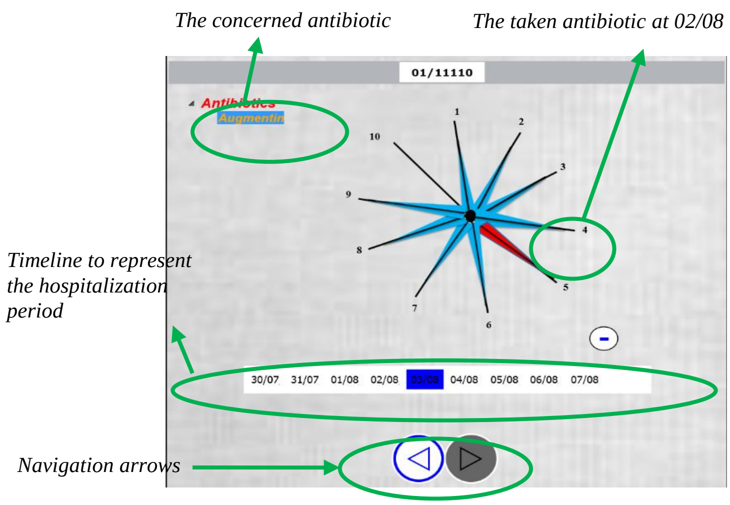

Figure 7. The star technique to visualize antibiotics

Visual interpretation: the star representation allowed visualizing sequentially one or more taken antibiotic for each period of 10 days. To change visualized antibiotic, the user accesses the TreeViewItem.

By selecting a specific date in the timeline, the corresponding part of the star will be colored in red. In our example, the antibiotic "Augmentin" was taken during 9 days; the physician decides to delete the next values because it became resistant.

3. The acts and biological parameters are linear data; therefore they can be representing using the tabular representation technique. The example of biological parameters is visible in Figure 8.

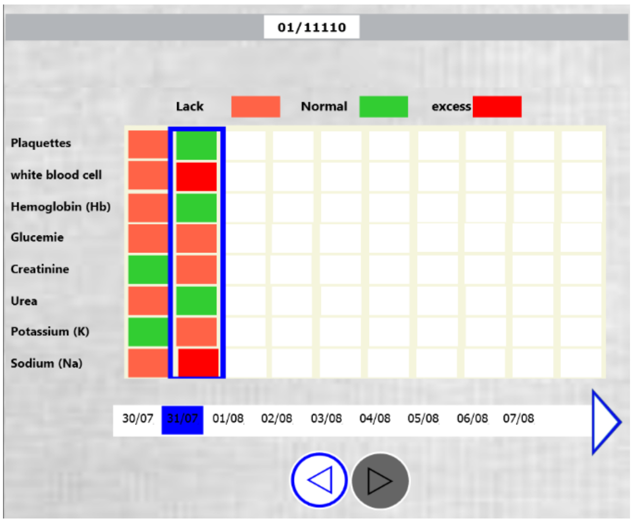

Figure 8. The tabular technique to visualize biological parameters

Visual interpretation: the evolution of biological parameters over time is presented by color change of the rectangles reflecting the data values. If the value of a biological parameter is normal (green) means that no influence on the NI; the user can thus delete this value in order to select only relevant data.

The nosocomial exams are also linear data; therefore we propose de visualize these data using superposed diagram technique (cf. Fig. 9).

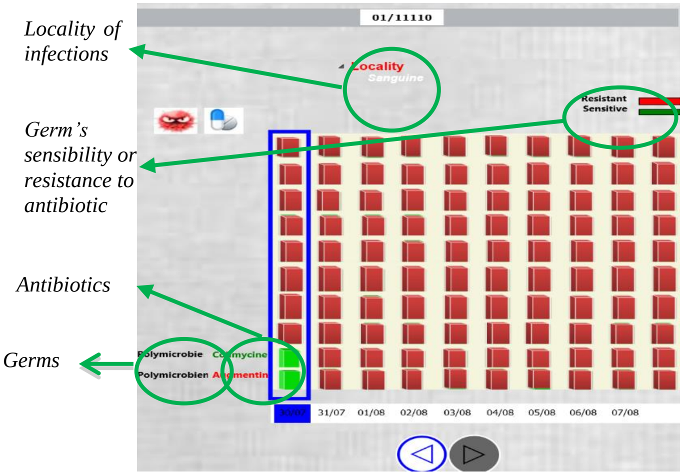

Figure 9. The superposed diagram technique to visualize NI exams

Visual interpretation: each structural value (NI) is defined with respect to a regular unit of time (day). The SDT allowed viewing sequentially one or more localities. Thus, germs and given antibiotics taken for each selected locality can be displayed at once. To view the other locality, the user must select TreeViewItem at the top. Each case (resistant or sensitive) is displayed in a different color, red or green.

B. Data mining stage

The developed KDD-based DSS uses the dynamic Bayesian networks (DBN) as the data mining technique to extract dynamic temporal patterns [14] [28]. More details on the design and implementation of this data mining technique have been discussed in [25] [26].

The DBN allows dynamically calculating the probability of NI occurrence. This probability is automatically generated everyday based on the temporal variables represented above.

The decision on the patient state is generated basing on the calculated probability. As time passes, the future decision in the current step becomes the basic decision in the next decision step. This link is repeated until the end of hospitalization.

The DBN generated graph is visualized using the Graph Representation Technique visible in Figure 10.

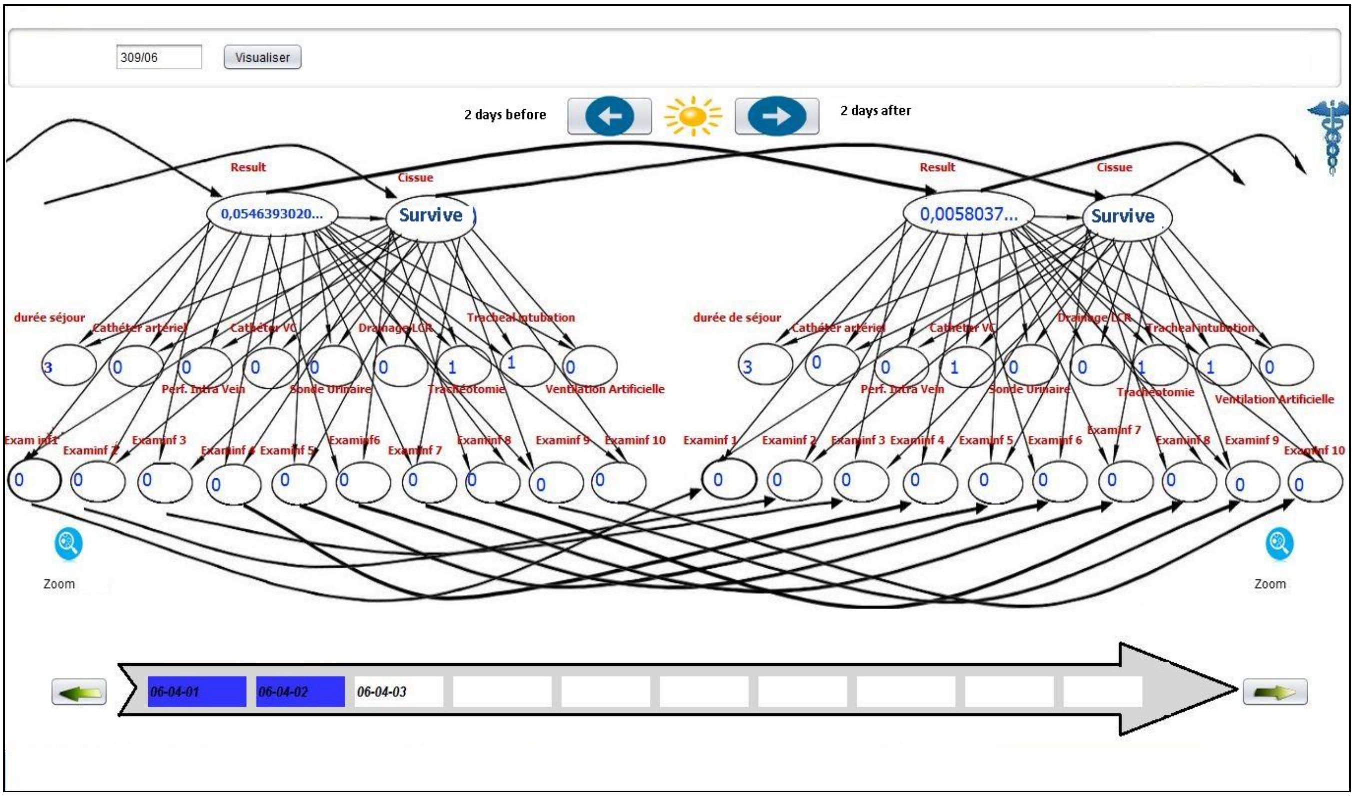

Figure 10. The Graph Representation Technique to visualize DBN

To present the input dynamic variables and the output probabilities (temporal patterns), we have used the tabular representation technique as recommended by our classification (Fig. 11).

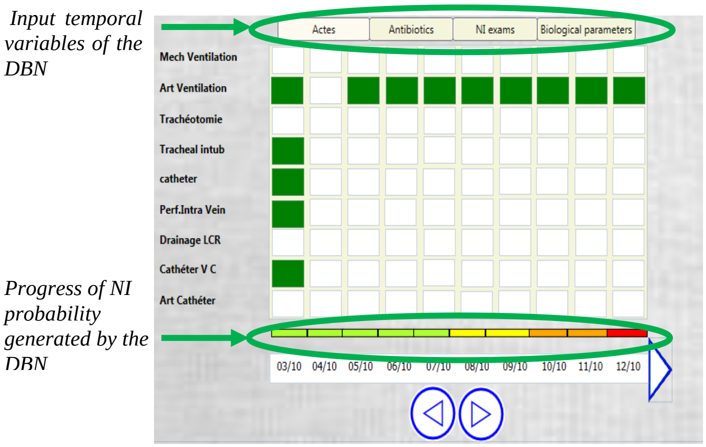

Figure 11. The tabular technique to visualize data mining process

Visual interpretation: figures 10 and 11 present the DBN graph and its input DBN parameters (Acts, Antibiotics...) for calculating the daily probability of acquiring NI. The progress of probability values is presented in Figure 11 by the variation in color (green < 50%, Yellow in [50%, 70%], Orange in [70%, 80%] and red > 90%).

A. Evaluation and interpretation of data mining results stage

In this stage, we propose to allow the user to visualize and interpret the evolution of the data mining results in order to validate or not the automatic possible solutions generated by the KDD-based DSS to fight against nosocomial infections. We have implemented the diagram technique to visualize these patterns and decision support solutions (cf. Fig. 12).

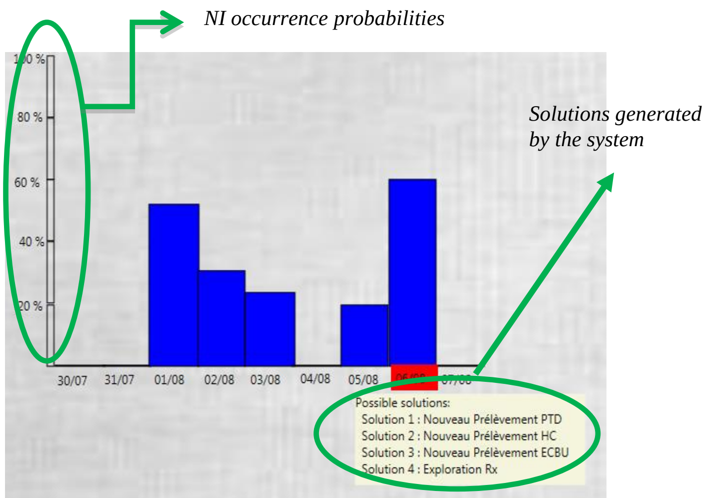

Figure 12. The diagram technique to visualize data mining results

The different representations generated by the temporal visualization techniques and integrated in the three KDD stages (cf. Fig. 6, 7, 8, 9, 10, 11 and 12) are used to reduce the cognitive load of the physician and to assist him/her in the interpretation of the temporal ICU data evolution of each patient over time.

The daily follow-up of these visualizations helps the physician to visual interprets them in addition of the intelligent patterns

generated by the DBN technique.
The two approaches allow physicians to have an idea about the occurrence of a nosocomial infection and then to make a medical decision to avoid it.

V. Evaluation

To evaluate the developed temporal visualization techniques usability for the KDD based DSS users, we used the evaluation method of Badjio [3] that works on the visual data mining themes. We take into account the user and usability topics.
The principle consists in attributing by the user a value to each criterion. The values vary between 5 (the system responds very well to the criterion) and 1 (the system does not respond to the criterion). The results are presented in the following table.

Criterion	5	4	3	2	1
System adequacy to its needs	X				
Communication facility		X			
Comprehension facility			X		
Effectiveness		X			
Conviviality	X				
Personalization				X	
Flexibility		X			
Learning		X			
Errors treatment			X		
Feedback		X			
Orientation		X			
User help					X
User's manual					X

Table 4. Usability evaluation

From these results, we generated the following histogram (Figure 13):

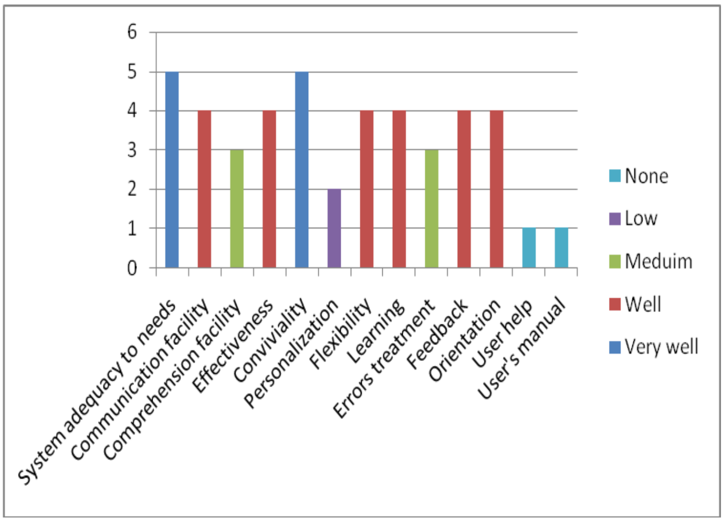

Figure 13. Usability evaluation of KDD HCI

The evaluation of the temporal visualization techniques usability has shown that users have, in general, appreciated using these techniques (except for the user help and manual).

VI. Conclusion

The DSS makes it possible to collect and produce knowledge from great quantities of temporal and non-temporal data in order to contribute to the decision-making. This system can be used in various fields such as the field of medicine; in particular to contribute to the fight against nosocomial infections in the intensive care units. The data exploration by the KDD process has become more and more difficult [17]. To overcome this problem, it is now essential to design and develop visualization techniques in order to exploit human pattern recognition capabilities to increase confidence and improve comprehensibility of the temporal data.
In this paper, we are integrated a set of selected visualization techniques of temporal data in the stages of an existing KDD-based DSS. This system was developed to fight against NI in the ICU of the Habib Bourguib teaching hospital.
The choice of the appropriate visualization techniques is made according to three criteria: time, structural data (the two dimensions of temporal data) and user tasks. The use of four visualization techniques in the process of KDD allows increasing the human computer interaction and therefore improving the quality of the decision. The Visual KDD-based DSS was evaluated considering the utility and the usability dimensions. As an outcome, its evaluation has shown satisfactory results.
We plan in further works to extend our visual KDD-based DSS by developing other data mining and temporal data visualization techniques such as the concentric circles, the LifeLines, the spiral techniques, etc. We plan also to provide further evaluation experiments with more participants (physicians) in order to assess the KDD-based DSS utility and the usability with regard to the user's tasks.

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