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Combination of cognitive and HCI modeling for the design of KDD-based DSS used in dynamic situations

Hela Ltifi [a,c], Christophe Kolski [b], Mounir Ben Ayed [a,d]

[a] *REsearch Groups in Intelligent Machines, University of Sfax, National School of Engineers (ENIS), BP 1173, Sfax, 3038, Tunisia.*
hela.ltifi@ieee.org, mounir.benayed@ieee.org.

[b] *Univ Lille Nord de France, F-59000 Lille, France,*
UVHC, LAMIH, F-59313 Valenciennes, France,
CNRS, UMR 8201, F-59313 Valenciennes, France
Christophe.Kolski@univ-valenciennes.fr

[C] *Computer Sciences and Mathematics Department, Faculty of sciences and techniques of Sidi Bouzid, University of Kairouan, Tunisia.*

[d] *Computer Sciences and Communication Department, Faculty of Sciences of Sfax, Route Sokra Km 3.5 - BP 1171- 3000 Sfax*

ABSTRACT

Recent work in dynamic decision support systems (DSS) has taken impressive steps toward data preparation and storage, intelligent data mining techniques and interactive visualization. However, it remains difficult to deal with the uncertainty and complexity generated by the Knowledge Discovery in Databases (KDD). This paper launches the challenge by introducing cognitive modeling for specifying decision-maker behaviours more naturally and intuitively. It consists in introducing cognitive modeling for dynamic situations involving visual KDD-based dynamic DSS. This research work presents an adaptation of a well-known cognitive model under the KDD specificities. We provide cognitive modeling application in visual KDD-based dynamic DSS for the fight against nosocomial infections in an intensive care unit. Finally, we built a series of evaluations verifying the system's utility and usability.

Keywords: Dynamic Decision support systems (DSS); Knowledge Discovery from Databases (KDD); Human-Computer Interaction (HCI); Cognitive Modeling; Visualization; Nosocomial Infections.

1. Introduction

Traditionally, decision support systems (DSS) were developed to assist in the choice of multiple decision alternatives based on a set of attributes. These DSS have focused on supporting the decision-maker to choose the best possible decision based on a rational decision-making model [78] [80] [81]. Such model can be extracted by a Knowledge Discovery in Databases (KDD) tool. This study focuses on the KDD-based DSS [19] [3] [2].

DSS and KDD are widely used in the medical field [26] [16] [57] [68] [38] [39], especially in the intensive care units (ICU) [23] [3] [52] [36]. Most of the exploited ICU data are temporal; hence the decision-making process is dynamic and requires a series of decisions, where the decisions are not independent. Thus, this paper is interested in KDD-based Dynamic Decision Support Systems (DSS) [3]. These systems allow for the routines of actualization, edition and addition of data, thus providing accurate information in the appropriate time, and adequately assisting the decision-making process [24]. The dynamic decisions must be taken in real-time, thus making time constraints an important issue of decision support.

KDD-based Dynamic DSS may be highly interactive [51] [54] [35]. It is therefore important to understand the role of the user who can also be seen as a decision-maker in the KDD and Dynamic DSS processes. In fact, the human creativity, flexibility and knowledge is joint with the huge storage capacity and computing power of computers in dynamic situations [44]. Hence the idea is to combine traditional data mining algorithms with information visualization techniques: we are interested in visual KDD-based Dynamic DSS. The decision-maker in charge of this kind of systems is required to simultaneously manage a set of KDD and decision tasks dynamically. This set of KDD evolves in time and requires frequent changes in the decisional situations. The classical modeling of these situations is disclosing new potentialities, which so far are still largely unnoticed. These are mainly related to what Occelli and Rabino [65] have called the structural-cognitive modeling shift.

In fact, dynamic DSS are designed and developed in the literature using: (1) classical design methods, (2) system dynamics[1] approach [11] or (3) cognitive modeling methods. Few works are devoted to the development of KDD-based DSS (e.g. our works presented in [3] (based on the Unified Process/U model) and [54] (an extended version of the Unified Process)). Design considerations of visualization integration in the KDD-based DSS process are also suggested in [55]. However, there is no approach proposed in the literature for the visual KDD-based dynamic DSS cognitive modeling. So, in this research work, we wanted to explore the following interrogations: (1) "which cognitive modeling approach should be followed to build a visual KDD-based dynamic DSS?" and (2) "Is it possible to take advantage of the existing cognitive modeling approaches?"

In this context, our goal is to propose a cognitive model that enables decision-makers to reason about their visual dynamic decision process based on the discovered knowledge from data. Our proposal consists in adapting the Hoc and Amalberti model [32] under the KDD specificities. To evaluate the proposed approach, its application was tested in the medical context to allow physicians (decision-makers) to fight against nosocomial infections in the Intensive Care Unit (ICU) of a hospital.

The remainder of this paper is organized as follows. Section 2 covers the theoretical foundations of our research, namely the visual KDD-based Dynamic DSS and the cognitive modeling. Concerning section 3, it introduces a discussion about the proposed approach that models decision-making in the context of KDD. As for section 4, it provides a case study pertaining to KDD-based DSS visualizations which demonstrates how our cognitive modeling approach allows the decision-makers to follow up the ICU patient state and provide decisions. Regarding section 5, it provides an evaluation of the proposed and applied approach. Finally, section 6 presents the conclusion and suggestions for future work.

2. Related work

This section contains two parts, the first of which is a review of the literature to clarify the context of our research on the dynamic situations of a visual dynamic decision support system based on KDD. As for the second one, it briefly describes the characteristics of this type of situation as well as the cognitive requirements that the decision-maker may face.

2.1. Visual Dynamic DSS based on KDD

Time is increasingly taken into account in the implementation of decision support systems [8] [63] [79]. It has become a critical dimension in decision-making. Indeed, the expert makes a decision after analysis; the decision creates a result that affects the data; another decision must be taken, and so on ... Actually, since the world is dynamic, DSS should be too, and thus rises the interest in the DSS.

The evolution of information technology has led to the availability of large volumes of data [6] [7] [30]. Therefore, the problem of the analysis of these data to extract information and knowledge to assist with decision-making has emerged [70]. Data mining has appeared as a solution to these problems. It does not consist only in extracting knowledge in the form of patterns but also understanding the relationships between the data [20] [22]. In fact, data mining refers to a central and crucial stage in a process known as KDD [50]. It is an interactive and iterative process that takes place following a series of stages. According to Cios et al. [14], the Knowledge Discovery Process (KDP) is a six-step model (see Figure 1) [14] [47]:

1) **Understanding of the problem domain**: includes the problem and project goals definition, identifying current solutions to this problem, translating the project goals into data mining goals to initially select the data mining tools to be used later in the process.
2) **Understanding of the data**: concerns collecting sample data and deciding which data to select according to their completeness and redundancy, missing values, etc. Finally, it is question to verify the data usefulness with respect to the data mining goals.
3) **Preparation of the data**: consists of deciding which data will be used as input for data mining methods. It includes data cleaning (check the completeness of data records, remove or correct for noise and missing values, etc.) and data transformation to reduce dimensionality (data discretization

[1] system modeling and simulation tool

and granularization). The results are the data that meet the specific input requirements for the data mining tools selected in the previous step.

4) **Data mining**: it is data miner that uses one or more data mining techniques to extract knowledge from prepared data.
5) **Evaluation of the discovered knowledge**: before proceeding to the knowledge integration, it is necessary to check if the models are novel and interesting to interpret them by an expert domain and evaluate the impact of the discovered knowledge.
6) **Use of the discovered knowledge**: it consists of the integration and the deployment of the discovered knowledge.

The arrows in Figure 1 indicate the frequent dependencies between the steps of the KDP.

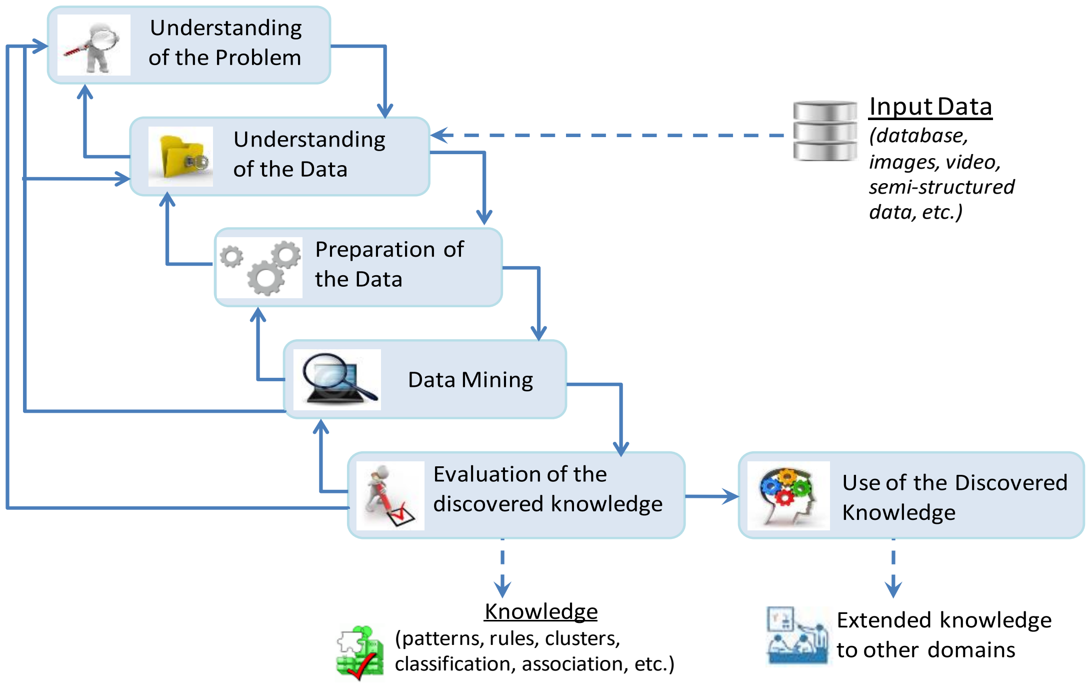

Fig. 1. The Knowledge Discovery Process (adapted from [14])

In our context, the interest is in Dynamic DSS based on the knowledge discovery in temporal databases process. This process allows providing knowledge for decision-making in real time. The KDD-based Dynamic DSS may be considered as an interactive system [54] and the interactivity means a strong user involvement. In fact, the majority of research works in the KDD field focused on the development of efficient automatic algorithms. Although the role of the user in a KDD process was highlighted in the early 90s [25], it is often overlooked [13] [51] [35]. The need for taking into account the user has led to the emergence of human-computer interaction and many visualization tools [48] [40]. Several research works [21] [13] [34] [35] [37] [69] emphasized the need to integrate the user in the KDD process to combine human judgment with the potential computing capacity of the machine.

The more the results of KDD-based Dynamic DSS techniques are interesting, the higher the cognitive load applied by the user to analyze and understand knowledge and take the appropriate decision. It therefore seems necessary to integrate visualization techniques to overcome this problem [51]. The essential role of data visualization is to help the user to make meaning and observe a large amount of data [12]. Visualization techniques aim to amplify cognition via perception, and particularly, to facilitate the understanding and the creation of ideas to make a decision.

The dynamic aspect of the different areas covered (DSS, KDD and Visualization) creates uncertainty, indeterminacy, many interrelationships and overlapping levels of representation, which increases the complexity of our decision support system. In such complex dynamic situations, it is fundamental to model the cognitive behavior of the decision-maker.

2.2. Cognitive modeling in dynamic situations

Cognitive modeling is a domain that deals with simulating human problem solving and mental task processes in a computerized model [43] [33]. Such model can be used to simulate or predict human behavior or performance on tasks similar to the modeled ones. Cognitive modeling is used in: (1) Artificial Intelligence (AI) field, such as expert and decision systems [83], neural networks [67], robotics [84], virtual reality applications [74], and (2) in the Human-Computer Interaction (HCI) field such as human factors engineering, user interface design and visualization [9] [35].

Cognitive modeling is useful to the field of HCI because it reveals patterns of behavior at a level of detail not otherwise available to analysts and designers [28]. The ultimate potential for cognitive modeling in HCI is that it provides the science base needed for predictive decisional situations analysis and methodologies [9]. Most cases of these situations are dynamic owing to the temporal data allowing monitoring and analysis of variations over time using displays representing past and current states of variables. In the context of this article, we are interested in cognitive modeling in dynamic situations for visual decision-making.

Modeling dynamism in decision support systems is a complex cognitive task involving many individuals working in close coordination. In fact, because they are dynamic situations, it is necessary to consider that cognitive processes must be based on appropriate representations, through different types of user interfaces. Within this framework, different cognitive models linked to dynamic situations, such as the well-known approach initially proposed by J. Rasmussen, were proposed.

Jens Rasmussen, in the 80's, proposed an original paradigm in risk analysis [71] [72] [73]; a synthesis on his works is available in [49]. The approach of Rasmussen is a specific modeling of a human operator in a situation of diagnosis or process control, which can be summarized as follows [31]: the operator reacts, formulates hypothesis, interprets and evaluates the situation according to the system objectives, defines a task and adopts a procedure and executes it, until a new alarm occurs again in this cycle. But many shortcuts of this cycle can lead to a decision without a thorough analysis of the situation when it is familiar (Fig. 2).

This model has disadvantages as well [31]. In fact, the operator has to be essentially reactive and the understanding of the state or the system's evolution would anticipate alarms. The process of selective attention is not highlighted; it would rather allow focusing on specific information to be more prone to make certain assumptions at the expense of others. In addition, the evolution of the process during the unfolding of diagnosis and decision-making is not taken into account.

There has been much research on cognitive models and many works have been inspired by the models proposed by J. Rasmussen [82] [76]. We are particularly interested in the Hoc and Amalberti work. Indeed, to overcome the disadvantages of the Rasmussen model, Hoc and Amalberti [32] have developed an alternative model of Dynamic Situation Management (DSM), as opposed to the sequential model of Rasmussen. These dynamic systems are defined by Hoc [31] as systems where "the human operator does not determine completely the changes in the work environment". The DSM model highlights the importance of four concepts in dynamic situation management: (1) the competition between two types of supervisory controls: process control and cognition control, (2) the cognitive concept of 'just enough', (3) the advantage of a dynamic adaptation of cognitive control, (4) and the importance of metacognition. The cognitive dynamic control of cognition tends to level down the maximum performance of isolated cognitive capacities [33]. This model allows taking into account the overall activity of the operator in the control and monitoring of dynamic systems. However, despite the addition of feedback, it does not model the representation of the actions effects of the human operator in question and introduces confusion between the different dimensions of cognitive control in a dynamic situation [61]. In addition, this DSM model does not take into account the visual representations specificities of visual dynamic situations of decision support based on the KDD process. Hence, in the following section, we propose to adapt the Hoc and Amalberti model according to these specificities.

3. Cognitive Modeling Approach

Researchers have proposed computational models, theories and cognitive architectures to provide frameworks of human cognition for simulating a human interacting with his/her environment to accomplish decisional tasks on dynamical systems (cf. section 2.2). However, to the best of our knowledge, there is no model that takes into account the technical specificities of visual KDD process. Thus, the aim pursued in this research work is to understand how the decision-maker gets the dynamic situations of visual KDD-based decision-making under control.

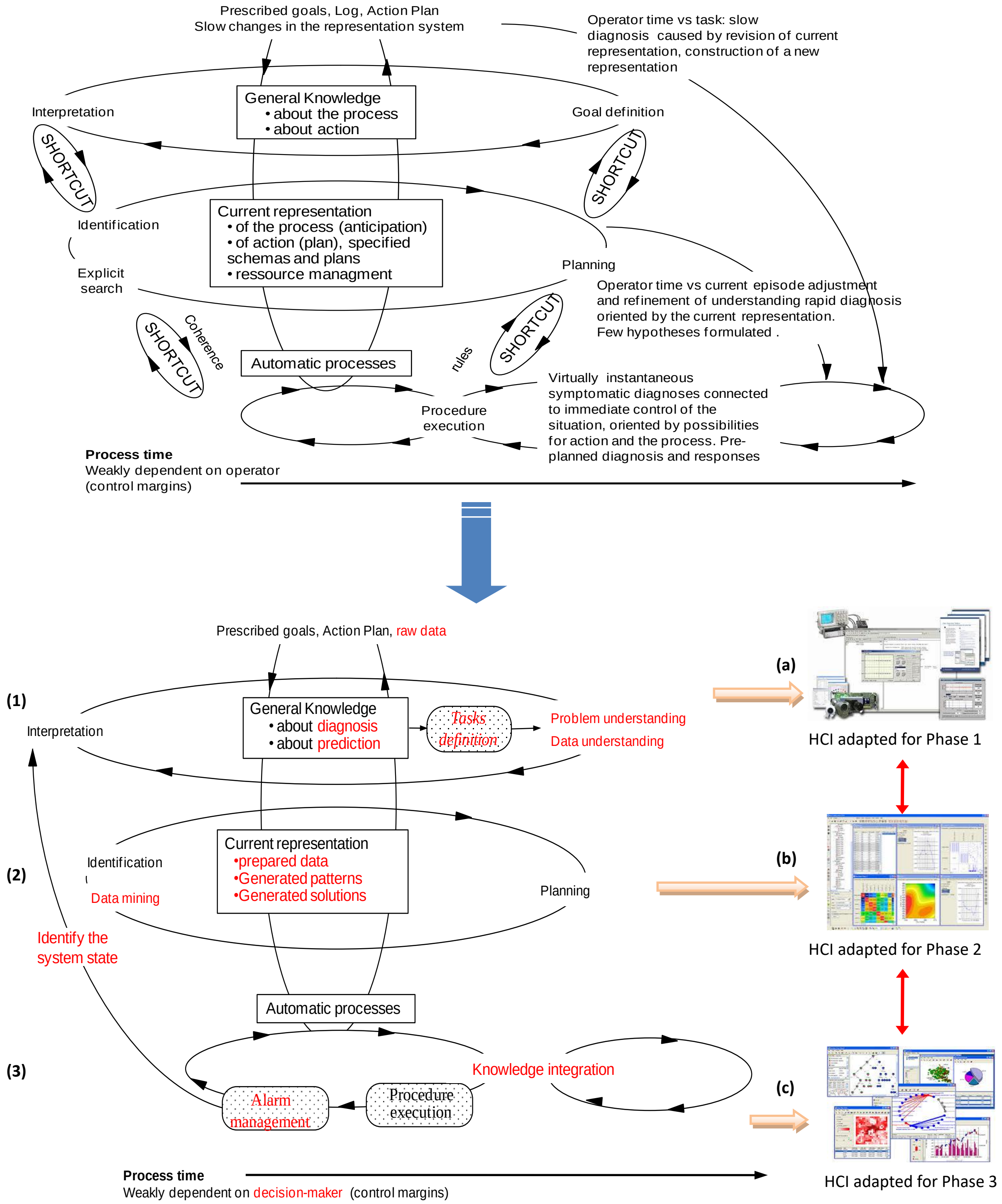

Fig. 2: From the multi-level diagnosis architecture (Hoc & Amalberti, 1995, p. 96) to the KDD-based diagnosis architecture.

Initially, cognitive modeling is decomposed into three related phases: (1) data acquisition and cognitive situation understanding, (2) data analysis and (2) decision-making and knowledge integration. These phases are now further described.

3.1. Phase 1: data acquisition and cognitive situation understanding (Fig. 2.b.1)

To solve a target problem, its goals need to be discussed to analyze it before trying to solve it. It is formulated on the basis of the user's input. This input has three kinds of domain information: (1) the prescribed goals which present required user activities and the state the user wants to achieve; (2) the action plan to be performed to attain those goals; and (3) the raw data which comes from different sources and has many types of formats, such as a collection of text or web documents.

The user input can be performed using various techniques: interviews, analysis of written work reports, questionnaires, analysis of critical incidents, event monitoring, expert reports, etc. [85]. It is designed to provide a structured framework of future activities as well as technical solutions. The main purpose is to clarify and specify the general knowledge of the problem diagnosis and prediction. The cognitive diagnosis and prediction analysis allows: (1) the identification of the list of the dynamic tasks to perform (2) the identification of the set of skills involved in each task; (3) the demonstration of which skills are required for correctly performing each task; and (4) the elimination of the skill mastery profiles for individual examinees based on task data [15].

As a result of this knowledge specification step, there will be a definition of the diagnosis and prediction tasks. A tasks definition enables the recording of the properties of each task and how they are related expressing the dynamics of the model, i.e. the logical and / or temporal constraints. All this information permits the problem understanding by getting a clear idea of what, why and how to design the dynamic decisional tasks before writing any code. The proposed cognitive decision model enables decision makers to gain an understanding of the problem, questions and objectives to be answered by the future KDD-based Dynamic DSS and formulating a concrete plan of how to proceed throughout the decisional process.

Once we have an idea about the raw data pertaining to the problem context, decision makers are ready for the data understanding by exploring and becoming familiar with the data characteristics. In fact, in KDD processes, raw data always contain errors and missing values. Thus, before data analysis, the quality of data can be assessed.

3.2. Phase 2: data analysis (Fig. 2.b.2)

Data analysis phase investigates cognitive processes and physical actions of KDD-based Dynamic DSS at a high abstraction level. Data mining is a particular data analysis technique that focuses on knowledge extraction for predictive rather than purely descriptive purposes [58] [66]. Phase 2 begins with data preparation, which takes place before the data mining itself. Preparation concerns access to data for building specific data sets and formatting data entries according to their type (numeric, symbolic, image, text, sound), as well as data cleansing, missing data treatment, attribute selection, etc. The information needed to make appropriate predictive and diagnosis patterns may be available in the data. The inappropriate choice of variables or samples may downfall the operation.

To better represent these prepared data, information visualization is an effective means to express and understand these data, because humans have a very well developed sense of sight [5] [29]. Particularly, in the case of a dynamic system in which the data is temporal, the construction of a mental representation of the data evolution is a difficult task for decision-makers. Thus, creating prepared data visualizations improves cognitive ability and allows learning patterns more intuitively [34]. In fact, it is necessary to design and develop appropriate visual representations to view prepared data in order to facilitate the understanding, interpretation and knowledge extraction for a decision-maker.

Data mining technique must be applied to obtain operational knowledge. This knowledge is expressed in the form of more or less complex patterns: probabilities, series of coefficients for numerical prediction model, logical rules like "if Condition then Conclusion" or instances. To have the status of knowledge, these patterns must be validated. Appropriate visualization techniques can also be used to represent patterns and generated solutions to solve initial decision problem (such as histograms, bar-graphs, tabular representation, mimic displays, etc.; see examples in [45] [46]). Once possible solutions are presented, the most appropriate actions must be planned with regard to the main goals. Planning activity involves the formulation, evaluation and selection of a sequence of thoughts and actions to be executed.

3.3. Phase 3: decision-making and knowledge integration (Fig. 2.b.3)

To execute the planned actions, the automatic cognitive process of decision-making occurs outside awareness. It is an unintentional and effortless process of cognitive operations execution. Since decision maker is submitted to a significant time pressure, controls are timely organized to better monitor the increasing errors risk.

He/she can be faced with the unpredictability of the dynamic automatic process, and his/her actions influence the evolution of this process [10] [59]. The automatic process prepares the decision-maker to execute the selected solution(s). The procedure execution could have two possible results:

1) Efficient running of the procedure allowing knowledge integration. It consists in incorporating discovered patterns associated with the executed problem solution into the knowledge base of the KDD-based Dynamic DSS.
2) Failure running of the procedure requiring an alarm management to alert the decision-maker about the system deviations from its normal operating conditions. He/she must search for alarm annunciation displays to visualize and analyze information and data. In response to the condition that was alarmed, he/she must perform action. A feedback seems necessary to identify the system state and interpret it to return the system to a consistent state.

As presented above, our cognitive model is structured in three iterative cycles relatively to the three phases (cf. §3.1, §3.2 and §3.3) and provides the decision-maker with a deterministic behaviour of the dynamic situation being modeled. This particular structure specifies and applies the cognitive causal links between the data acquisition and the situation understanding, the analysis and the dynamic knowledge integration in the decision-making process. The application of the proposed model will be presented in the following section.

4. Case study in the medical domain

The importance of the decisions in the medical field and the huge volume of temporal complex data in this field require the use of DSS [1]. Such system can be particularly useful in intensive care units. Indeed, the nosocomial infections are regarded as a major health problem [27]. They are defined as being infections, which appear at least 48 hours after the admission of a patient at the hospital. To detect these infections the physician must follow the state of the patient according to the evolution of his/her data in time [52].

The objective of our case study is to develop a KDD-based Dynamic DSS for the fight against Nosocomial Infections (NI) in the ICU of Habib Bourguiba Hospital of Sfax, Tunisia. In fact, this topic has already been presented and discussed [3] and [54], and provided various applications to calculate the NI occurrence percentage using different data mining techniques. Although the preliminary results were promising, the cognitive load exerted by the physician to analyze, understand and take the appropriate decision is very high. It therefore seems important to look for cognitive modeling solution to overcome this problem.

In this section, we present the way in which our KDD-based DSS has been implemented, building on the cognitive considerations (visible in Fig. 2) of the proposed KDD-based diagnosis architecture by following its three phases. Each phase allows the generation of a system prototype, as presented in Fig. 3:

- The first prototype consists of a set of user interfaces using visualization techniques and allowing fixed and temporal data management and exploration for the problem and data understanding;
- The second prototype contains the data mining results in order to generate problem solutions; and
- The final prototype allows the knowledge integration or the alarm management.

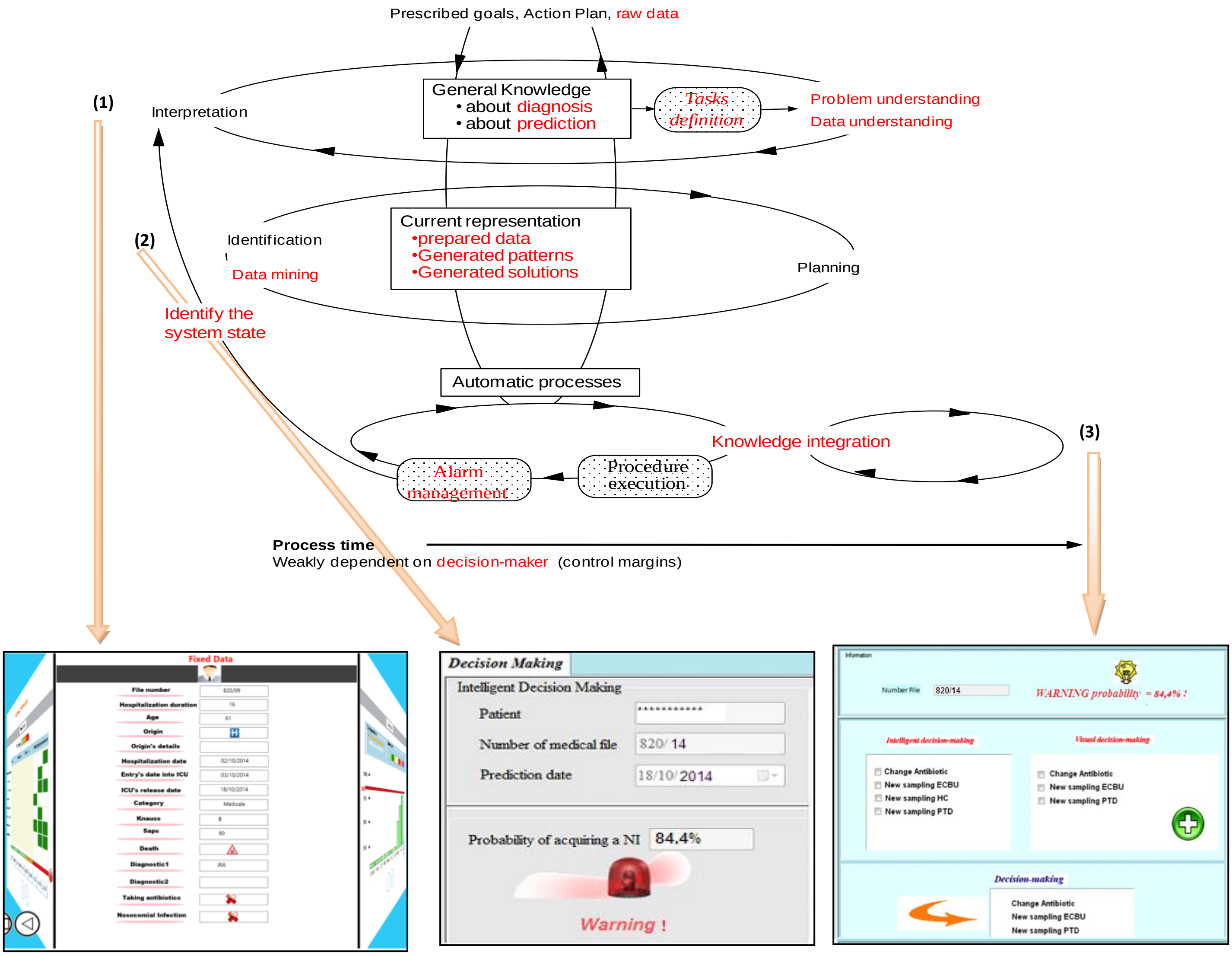

Fig. 3: KDD based diagnosis architecture for the fight against nosocomial infections: each phase is associated with one or several adapted user interface (one in our case study)

The following tables describe the steps for applying cognitive considerations to design interactive visual KDD-based Dynamic DSS and develop its three prototypes. The goal is to illustrate how they can help designers generate and share ideas, get feedback from users, choose among modeling alternatives, and articulate reasons for their final choices.

4.1. Phase 1: data acquisition and cognitive situation understanding

Table 1 presents the different steps of phase 1 applied to our case study. This phase allows the application of relevant cognitive modeling considerations in order to define the system tasks and thus to understand the decisional problem and the data used for the fight against nosocomial infections.

Table 1: data acquisition and cognitive situation understanding

Cognitive modeling step	**Brief description**
Prescribed goals	- Application of intelligent dynamic data mining technique to solve decision problem for the fight against nosocomial infections in the ICU. - Interactively analyze the patient state evolution.
Action plan	- Daily calculating the NI occurrence probability by automatically using an appropriate data mining technique. - Using interactive graphic methods by applying data visualization techniques which bring their contribution to the decision-making process [44].
Raw data	The DSS was developed in collaboration with the ICU team of Teaching Hospital Habib Bourguiba of Sfax, Tunisia. This ICU produces vast amounts of temporal and non-temporal data. For each patient, there is a range of critical decision factors. These factors are classified into two categories: (1) the characteristic data collected at the patient admission, known as fixed data; (2) the temporal data: the control measures to be taken daily during hospitalization. The quantity of the temporal data in the ICU database is much larger than the non-temporal data.
General knowledge of the problem diagnosis and prediction	The daily decision on the patient state depends on the NI probability and thus on the static and temporal data values not only at the current date but also at the previous days, as well as the acquired knowledge: - A basic decision is taken at the admission of the patient (t0). - The future decision refers to a decision to be made after the consequences of the basic decision and the temporal data values. As time moves on, the future decision at current stage (t) becomes the basic decision at the following decision stage (t+1), when a new knowledge extracted by the data mining technique and future decision should be taken. This dynamic process repeats itself during the patient hospitalization
Tasks definition	- Temporal data acquisition and preparation: in our database, the structure of the data is linear and generally based on lists. - Temporal data visualization: According to the critical choice of the temporal visualization technique proposed by [53], temporal data can be represented by the perspective wall technique [56]. This technique allows joining together temporal and structural dimensions to present a global view (cf. Fig. 4). The perspective wall displays the use of the perspective wall technique to present the fixed and temporal data of each patient. The patient data is expressed in forms and distributed in the walls. The time line presented in Figure 3 uses a simple and linear distribution of time values. The time navigation is carried out by the navigation buttons. The scale of progress in time is equal to one hospitalization day in the ICU. In our system, we used the timeline as a reusable component to view the time dimension of temporal data. It is integrated in a wall with a temporal visualization technique: star, tabular and histograms.
Interpretation	The different representations of the prepared data generated by the three temporal visualization techniques are used to reduce the cognitive load of the physician and assist him/her in the interpretation of the evolution of the temporal ICU data of each patient over time. The daily follow-up of these visualizations helps the ICU physician to have an idea about the occurrence of a nosocomial infection.

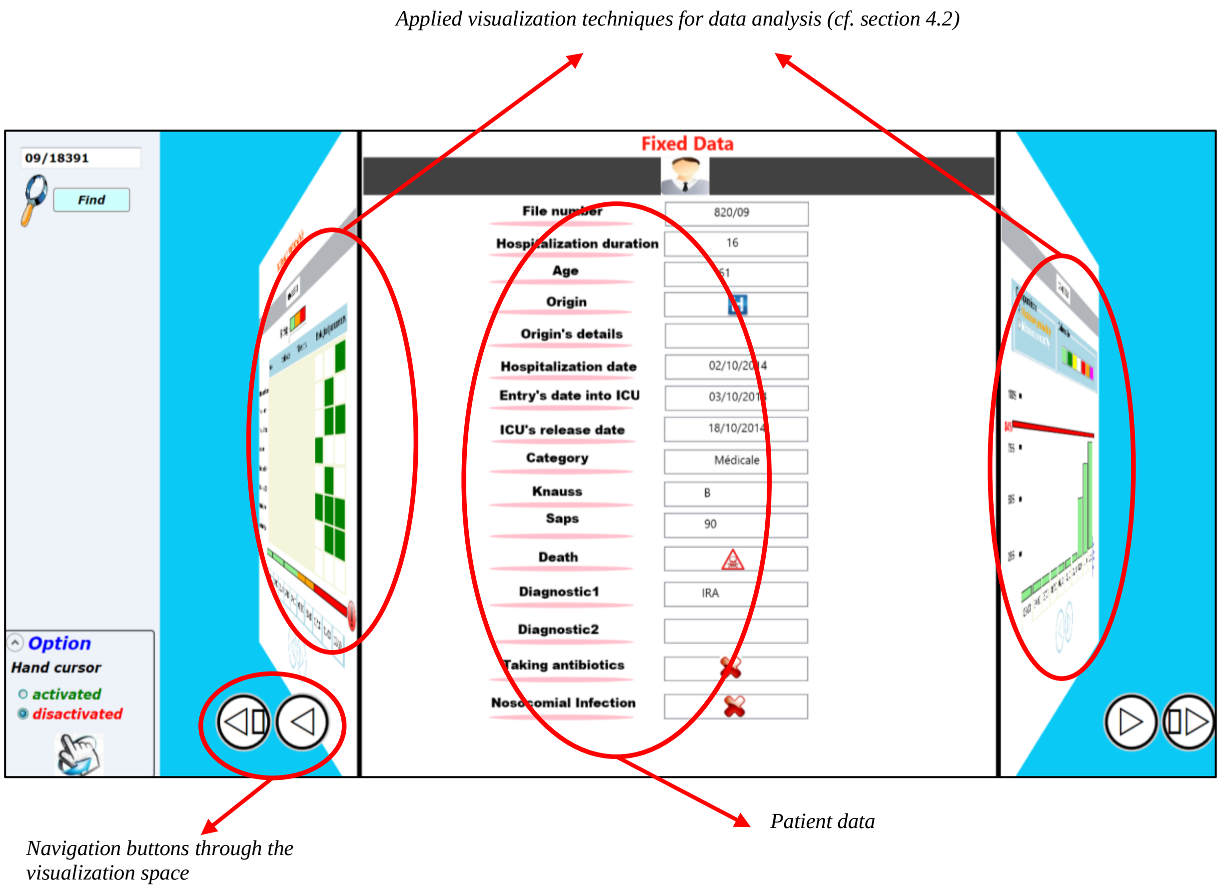

Fig. 4. Perspective wall [56] technique for patient data acquisition

4.2. Phase 2: data analysis

Data analysis is performed by data mining and visualization techniques that must closely connect to each other. In fact, the cognitive aspect can be realized by using visual techniques. Table 2 presents the application of the different data analysis steps.

Table 2: data analysis

Current representation	Figure 5 shows the star (cf. Fig. 5.a), tabular (cf. Fig. 5.b) and histograms (cf. Fig. 5.c) representations with the reusable component timeline. The data observed are represented in the form of a star (cf. Fig. 5.a). This technique must have a timeline to navigate according to the temporal dimension of data [17]. The star represents the values of an observed antibiotic (Colimycine in our example) taken by the patient during the hospitalization period. Each antibiotic can be visualized at once. To view another antibiotic, the user must select its corresponding box in the wall. The tabular representation (cf. Fig. 5.b) consists in representing data in a space with two dimensions. It can, however, make it possible to visualize two variables and pass from one to the other. The data are represented by graphic objects (right-angled filled), whose color intensity is proportionally defined with the values of the corresponding data. This technique must have a timeline to navigate according to the period. This tabular representation allowed the physician (decision-maker) to: 1. Observe the evolution of acts over time through the observation of the change of the graphic objects color. 2. Compare acts over time. This comparison determines if a given act evolves differently beside another. 3. Identify concentration areas of acts and corresponding times. These acts were represented by specific color intensity. The histogram allows the representation of quantitative data. It explicitly uses the relation of dependence between units of observation, by considering the data in two dimensions [17]. This technique allows the physician to visualize sequentially the different infectious examinations in a superposed way and then to compare periods and interpret these structural data. This type of representation is essentially guided by the Bertin recommendation [Bertin, 67]: *if the user's task is to compare periods, it is advisable to represent them in a superposed way*.
Data mining	The intelligent decision-making [86] aims at daily estimating the risk probability of the NI appearance during the patient hospitalization. This probability is calculated on the basis of the features described above (cf. Table 1). Each day, the decision on the patient depends on the NI 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. This decision-making model is temporal. For this reason, we chose to use a dynamic data mining technique, which is the Dynamic Bayesian Networks (DBN) [18] [60]. The diagram of the DBN process is presented in Figure 6. More details on the design and implementation of this data mining technique are available in [52]. The Figure 3.2 presents the result of DBN application of a patient registered in the ICU database. This result is presented in the form of a probability.
Planning	Our KDD-based temporal DSS allows to: 1) Extract **intelligent patterns** using the DBN technique. Basing on these patterns, the DSS proposes possible solutions. 2) **Visual interpretation** of three visualization techniques. Building on this interpretation, the decision-maker proposes three solutions. The integration of the different solutions made it possible to generate a more efficient and appropriate final decision.

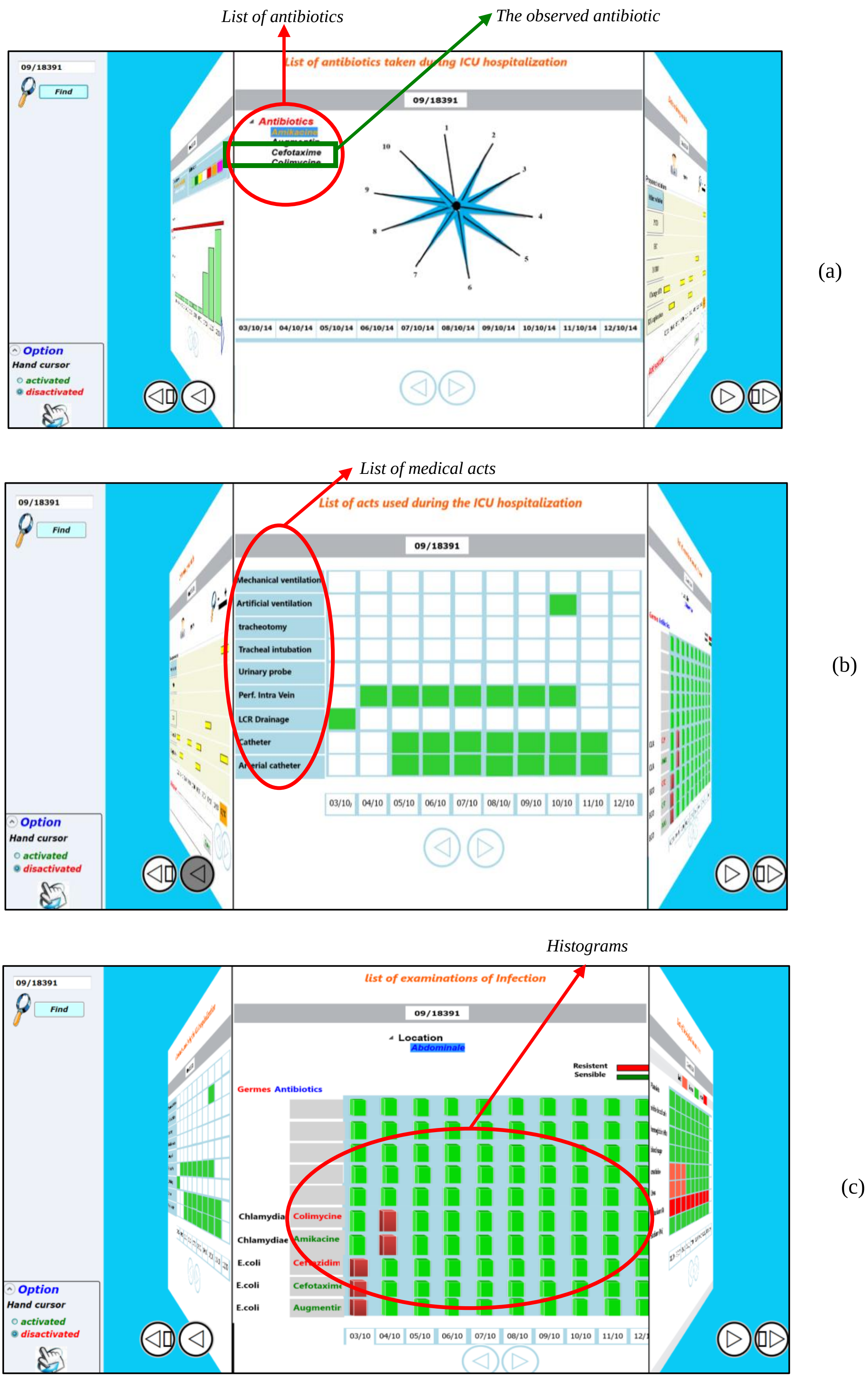

Fig. 5. (a) Star representation for visualizing antibiotics catch, (b) The tabular representation for visualizing the acts, and (c) the Diagram for visualizing the infectious exams

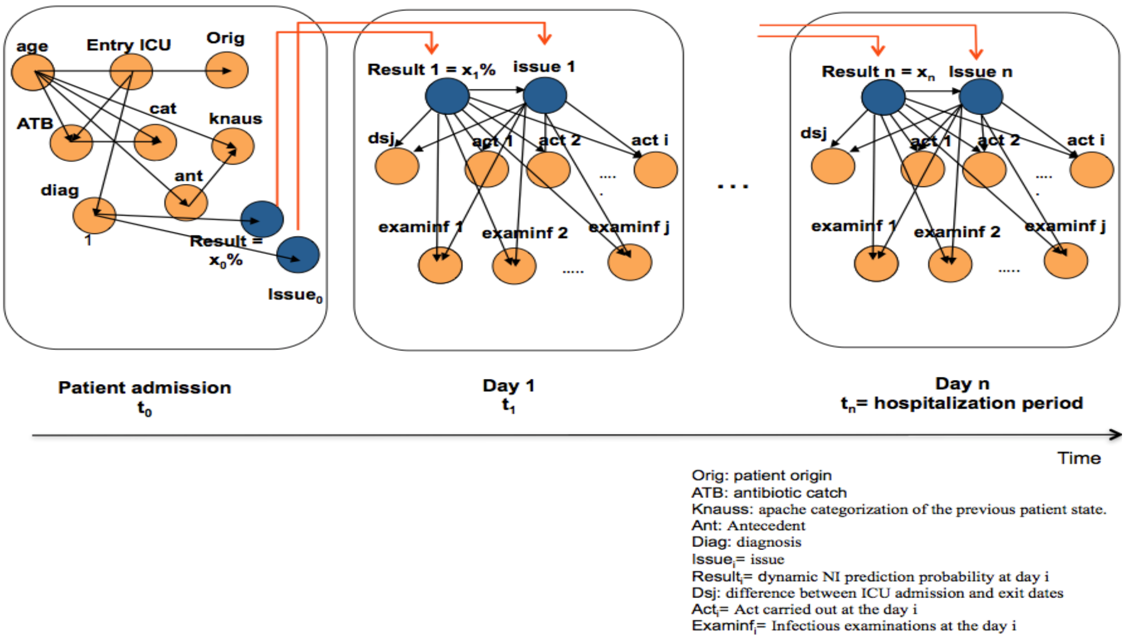

Fig. 6. The DBN process diagram

4.3. Phase 3: decision-making and knowledge integration

The first and second phases allow generating a set of possible solutions. Table 3 consists in identifying how the best solution is integrated and how new information is incorporated into the system knowledge base building on the cognitive considerations of phase 3.

Table 3: decision-making and knowledge integration

Automatic processes	The interpretation of the visual representations generates a set of possible solutions. For example, as shown in Figs. 4 and 5, the physicians extracted the following solutions: - In Figure 4, the highlighted antibiotic was taken during 8 days. For this reason, the physician decided to change this antibiotic, which became resistant. - After interpreting the data presented by the tabular representation, the physician decided to make a new sampling ECBU (cytobacteriological examination of the urine). - The interpretation of the two histograms associated with the two infectious examinations presented by Figure 5 helped the physician to decide on making new sampling PTD (diastolic pressure) and ECBU. These solutions are integrated in the KDD-based DSS in the visual decision-making panel visible in Figure 7. The automatic decision-making based on the NI occurrence probability (calculated by the DBN algorithm) generated four possible solutions in the intelligent decision-making panel presented in Figure 7. The physician (decision-maker) has the possibility to make the better decision based on the visual and intelligent solutions and then to continue the procedure execution.
Knowledge integration	The efficient running of the procedure execution allows knowledge integration; the executed solutions are incorporated in the knowledge base of the KDD-based Dynamic DSS.
Alarm management	The failure running of the procedure execution requires an alarm management to alert the physician to the system deviations from its normal operating conditions. The decision-maker proceeds to the identification and then the interpretation of the system state in order to return it to a consistent state.

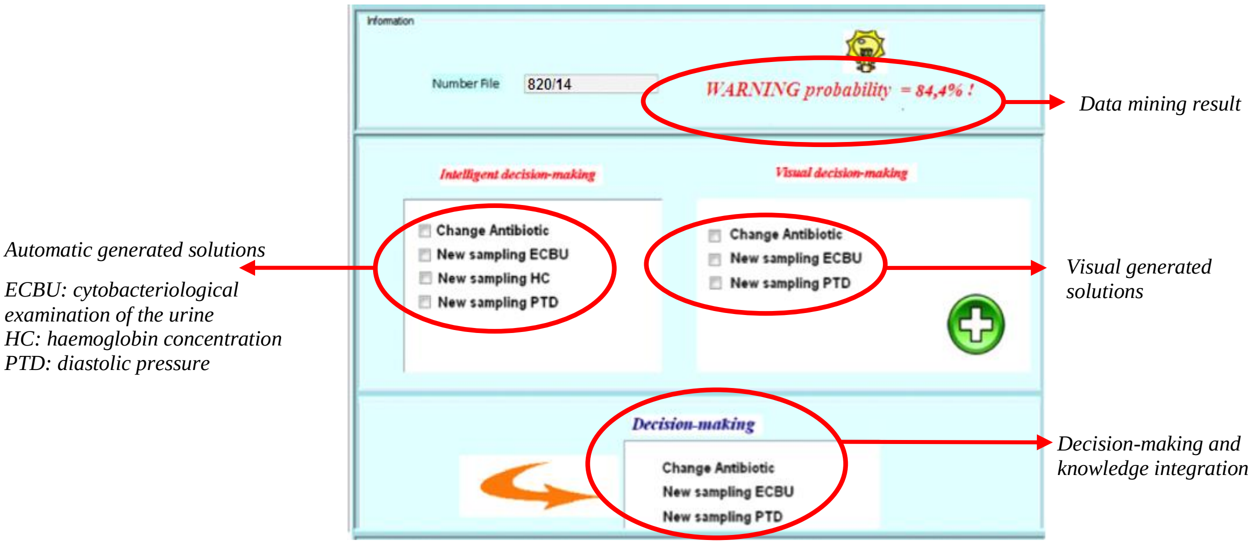

Fig. 7. Decision-making and knowledge integration interface

Our developed system is now under use in the Intensive Care Unit of the Habib Bourguiba Hospital of Sfax, Tunisia. Its evaluation is explained in the following section.

5. Evaluation and results

KDD, visualization and DSS are increasingly used in the medical field. The evaluation of such systems is especially critical. The developed visual KDD-based Dynamic DSS has been accepted by the end-users (physicians). Hence, it was possible to deduce a first validation of the proposed approach. The objective of this section is to highlight the evaluation of the developed system. The interest, at this level, is in two traditional dimensions of evaluation in the HCI field: utility and usability [62] [41] [75] [77] [4].

5.1. Utility Evaluation

To evaluate the utility of our visual KDD-based Dynamic DSS, the verification of its predictive capability is proposed. We have generated the confusion matrix (cf. table 4) and based on the results produced following the use of the system by the physicians during 15 days (test set). It contains information about empirical produced and predicted classifications done by the DBN combined with the visualization interpretations. Our system performance is commonly evaluated using the data in the matrix.

The entries in the confusion matrix have the following meaning in the context of our study:

(a): the number of correct predictions that an instance is positive,
(b): the number of incorrect predictions that an instance is negative,
(c): the number of incorrect predictions that an instance is positive,
(d): the number of correct predictions that an instance is negative.

Table 4: confusion matrix

		Predicted results		
		Data Mining technique (DBN) results combined with visual interpretations		
		Yes	No	Total
Observed results	Yes	10 (a)	4 (b)	14
	No	8 (c)	34 (d)	42
	Total	18	38	56

We began by calculating the rates of evaluation starting from the prediction results obtained by our system. We found that the classification rate was correct to 78,6% (the accuracy = a+d/a+b+c+d), the error rate = 21,4% (c+b/ a+b+c+d), the positive capacity of prediction = 71,4% (the sensibility = a/a+b) and the negative capacity of prediction = 80,9% (the specificity = d/c+d). Consequently, this utility evaluation of the proposed KDD-based Dynamic DSS has shown satisfactory prediction results, which were appreciated by the physicians. However, they propose to improve the system by implementing another data mining technique and comparing its performance with that of DBN. We noticed that despite the dependence of the physicians' interaction on their previous computer literacy, all of them learn to use it easily. Finally, their opinion about the system utility is positive.

5.2. Usability Evaluation

This section describes the process of visual KDD-based Dynamic DSS usability evaluation and presents the main results. It refers to the assessment of the User Interfaces, including the temporal visualisation techniques by testing them with representative users. For this reason, we have used the evaluation usability function F of Daassi [17], whose principle is to measure the values of the usability function for each technique (which will be explained subsequently). To calculate this value, we have used a 7-item questionnaire in relation with the user's tasks (cf. Table 6).

Participants' profile: we perform the usability evaluation of the different developed User Interfaces based on three user profiles:

1) Profile 1: no knowledge on nosocomial infections; this is the example of a computer scientist
2) Profile 2: a little knowledge on nosocomial infections; this is the example of a health worker
3) Profile 3: expert who has most of the knowledge on the area; the users of this profile are physicians.

The number of participants in the evaluation process is twenty, whose characteristics are presented in Table 5.

Table 5: profile of the participants in the evaluation process

Users' characteristics	
Number of participants	20
Gender	11 men 9 women
Age	Average age: 39 years Minimum age: 20 years Maximum age: 57 years
Profile	6 with profile 1 6 with profile 2 8 with profile 3
Sample of users	Three age categories were identified: (1) a group of 20 to 25 years; (2) a group of 26 to 45 years; and (3) a group of 46 and over.
Familiarity with computer	All the participants were familiar with computer.

Evaluation protocol: it consists of individual tests of about two hours each. User testing grouped twenty users. Test sessions were held as follows:

1) Welcome of the participants
2) Questionnaire on the participants' characterization (profiles, habits, computer use, etc.)
3) Illustration of examples of the different visualization techniques
4) First interview to apprehend the interest of the perceived visual User Interfaces
5) Familiarization tasks with demonstrators
6) Usage scenarios of the visual KDD-based Dynamic DSS
7) Second interview for gathering user feedback on using the system. It consists in answering a questionnaire in which each question, with multiple choices, is evaluated by a note ranging between 0 and 20. The usability of a given visualization technique Vi with regard to a given user's task Tj is defined as the value of the function F(Vi, Tj) with: ***F(Vi, Tj)*** *= the average of notes given by the participants for the technique Vi compared to the task Tj*.

8) And finally a debriefing session to give the participants an opportunity to express the impact that the evaluation program had on them, and inciting them to do that by asking a set of directed questions.

Evaluation results:

The user tasks of our system are data analysis tasks that are classified into four categories:

1) *Observation tasks*: The user is often interested in the exact values of the data, while in other situations he/she wants to observe trends in the evolution of the data over time. For example, the user wants to predict the future from the observation of the history of the evolution of data over time.
2) *Navigation tasks*: we associate the navigation task with the two dimensions of a temporal data. Thus, navigation can be related to a temporal or structural value if the user is interested in the temporal or structural dimension of a given variable.
3) *Comparison tasks*: comparing two elements (periods or values) is a frequently observed task. For this reason, the user needs to move or swap the visual elements of the data space to bring them closer into the representation space for easy comparison. He/she wants, for example, to switch between two curves or overlay them to compare the changes they represent.
4) *Manipulation tasks*: relate to the user interaction with the data and its manipulation to support their analysis. They allow the identification of the patterns, moments of ruptures and points of concentration. According to Norman [64], the users develop conceptual models that determine their behaviour during the data analysis process. Depending on the type of applications in which it is involved, the user judge differently the way in which the data are presented.

Table 6: Usability evaluation of the visual KDD-based Dynamic DSS User Interfaces

	HCI of the Phase 1 and 2												**HCI of the Phase 3**		
User tasks	Perspective wall			Histogram			Star representation			Tabular representation					
	P1	P2	P3	P1	P2	P3	P1	P2	P3	P1	P2	P3	P1	P2	P3
Observe tendencies	0.6	0.75	0.75	0.73	0.78	0.8	0.71	0.76	0.75	0.69	0.74	0.73	0.61	0.64	0.7
	0.7			**0.77**			**0.74**			**0.72**			**0.65**		
Compare values	0.84	0.87	0.96	0.68	0.7	0.69	0	0	0	0	0	0	0.88	0.92	0.9
	0.89			**0.69**			**0**			**0**			**0.9**		
Compare periods	0.76	0.83	0.87	0.7	0.75	0.74	0.8	0.84	0.85	0.71	0.75	0.76	0.87	0.9	0.93
	0.82			**0.73**			**0.83**			**0.74**			**0.9**		
Navigate in time	0.59	0.67	0.72	0.82	0.82	0.91	0.81	0.83	0.82	0.82	0.84	0.83	0.62	0.67	0.72
	0.66			**0.85**			**0.82**			**0.83**			**0.67**		
Identify moments of ruptures	0.74	0.83	0.8	1	1	1	0.62	0.65	0.71	0	0	0	0.72	0.83	0.79
	0.79			**1**			**0.66**			**0**			**0.78**		
Identify patterns	0	0	0	0	0	0	0	0	0	0.6	0.61	0.65	0.6	0.63	0.69
	0			**0**			**0**			**0.62**			**0.64**		
Identify points of concentration	0	0	0	0	0	0	0	0	0	0.8	0.87	0.88	0	0	0
	0			**0**			**0**			**0.85**			**0**		

From the results presented by Table 6, we conclude that our approach has enabled decision-makers to integrate much information in the four kinds of visual representations to be sure not to ignore a crucial factor during the process of data acquisition and cognitive situation understanding. The use of the combined visualization techniques makes it possible to answer the diversity of user tasks in terms of handling the temporal

[1] 0 means that the visual representations in question do not allow the achievement of task.
1 means that the visual representations are very suitable to the user task.

data. Each technique must be conceived taking a limited number of user's tasks into consideration. The values of the usability evaluation vary between 0.62 and 0.9, which shows that the HCI (in particular the visual representations) answers satisfactorily to the user tasks. Our results show that novices (users of the first profile) who are unfamiliar with the nosocomial infections topic provide the minimum values. The other values (given by the health workers and the physicians) tend to be close. This can be explained by the importance provided by our user interfaces to the nosocomial infection problem in the intensive care unit.

However, the usability values (cf. Table 6) are less than 1, which means that the user interfaces need to be improved. In fact, rather than developing interactive visualization techniques independently, users have proposed to develop a platform for managing multiple dynamic views that can simultaneously integrate several techniques as well as a specific components for the selection of the technique (or several complementary techniques) most suited to the task of the user. What is worthy to mention is that this new type platform is the interest of a study in progress.

The time constraints are an important factor for acquiring control of the KDD-based DSS. To evaluate such a factor, all physicians run the dynamic KDD-based DSS tasks simulation for three days. Time of completion is presented in Table 7. We have found three time constraints levels:

1. Fast mode for the first phase tasks where each trial lasted 6 minutes,
2. Slow mode for the second phase tasks where each trial lasted 18 minutes per trial for the two first days and 6 minutes per trial for the last day, and
3. Medium mode for the second phase tasks where each trial lasted 12 minutes per trial for the two first days and 6 minutes per trial for the last day.

Table 7: KDD-based DSS time constraints

	Phase 1	**Phase 2**	**Phase 3**
Day 1	6 trials	2 trials	3 trials
Day 2	6 trials	2 trials	3 trials
Day 3	6 trials	6 trials	6 trials
Number of trials	18	10	12
Total time on task (in minutes)	108	108	108

While the total time on task was the same for the three phases, participants in the fast mode performed the task 18 times vs. 10 times in the slow mode vs. 12 times in the medium mode. These results are explained by the fact that physicians spent more time with data mining and visualization tasks during the two first days. After they learned the process, all participants in the third day have taken the minimum time per trial.

6. Discussion

It is challenging for decision-makers to face complex and uncertain problems and to automatically take real-time decisions. Simply observing temporal data is ineffective in supporting new decisions. Furthermore, real-time decisions require reliable knowledge on the data and the historical decisions to be generated. Our solution was to integrate knowledge discovery and visualization in the dynamic decision-making to visually and automatically analyze and classify temporal data to predict future outcomes. Cognitive modeling of decision-maker behaviour of such systems allows: (1) to control the complexity of the decision-making process based on data mining and visualization techniques and (2) to perform significant support for formulating dynamic decision solutions.

In fact, the present study has shown that the design and the development of visual KDD-based Dynamic DSS must be based on cognitive considerations to provide human cognition framework for simulating a human (decision-maker) interacting with his/her environment to accomplish his/her dynamic decisional tasks. In this context, we have proposed to adapt [32] model under the KDD specificities (cf. §3, Fig. 2). It consists in an extension of the generic diagnosis and decision-making model initially proposed in [32] to cope with KDD-based dynamic decisional situations. Our proposition structures the adapted model into 3 phases: (1) data acquisition and cognitive situation understanding, (2) data analysis, and (3) decision-making and knowledge integration, each of which has to be associated with an adapted HCI.

The principal contribution of this research work is the proposed adapted cognitive model to develop a visual KDD-based Dynamic DSS. It is a generic approach that helps data miners to develop dynamic and visual systems by studying the decision-maker behaviour all along the visual KDD-based Dynamic DSS process. Usually, in such systems, data miners think about the efficiency of data mining algorithms, rather than about the cognitive principles. Our proposition motivates the system developer to build up a visual KDD-based Dynamic DSS and evaluate the tasks he/she achieves following the three phases of the model in question. It allows also diminishing uncertainty (provided by the complexity of the temporal data, we are working with) using: (1) Temporal predictive patterns discovered by the data mining algorithm (i.e. DBN) and its ability to predict the outcome variable and assess its quality in terms of predictive probability, and (2) temporal visualizations for obtaining a high-level qualitative description of the temporal data.

As a practical implication, the development of the visual KDD-based Dynamic DSS based on our proposition was concretely applied, leading to a prototype of visual KDD-based Dynamic DSS for the fight against nosocomial infections following its three phases. The progress of each phase is presented by Tables 1, 2 and 3, showing the contribution of the KDD specificities and its visual representations according to the cognitive modeling. The substantial implication for the practice of this study is the final product set up in the ICU of Habib Bourguiba Hospital of Sfax, Tunisia. Indeed, currently the visual KDD-based Dynamic DSS is set in that ICU and it is used to explain and prevent nosocomial infections. Each patient entering the ICU has his/her temporal data collected and treated to predict and prevent possible nosocomial infections.

The conducted utility and usability evaluation was based on a preliminary study of the system functionalities and the cognitive activities they allow. These activities help the users achieve their tasks of handling patient temporal data and dynamic decision-making to fight against NI. Table 8 shows that the overall performance is better than the results obtained in the two previous versions of our system presented in [3] and [54].

Table 8: comparison of the different versions of the KDD-based DSS

<table>
<tr><th></th><th>The first version of DSS [3]</th><th>The second version of dynamic DSS [53]</th><th>Current version of dynamic DSS</th></tr>
<tr><td>Contribution</td><td>Data mining technique: case-based reasoning</td><td>Data mining technique: Dynamic Bayesian Networks</td><td>- Data mining technique: Dynamic Bayesian Networks
- Temporal visualization
- Cognitive aspects</td></tr>
<tr><td>Utility evaluation</td><td rowspan="2">The final users (physicians) were involved from the beginning to the end of the human-centered development process. The evaluation results are not measured but expressed in term of system acceptance.</td><td>- The accuracy rate = 74%
- The error rate = 26%
- The sensibility rate = 56%
- The specificity rate= 81%</td><td>- The accuracy rate = 78,6%
- the error rate = 21,4%
- the sensibility rate = 71,4%
- the specificity rate = 80,9%</td></tr>
<tr><td>Usability evaluation</td><td>Execution of user tests in the framework of the development process.</td><td>- 20 participants
- Three user profiles
- 7-item questionnaire in relation with the user's tasks
- usability evaluation results in [0.62 0.9]</td></tr>
<tr><td>Conclusion</td><td>- The system is not dynamic.
- The prediction results are not measured.
- The usability evaluation is not done in situ (i.e. hospital).</td><td>- The system is dynamic.
- The prediction results are measured.
- The usability evaluation is not done in situ.</td><td>- The system is dynamic.
- The prediction results are measured and the efficacy rates were increased.
- The usability evaluation is done in situ and presents interesting results.</td></tr>
</table>

Certainly, there is always more to be done and numerous improvement of our system. We begin with the users' proposition, which consists in the implementation of a specific component for the selection of a one, or several complementary techniques, most suited to each user task.

On the methodological side, and within the framework of our research especially aiming at designing visual KDD-based dynamic DSS, the challenge is to decode the decision-makers behaviours. Many of these behaviours are, in fact, largely modulated and directed by functional representations [42]. Therefore, it seems necessary for the accurate analysis of a dynamic decision-making activity to implement a methodological approach that allows sweeping the implicit and explicit aspects of this activity. Before establishing a model of this activity, it should be specified which processes of information processing are involved in human activities. These are the processes that determine the construction of a functional representation and the knowledge activation in the long-term memory. They culminate in the decision-making that leads to action.

7. Conclusion

Health care domain is a very important application area for dynamic decision support systems, especially due to the huge quantity of time-oriented data. They make it possible to collect and produce knowledge in order to contribute to the decision-making process and to diminish its uncertainty. The data analysis and exploration by the data mining process has become more and more difficult [51] [35]. To overcome this problem, we have developed user-centred techniques in order to use human pattern recognition capabilities and then to increase confidence and improve the comprehensibility of the temporal data by using the visualization techniques.

Our methodological contribution consists in designing the visual KDD-based Dynamic DSS using a cognitive model. This kind of modeling allows understanding the human behaviour to accomplish complex dynamic decision-making tasks and producing logically valid predictions. In this context, we proposed an adaptation of the well known Hoc and Amalberti model cognitive model [32] under the KDD specificities. Our proposition structures the KDD-based diagnosis architecture into three phases: (1) data acquisition and cognitive situation understanding, (2) data analysis, and (3) decision- making and knowledge integration. These phases propose taking into account a set of cognitive considerations in which each developed visual KDD-based Dynamic DSS has to be associated with an adapted HCI.

We have applied our cognitive modeling approach to design and develop a visual KDD-based Dynamic DSS for the fight against nosocomial infections in the intensive care unit of the Habib Bourguiba Hospital of Sfax, Tunisia. The combination of data mining and visualization techniques building on the proposed cognitive considerations was developed to generate intelligent and visual medical decisions. The developed system was evaluated considering the utility and the usability dimensions. As an outcome, this evaluation has shown satisfactory results except for a few users suggestions for improvement related to the selection of the most appropriate technique to the user task.

This work can be extended to model the decision-maker cognitive behaviour in dynamic decisional situations of a visual KDD-based Dynamic DSS implemented on mobile devices. We plan also to extend the system by developing other data mining and temporal data visualization techniques (such as the concentric circles, the spiral technique, etc.) using the proposed KDD based Dynamic DSS diagnosis architecture. This proposition can be improved by taking into account functional representations in relation with decision-makers behaviour. Finally, we propose to carry out further evaluation experiments with more participants (ICU physicians) in order to assess the utility and the usability of our system with regard to the user's tasks, user profiles and strategies.

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