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Adapted Visual Analytics Process for Intelligent Decision-Making: Application in a Medical Context

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The theoretical and practical researches on Visual Analytics for intelligent decision-making tasks have remarkably advanced in the past few years. Intelligent Decision Support Systems (IDSS) introduce effective and efficient paths from raw data to decision by involving visualization and data mining technologies. Data mining-based DSS produces potentially interesting patterns from data. The transition from extracted patterns to knowledge is a delicate task. In this context, we propose to adapt a common visual analytics process for creating a path that enables the user (decision-maker) to automatically explore and visually extract insights by interacting with the patterns. This proposal is inspired from integrating traditional visual analytics concepts with the mental model of knowledge visualization. The idea is to combine an automatic and visual analysis of patterns to generate knowledge for the purpose of decision-making. To validate our proposal, we have applied it to a medical case study for the fight against Nosocomial Infections in Intensive Care Units. The developed platform was evaluated according to the utility and usability dimensions.

Keywords: Decision support system; data mining; visual analytics; knowledge; pattern.

1. Introduction

The complexity of data and decision-making environments create the need for computerized decision support systems (DSS). Theoretical research and case studies ensure that a well-designed and appropriate DSS can improve the decision quality and the effectiveness of decision-making processes.[1,2]

Nowadays, organizations seek for more analysis and specific relevant decisions.[3,4] To do so, the goal of current DSS is to enhance the use of data to produce knowledge. In fact, such knowledge can be extracted using data mining technology.

Applying data mining algorithms automatically helps in finding hidden but relevant patterns from raw data. Validated patterns generate knowledge valuable for decision-making tasks. In this context, data mining integration makes decision support as an intelligent process. Such process begins with the problem definition and ends with best alternative generation.

To improve the quality of the extracted patterns and decision-making, visualization integrates the human intelligence to the machine intelligence. Literally, visual data mining technology addresses the interaction between the two. It inspires solutions from data mining, as well as information, representation and interaction paradigms for supporting decision-making processes. In this context, our research focuses on the visual data mining based decision-making support. We name these systems as Visual Intelligent Decision Support systems (VIDSS); where the visual intelligence refers to the visual data mining technology integration in the decision-making activities.

The visual data mining allows us to visually discover patterns.[5] These patterns, if validated, will be considered as knowledge useful for decision-making.

The transition from extracted patterns to knowledge must follow a transfer process. This process must allow the creation and transfer of knowledge, which is one-step further of these patterns. An interesting solution introduced by Refs. 6 and 7 is to use visualization for knowledge acquisition and communication.

Knowledge acquisition from data mining patterns is a delicate task. It is in this context that we propose to apply a visual analytics approach to analyze and interpret the extracted patterns visually in order to generate associated knowledge. It is a visual analytics of visual data mining results for knowledge generation.

Our paper aims to elaborate and complement the existing frameworks focusing on the visual analytics process.[8–11] We deem that this work will be useful for visual analytics research and practice, since it aims at facilitating the whole analytical process in a comprehensive manner. As we present in this paper, our contribution can be stated as follows:

– We introduce a generic conceptual framework for considering the visual analytics process as a cognitive modeling approach of IDSS.
– On this basis, we apply the proposed process to a medical case study in order to validate its sustainability. It is an example of case study that illustrates decisional benefits. Further case studies can be planned in future work.
– We evaluate the developed VIDSS prototype according to the utility and the usability dimensions. We aim by this evaluation to prove the applicability of our approach.

Figure 1 presents the summary of our research work process.

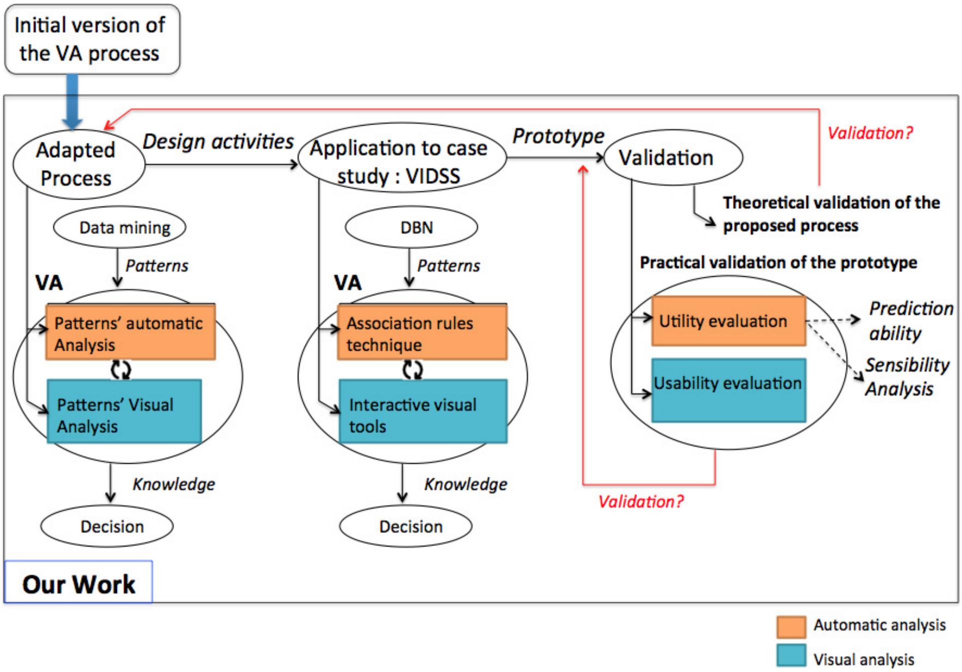

Fig. 1. Summary of our research work process.

The remainder of this paper is structured as follows. Section 2 presents the background of this study including visual data mining-based decision-making, knowledge visualization and visual analytics concepts. Section 3 suggests a new adapted cognitive approach for knowledge generation from extracted patterns. In Sec. 4, we show the implementation of the proposed approach in the context of medical informatics. Section 5 evaluates the approach application. Finally, we conclude the paper with a summary of our contribution and areas of future research.

2. Background of the Study

In this section, we aim to introduce and describe the concepts related to the research problem under study.

2.1. *Intelligent decision-making*

Decision-making plays a major role in information systems, particularly because of the changing environment where relevant information is of increasing value.[12] The purpose of a decision-making system is to generate answers to decisional questions.[13] In this sense, DSS should be used as often as possible.

Before taking each important decision, the organization must analyze the situation and understand the impacts of its decisions. In order to avoid the need for rigorous analyzes, which require the input of experts (who must take over the calculations and analyzes for each scenario under consideration), the system must integrate intelligent analysis techniques.[14] This has led to methodological approaches that attempt to extract not only valid and reliable information, but also generally more patterns to support the decision-making.

Two main types of approaches can be distinguished in the analysis of data: the first one is decision-making that most often focuses on modeling; the other one is exploratory and aims to synthesize a more or less heterogeneous set of information (this approach is then essentially descriptive). Moreover, the logic of data analysis evolves and changes of perspective. The tools for data science are clearly part of the exploratory side of statistical and machine learning studies but are also rooted in the predictive type of logic.

Data science is the field of study that includes everything from big data analytics, predictive modeling, data visualization and data mining. Data mining is defined as "the acquisition of new, intelligible and potentially useful knowledge from hidden facts in large quantities of data".[15] This knowledge is communicated in the form of more or less complex models: a series of coefficients for a numerical prediction model, logical rules of the type "if condition then conclusion" or instances.

For these models to acquire knowledge status, they must be validated. This involves implementing a series of so-called post-processing operations aimed at assessing the validity of models, making them intelligible if they are to be used by human beings, or expressing them in an appropriate formalism understandable by a machine. Indeed, a model understood by the user will be utilized and therefore criticized and perfected. Users generally do not like to use patterns in the form of "black boxes".[16]

The principal problem in the exploration of data mining models is the development of methods allowing experts to quickly select the most relevant models according to their perception of the domain. In order to avoid this tedious and difficult phase, the information visualization allows the experts to select in a very intuitive way the models most likely to interest them.[17–19] In this way, the visual search of data implicitly employs the user's view as a means of exploring the many solutions and converging very naturally towards those which appear to him or her to be the most interesting or the most promising: visual data mining.

There are three visual data mining paradigms[16]:

(1) *The Preceding Visualization*: the data are visually explored before an algorithm is implemented. This makes it possible to discover interesting motifs;
(2) *The Subsequent Visualization*: an algorithm is used to extract patterns. They are then visualized to be analyzed by the user. Depending on this visualization, the user may have to modify the parameterization of the algorithm to re-execute it; and
(3) *The Tightly Integrated Visualization*: the intermediate results of the data-mining algorithm are visualized and allow the user to interactively detect interesting

patterns, according to his or her knowledge domain. As an algorithm cannot be suitable for all situations, its choice is made by the user, and the results are thus adapted to his or her domain. This process can be repeated until the desired result.

The transition from data mining results to knowledge is within the scope of the knowledge visualization framework. The Tightly Integrated Visualization allows an iterative visualization of patterns to visually obtain knowledge by experts without applying any analytical judgment. This is the context in which our contribution fits.

2.2. *Knowledge visualization*

Knowledge is recognized as an important resource for organizations. The status of knowledge in the organization's strategy is a key factor that promotes the continuity of knowledge management in organizations. Thus, knowledge representation is a major concern of knowledge management projects.[20] Therefore, literature has shown the important impact of applying visual representations for reasoning, communicating and facilitating knowledge acquiring in organizations.[20]

Burkhard[7] introduces the knowledge visualization as a new research field. It is an interesting part in knowledge management that allows to effectively create and transfer new knowledge through using visualizations. According to Eppler,[21] visualization can improve the productivity of knowledge sharing radically. Visualization is beneficial for decision-makers' communication, collaboration and learning.[18]

Admittedly, Burkhard[6,7] differentiates between knowledge visualization and information visualization. Information visualization is the use of visual representations of abstract data to increase human cognition. In counterpart, knowledge visualization is the use of visual representations of knowledge for the purposes of creation and sharing. Nevertheless, these two communities claim the same paradigms.

Burkhard[7] proposed a knowledge visualization framework based on four perspectives: (1) *function-type perspective*, which refers to the objective to be achieved; (2) *knowledge-type perspective*, which focuses on the suitable type of knowledge to be transferred; (3) *recipient-type perspective*, which focuses on the target group; and (4) *visualization-type perspective*, which focuses on the visualization categories.

This framework aims to provide a support for the selection of appropriate visualizations for individual and collaborative decision-making processes. Furthermore, Burkhard[7] introduces a knowledge visualization model based on the insight that knowledge cannot be transferred directly from a sender to a receiver. The knowledge recipient has to integrate it into his/her own cognition knowledge depending on his/her individual background and experience. This model is divided into three components (cf. Fig. 2):

(1) The mental model of the sender to externalize his/her knowledge into visualizations (Figs. 2(a) and 2(b)), which are the source for the recreation process of the receiver (Fig. 2(c)). In case of misunderstandings, the receiver can make or

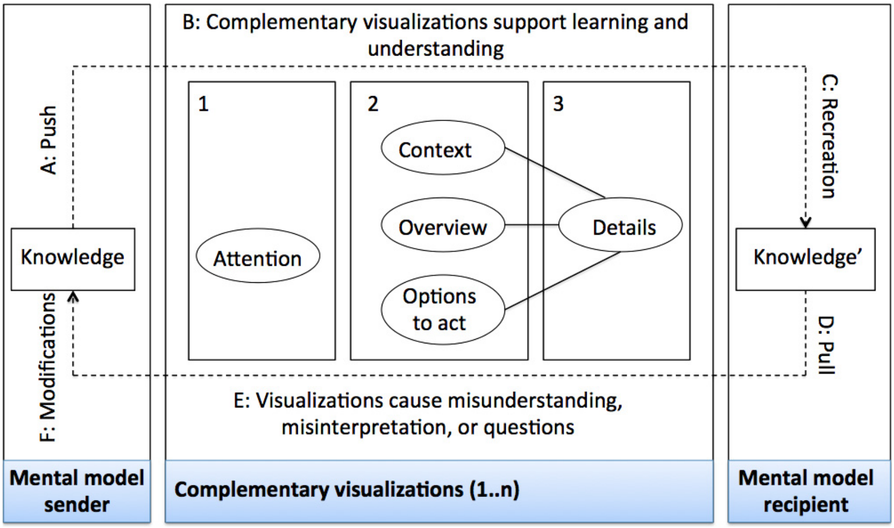

Fig. 2. Knowledge visualization model (inspired from Ref. 7).

send feedback to the sender to modify existing visualizations or create new ones corresponding to his or her needs (Figs. 2(d), 2(e) and 2(f)).

(2) The medium component that is built from the external visual representation of the knowledge. As a matter of fact, complementary visualizations are needed in transferring knowledge. The visualization must catch the attention of the receiver (Fig. 2(B.1)) in order to make him/her open for the knowledge from the sender (using an attractive interactive dashboards for example).

Then, the knowledge context must be illustrated to show the relevance of the knowledge sent to the receiver (Fig. 2(B.2)). Then an overview must provide all the aspects of the idea followed by some options to act (Fig. 2(B.2)) and allow the receiver to interact with it by focusing on details of interest (Fig. 2(B.3)) for recognizing relationships between ideas to understand.

(3) The recipient's mental model to internalize the visualizations into his/her knowledge.

This model presents general guidelines for using knowledge visualization to transfer knowledge from a sender to a recipient. However, we can identify two limits:

(1) It does not take into account the data mining patterns specificities and transformations.
(2) It does not take into account that humans have different abilities to interpret visual stimuli.

It is within this context that we propose to overcome these limitations by leveraging the visual analytics principles.

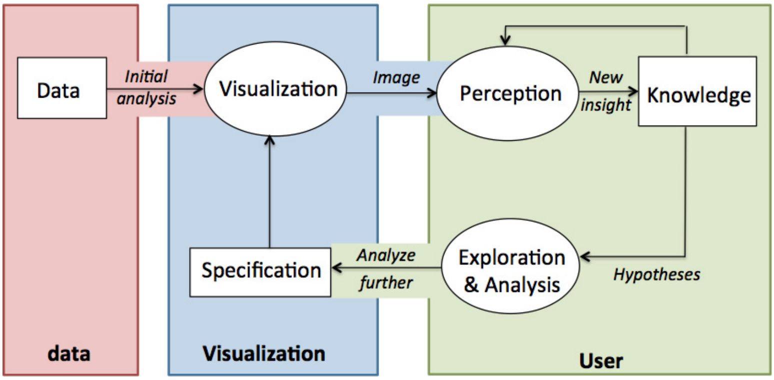

Fig. 3. The generic visual analytics process (inspired from Ref. 11).

2.3. *Visual analytics*

By representing data in the form of rapidly accessible and exploitable information, visual data analytics platforms act as decision support tools. This feature makes visual analytics an efficient solution to gain knowledge useful in generating decisional recommendations.

The visual analytics is the process of combining visual intelligence and automatic analysis techniques with interactive technology to get relevant information out of data.[22]

Visual intelligence enables the interpretation of what is constructed, based on user's prior experience. It is an interactive technology that allows users to not only visualize data but to also zoom in and out between the details and the big picture at about the same speed as our thoughts.[5] It takes advantage of the human eye's broad bandwidth pathway into the mind ability. Thus, it allows decision-makers to see, interpret, explore, and comprehend wide range of data at once.

Several research works proposed visual analytics processes. We begin by presenting the Wijk pipeline[11] (cf. Fig. 3). It consists of producing visual representations from data to generate knowledge. This pipeline begins by applying initial analysis methods to derive visualization. Based on this visualization, the user enters a loop to visually gain knowledge on the data. The interaction with visualization allows the user to acquire a better comprehension of the visual representation itself by ordering diverse insights to help him/her to go beyond the visual and to confirm the previously extracted results.

Later, Keim *et al.*[8] proposed the visual analytics process visible in Fig. 4. It begins with the data transformation to derive graphical representations for exploration purposes. Then, the human analyst can apply automatic analysis or visual methods.

The automatic analysis involves data mining methods to extract interesting patterns from original data.[a] Once a pattern is created, the analyst has to

[a] Let us take for example, a company that uses Data Mining (for automatic analysis) to analyze local purchasing patterns. The algorithm discovers that when customers buy an item x, they also tend to buy item Y. This new discovery information can be used in different ways to increase sales. For example, the article radius Y must be moved closer to the radius of the article X.

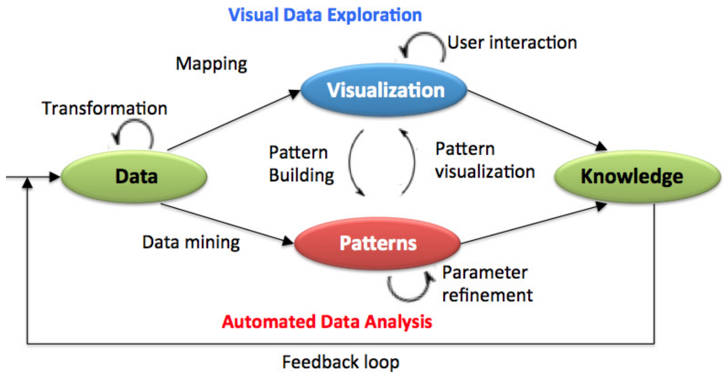

Fig. 4. The conventional visual analytics process (inspired from Ref. 8).

interactively assess it and refine its parameters using visualization. Patterns' visualization can subsequently be used in evaluating the previously generated data mining results. Interacting with the visualization is required to better understand these results.

Alternating between visual data exploration and automatic data analysis leads to a continuous refinement and verification of the data mining results in order to gain knowledge.

Sacha *et al.*[9] proposed an adaptation of the Keim *et al.*'s visual analytics process (cf. Fig. 4). It is a knowledge generation model composed of computer and human parts. The left-hand side of Fig. 5 introduces the visual analytics system (corresponding on Keim *et al.*'s model[8]), whereas the right-hand side of Fig. 5 presents the knowledge generation process of the human (corresponding to an enrichment of the knowledge step of the Keim *et al.*[8] model).

The capital gain of this model is in the reasoning process. This process is composed of three loops: (1) exploration that grants the taking of appropriate actions on the visualization based on the findings, (2) verification of the insights to automatically formulate hypotheses about the data analysis from findings, and (3) knowledge generation.

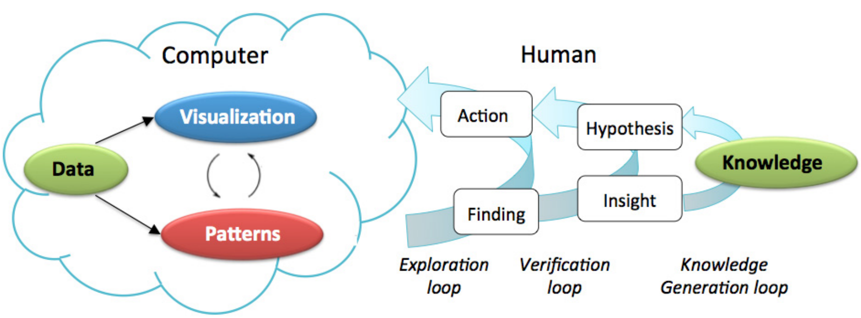

Fig. 5. Sacha *et al.*'s visual analytics process (inspired from Ref. 9).

Authors think that automating the steps, from insights to knowledge or from knowledge to new hypotheses, is not possible.[8,9] Veritably, analysts gain new knowledge when the evidence gathered with a visual analytics system is convincing (Knowledge Generation loop). The best way to support knowledge generation through visual analytics is to use systems that can look at data treated by computer from different angles (Exploration loop). This gives analysts the opportunity to collect versatile evidence and increases the level of confidence in results or insights (Verification loop).[9]

Additional related work on knowledge assisted visual analytics is by Federico *et al.*[10] and model building by Andrienko *et al.*[5] The first one suggested an extension of the model of van Wijk[11] by integrating the function and role of tacit and explicit knowledge in the analytical reasoning process. Such extension aims at designing a broad range of analytics systems.[10] The second one extended the model of Keim[8] to propose a comprehensive conceptual framework considering the visual analytics process as a goal-oriented workflow and providing a model as a result.[5]

We can see after the nonexhaustive but representative study of the models of knowledge visualization and those of visual analysis that the two domains complement each other in improving the decision-making process. It is in this context that our contribution fits.

3. Proposed Adapted Visual Analytics Process: From Extracted Patterns to Knowledge

We aim in this section to present how VA process can efficiently generate knowledge from data mining extracted patterns. Using knowledge visualization is not sufficient. In fact, what is needed is to make such visualization analytic and interactive so that the decision-makers can manipulate the patterns during the decision-making process.

From this perspective, we based our proposal on the commonly accepted visual analytics model of Keim.[8] We have extended it with additional details. These details are related to human cognition concepts and knowledge visualization activities.

The extended model is a form of a cognitive visual analytics process for decision-making (visible in Fig. 6). It aims at supporting the understanding of a holistic process from data to decisions. It is structured in three main levels: *Patterns, Analysis and Knowledge.*

In the following sub-section, we present our cognitive process in detail through its three levels: patterns level, analysis level and knowledge level.

3.1. *Patterns level*

This level begins with applying one or several data mining algorithms. It is a fully automatic approach aiming at extracting interesting patterns from a set of prepared data in order to make predictions and decisions. These patterns are presented in a symbolic form (probabilities, association rules, etc.).

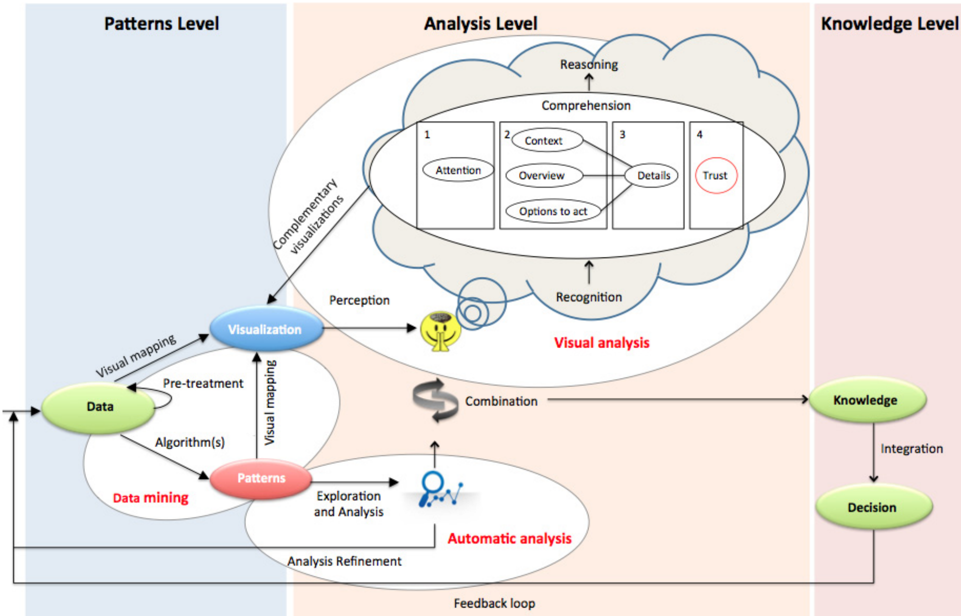

Fig. 6. Adapted cognitive visual analytics process for decision-making.

Visualization is effective for transforming the symbolic into geometric. It allows gaining insight into data.[23] The visual mapping creates graphical view using information, having a displayable format.[19]

Combining visualization with data mining has an important influence in improving the quality of the extracted patterns. It supports human intelligence with machine intelligence to assist in solving decision problems. The results derived in this level are: (1) extracted patterns in their automatic form (such as probabilities, association rules), and (2) image representing these patterns in a visual form. For each representation, a specific analysis will be applied in the second level of the proposed process.

3.2. *Analysis level*

At this level, we are interested in the extracted patterns' computational and interactive analysis. Two parallel analysis procedures of the automatic and visual patterns[b] will be carried out. The interplay between the two procedures aims at ensuring and enhancing the quality of knowledge generation from the patterns (combination step in Fig. 6).

[b] A visual pattern is a sequence of pictures or geometric objects that have been created to discover hidden and interesting information.

3.2.1. *Automatic analysis: Computer interpretation*

It consists of the exploration and the analysis of the automatic prediction patterns. It applies a set of analytics' algorithms and metrics to assess the prediction ability of these patterns to eventually obtain the desired result. It is based on an automatic reasoning that aims at retrieving the patterns' occurrences and interpretations.

If an exact analytics algorithm does not derive enough satisfying results, a fuzzy analytics algorithm can be used to return similar patterns based on the fuzzy logic theory.[24,25] These similar patterns can give more adapted and satisfying results. The nature and complexity of the used algorithm depends on the data mining patterns category (IF-THEN rules, decision tree, neural Network, probabilities, etc.).

This computational analysis must produce the validation of the learned patterns. It aims to detect the expected in these patterns (what we think is there). The results of this phase must be combined with those of patterns' visual analytics.

3.2.2. *Visual analysis: Human interpretation*

The principal objective of this phase is to visually analyze the image representing the extracted patterns (produced by the first level of the process). In this phase, we propose to integrate cognitive activities. It must enable the discovery of the unexpected in these patterns. To do so, users (i.e., decision-makers) must better understand the links between these elements.

Visual analytics is the key solution to really make sense and understand the displayed patterns. Decision-makers will be able to visually build knowledge structures that can be used to make decisions. This phase aims to improve the patterns' analysis by putting the human in charge of the analysis loop. It consists of four cognitive steps:

(a) Perception: it relies on the human mind's ability to perceive shapes, colors, lines, spaces, motions and interactions. These graphic elements form how decision-makers perceive what composes the display.[26,27] The human perception affects the way that the decision-maker should structure the visualized patterns. The human mind looks at the visualization in its entirety, before or in parallel, with perception of its individual parts.

The idea here is that the human mind has the ability to perceive differences and similar relationships and brings them together. The purpose is to perceive the specific story behind the displayed patterns by matching their properties and thinking about them.

(b) Recognition: after perceiving the graphic elements of the displayed patterns, the decision-maker recognizes them by comparing their appearance with the representation in his/her memory.[28] It is a representation whose nature raises many interpretations. It must lend itself to a matching with various and multiple appearances of the display (variations in size, orientation, lighting, etc.). The recognizable elements of the patterns increase their memorability.[29]

(c) Comprehension: this step proposes an adaptation of the knowledge visualization model of Ref. 7. To understand the displayed patterns, the decision-maker cannot interact only with one type of visualization but with a set of complementary visualizations for different purposes.

The process of comprehension begins after the recognition of the visual patterns elements that catch his/her attention. This latter makes him/her open for the knowledge from the displayed, perceived and recognized patterns. Then, the knowledge context must be illustrated to make the decision-maker focused on the importance of the knowledge according to him/her. An interaction with the visualization may require a combination of an overview and local views (details).

A local view can be seen as the result of a query on the overview, in which case it is of interest to authorize a dynamic and interactive control of the query through advanced interaction techniques (Options to act). All these actions allow comprehending/understanding the visualized patterns.

If the user understands what has been perceived, he/she will explore building trust for the visual creation of knowledge. Trust grants the decision-maker the ability to build strong confidence in every step of the decision-making process.[30] It is essential in cognitive analysis to comprehend the perceived data, to reduce complexity and to resolve uncertainty in decision-making.

(d) Reasoning: it is based on the decision-maker's visual thinking. It is a part of the decision-maker's nonverbal intelligence. The decision-maker looks at the patterns' visualization, determines what kind of information is displayed and then analyzes the information using his/her visual reasoning skills. Visual reasoning on perceived and understood information permits the visual building of knowledge.

(e) Combination: as automatic analysis algorithms can learn through experience from data in order to gain knowledge and then to make appropriate decisions and predictions, visual analysis generates visual knowledge that improve human expertise of the decision-maker. This latter optimizes the automatic learning behavior.

Combining automatic and human knowledge allows integrating human in the decision-making loop. In this context, automatic analysis that selects unlabelled data collaborates with visual analysis for interactive labeling. Such collaboration leverages our innate ability of reasoning as humans to improve automatic data exploration for better knowledge-based decision-making.

3.3. *Knowledge level*

At this level, the question is how to integrate automatically and visually discovered knowledge in the decision-making process. Knowledge is judged as interesting if it is relevant to the decisional analysis goal. Therefore, the outcome of visual analytics activities is not only a reliable insight but also a knowledge product that meets the purpose of the analysis.

Human decision-maker and the VIDSS, on which he/she wants to intervene, define a cognitive situation where the human operator must adapt to the situation, that is to say, to give his/her cognitive structures to the situations of the validated knowledge (the object of his/her action) in order to make relevant provisions to achieve the intended purpose (the draft action). The idea is to focus on the understanding and evaluation of knowledge. On the basis of a diagnosis (related to the application domain), the decision-maker is generally able to adapt his/her action plan or anticipate the reaction of the system on which he/she is working.

To do so, when designing the VIDSS, it is necessary to collaborate with the domain's experts to generate the different possible solutions (i.e., recommendations) to the decision problem, based on the knowledge generated from the data mining patterns. The decision-maker can thus interactively validate one or more solutions to make the appropriate decision. Otherwise, he/she can propose a subjective solution, as a domain expert. The system learns such information and considers it as tacit knowledge.[31]

4. Case Study

In the previous section we synthesized visual analytics with data mining, pattern recognition and cognitive visualization as a framework. To validate our proposal, we present in this section our case study showing how it can be used to guide the designing process of VIDSS in healthcare application.

4.1. *Context*

The purpose of our case study is to fight against Nosocomial Infections (NI) in a hospital's Intensive Care Units (ICU). NI constitutes a major public health problem due to the morbidity and mortality that they generate, as well as their cost of care.[32] The prevention of these infections has become a priority for several years in The Teaching Hospital Habib Bourguiba — Sfax, Tunisia.[33]

This work falls within the framework of a research project realized by our research team since 2016 in collaboration with the ICU physicians of the Teaching Hospital Habib Bourguiba — Sfax, Tunisia. We aim to apply our research for real-world impact in health. Hence, we aim to design and develop a VIDSS for the fight against NI. To implement such VIDSS, we apply our proposed visual analytics based knowledge generation process.

4.2. *Process application*

In this section, we present the medical application of our adapted visual analytics process according to its three levels described above (cf. Sec. 3). Input data have been processed as described in Fig. 7.

4.2.1. *Patterns level*

In this section, we begin by explaining how we have applied the proposed sub-process of pattern level to our case study (cf. Fig. 8). In fact, we remind that, according to our

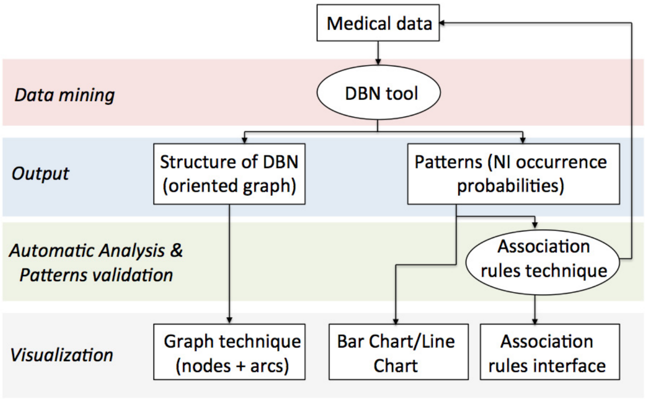

Fig. 7. Data processing during visual analytics process.

generic proposed approach, we can apply any data mining technique depending on the data to be processed and the decisional context (such as the association rules to analyze green manure decomposition parameters in the food sector[34] or the decision tree technique to mine gene expression data[35]). In our case study, we have applied the Dynamic Bayesian Networks technique.[36,37]

Data collection: this study was administered on 165 patients hospitalized in the ICU of the Teaching Hospital Habib Bourguiba — Sfax, Tunisia. The data collection took place at the time of the administrative registration. The NI occurrence prediction concerns all new entrants to the ICU.[33]

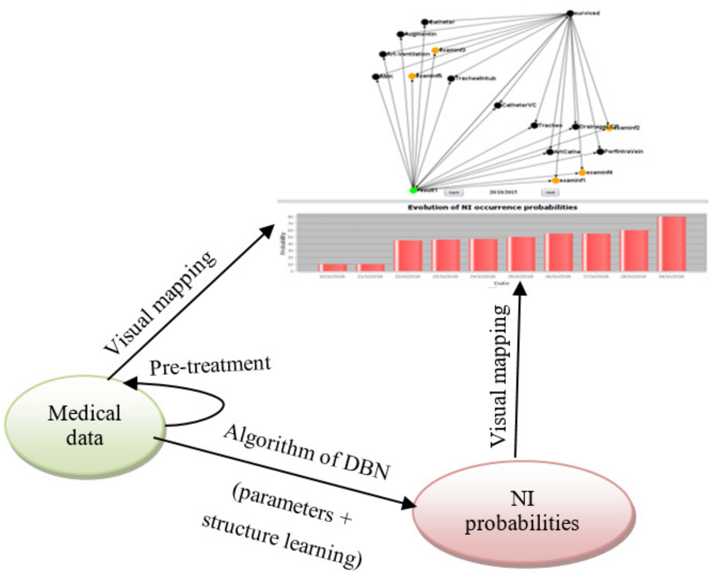

Fig. 8. Application of pattern level sub-process for fighting against NI.

Algorithm: the Dynamic Bayesian Networks (DBN) is an appropriate predictive data mining technique[36,37] for automatic prediction. Our choice considered the criteria of uncertainty and the dynamic aspect of the learning process as well as the temporal aspect of the ICU data. It determines the joint probability distribution of a dynamically ordered set of variables.

It is a long-term medical project for the fight against nosocomial infections in Intensive Care Units. The first prototypes were published in Refs. 20, 38 and 39. In this paper, we have improved the last one[20] by: (**Point 1**) refining the developed algorithm for the dynamic structure learning, and (**Point 2**) making the DBN learning structure interactive.

(Point 1): A DBN is a specific Bayesian Network that is used for stochastic dynamic process models. It is based on the following constraints: (a) it has the same structure at any time (Time-invariant) (b) at each period of time (a day of the hospitalization stay), it is extended from a time slice t to a time slice $t+1$, and (c) the variables in each time slice are connected in the same way.

In fact, the estimation of the NI occurrence probability at a day$_i$ (i.e., result$_i$) is based on the following variables: calculated NI occurrence probability at a day$_{i-1}$, acts carried out at a day$_i$, and infectious examination at a day$_i$. The decision to be made is based on this probability. Learning the DBN structure consists of two types of arcs: (1) *Intra-slice arcs* representing the interdependence between the variables of a time slice, and (2) *Inter-slice arcs* representing the arcs of time and symbolizing the interdependencies between a variable for different and successive time slices.

```
Inputs:
   D: Data Base
   m: Examples of variables (node xi) for each transition
   t[i]
   n: summits
   u: maximum of parents number
Outputs:
   xi: node
   πi: set of parents of the node xi
B0:
   For (i=1, i<n, i++)
        πi ={}
        Scoreold = score (i, πi[0]){ πi is in time 0}
        OKToProceed= True
        While  (OKToProceed and |i, πi[0]|<u) do
```

```
        z is the node maximizing the score(i, πi[0]) U {z})
        Scorenew = score (i, πi[0] U {z})
        πi[0]= πi[0] U {z}
        Else
        OKToProceed=False
       End
   End
B →:
   For (i=1, i<n, i++)
      πi[t]={}
      OKToProceed= True
      While OKToProceed and |πi[t]|<u  do
         Scoreold = score (i, [t], πi[t]){ πi [t] is in time
         t or t-1}
         For (t=1, i ≤ T, i++) do
          Scorenew [t] = score (i, πi[0] U {z})
         End
         If Scorenew [t] > Scoreold
          Scorenew [t] = Scoreold
          πi[t]= πi[0] U {z}
         Else
          OKToProceed=False
      End
   End
   If xi[t]→ xj[t+1]
    xi→ xj
   End if
End
```

For the construction of intra-slice arcs, we developed the K2 dynamic algorithm to learn the structure of DBN by adapting it to our medical database. Following the subsequent algorithm:

For the construction of inter-slice arcs, it is necessary to detect the dependencies between time slices $t-1$ and t, by using the joint probability distribution. It is calculated as follows:

Let $X[t] = \{X_1[t], \ldots, X_N[t]\}$ the set of the DBN variables with T time slices and N variables. The applied joint probability of X_T is $P(X_T)$, which is equal to $P(X[1], \ldots, X[N])$ is calculated by Eq. (1).

$$P(X_T) = \prod_{t=1}^{T} \prod_{i=1}^{N} P(X_i[t] \,|Pa(X_i[t])), \tag{1}$$

where $Pa(X_i[t])$ is the parents of $X_i[t]$.

More details about this calculation are provided by Ref. 38.

(Point 2): The visualization technique builds on the graph visualization. It consists specifically of node and arcs (node links) to provide an effective representation of the structure of DBN during time. Five sub-groups and their direct links are represented to demonstrate the change of structure through time progression.

Each sub-graph represents the dependence between the variables of our datasets. The visualized links indicate the causality between medical variables, such as acts (Catheter VC, Urinary Probe, Art-Ventilation, Tracheotomy, Perf-Intra-Ven,...), infectious exams, taken antibiotics at day i, and being infected or not (result i). As shown in Fig. 9, at the third day, five interventions are introduced which are Catheter, urinary probe and three infectious exams representing the causes of the predicted result.

Our improvement consists of involving the expert (i.e., physician) for the DBN learning structure. We aim to allow him/her to make different modifications based on his/her prior knowledge. He/she can intervene to add one or more arcs or nodes that seem logical or to remove illogical arcs or nodes. The use of expert-visualization interaction tools, such as zoom, facilitates the analysis, understanding and correction of the resulting learning structure.

Our objective is to improve the structure of DBN because its importance in result prediction. For instance, as shown in Fig. 9, we present the case of deleting the node CV4. The expert indicated that the act “Catheter VC” has no longer an influence on the result. On the other hand, the automatic learning of the structure showed that it was a factor to consider. This refinement allows improving the visualization (graph of the structure). This latter can be re-used to further analyze the patient’s state for new knowledge generation.

Visual mapping: the developed DBN allowed building a temporal predictive model that meets the needs of ICU physicians. It is based on patient temporal data and predicts the NI occurrence probability (p_i) at each day during the patient’s hospitalization period. The decision to be made at a current stage takes into account the taken decisions at previous stages, when a new discovered knowledge (p_{i+1}) should be addressed.

This link repeats itself during the decision process. The learn-to-decide-then-learn-to-decide model describes how the decision-maker learns the new extracted knowledge for making a new decision.

The visual mapping of our DBN is presented in Fig. 10. We aim by this visualization to represent dependant medical variables using a set of colored nodes and arcs. The relationships between the linked nodes and the result make it possible to visualize the causes of the predicted probability (infected or not). As a matter of fact, to make the extracted patterns more effectively communicated to decision-makers, we used the histogram technique to represent the patterns.

An example of visual pattern is presented in Fig. 11.

The edges and the distribution of probabilities extracted using the BN algorithm actually represent the patterns.[40] For instance, in Fig. 7, subparts of DBN (three days: from 20/10 to 22/10) are shown to describe the dependence relations between

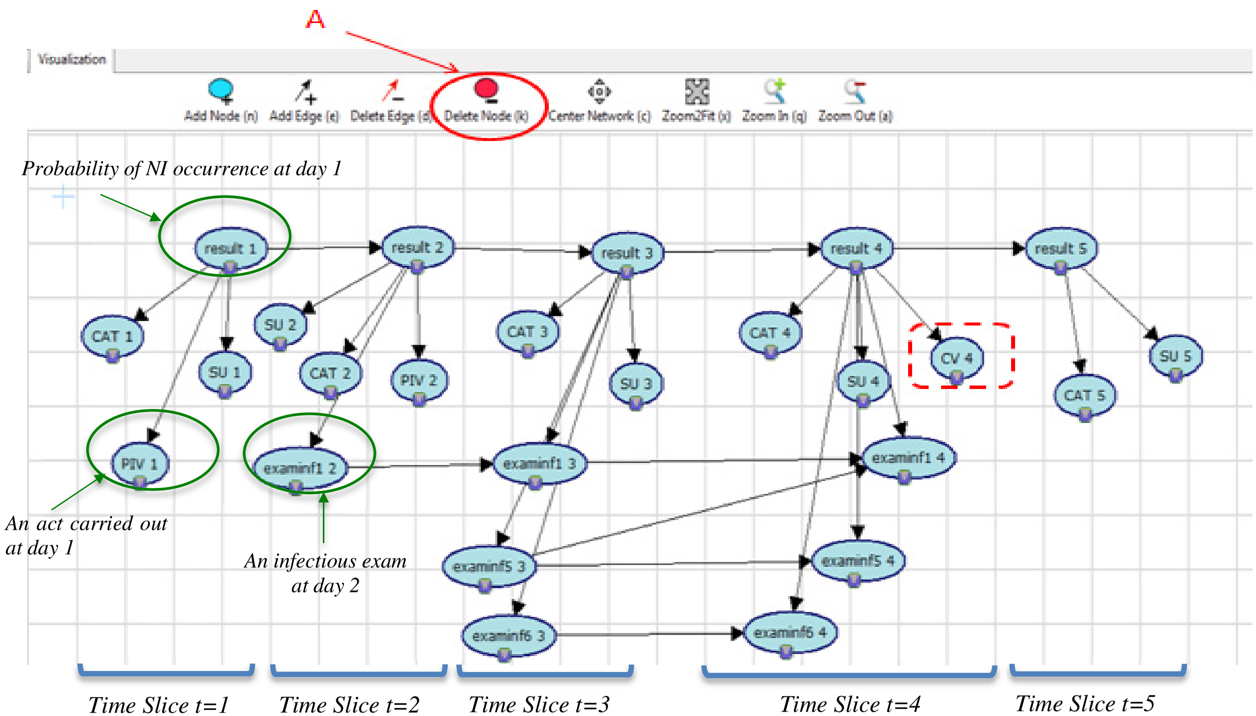

Fig. 9. User interface of the interactive DBN learning structure.

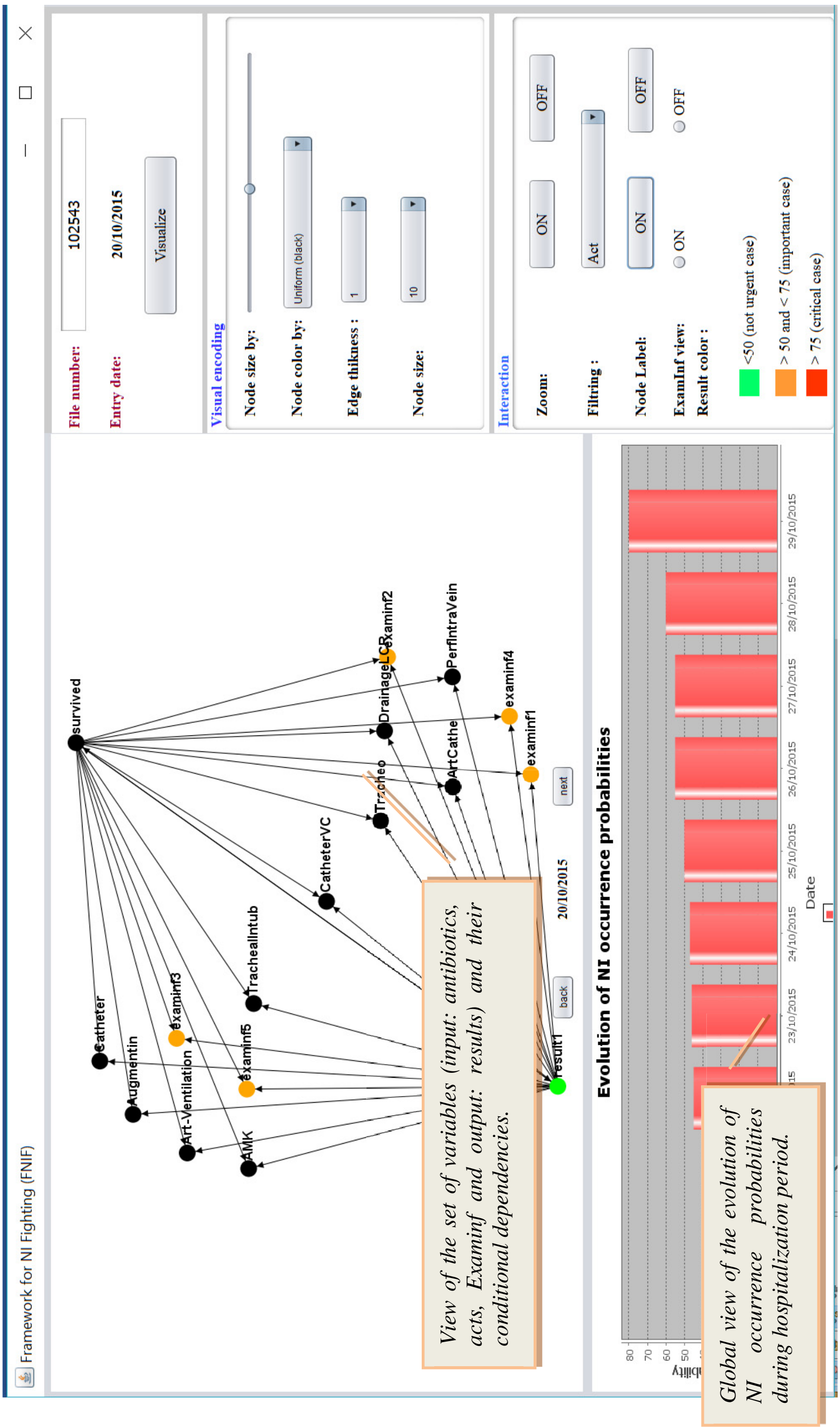

Fig. 10. User interface of the VIDSS for the fight against NI.

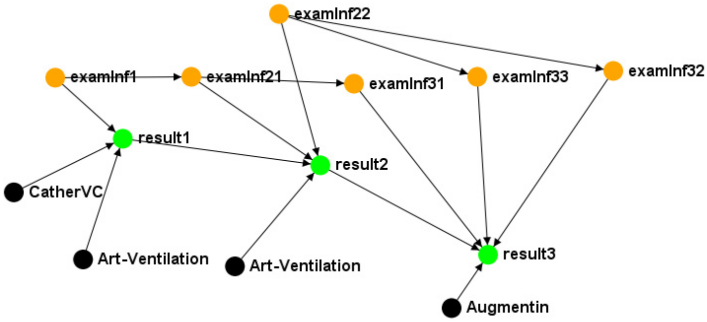

Fig. 11. An example of visual pattern.

medical variables. In the first day, two acts that are Catheter and Artificial ventilation and an infectious exam influence the NI appearance (is not an urgent case). Then in the second day, the case is also not urgent and it depends on the previous result, the use of artificial ventilation and infections test.

As shown, the previous tests act on the infectious exams and on the applied acts. For example: if the test indicates that the germ X resists to an antibiotic, the physician should propose another antibiotic to reduce the probability of acquiring NI. Accordingly, in the third day, a new infectious test and new antibiotic have been added in order to influence the result.

4.2.2. *Analysis level*

The analysis is based on combining human interpretation (visual analysis via interaction) and automatic analysis using association rules tool (cf. Fig. 12).

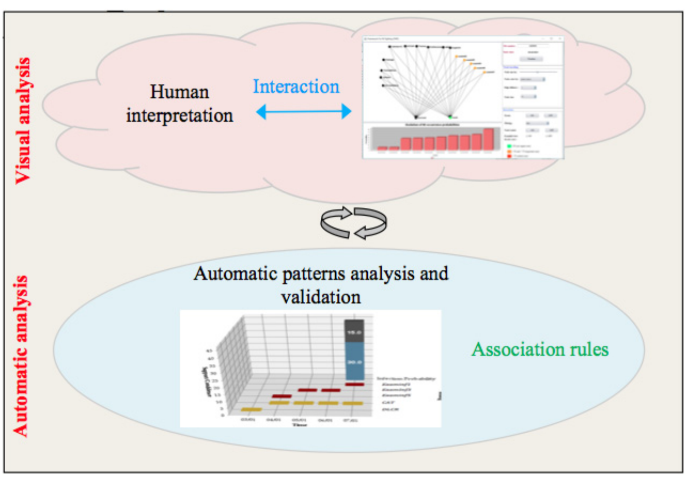

Fig. 12. Application of analysis level sub-process.

In the literature, an improved nontemporal version of the AR mining technique named Association Rule Networks (ARN) has been proposed. The ARN offers a synthesizing method of obtained association rules in a structured manner (graph representation).[41]

To automatically explore and analyze the calculated NI occurrence probability, we have re-used the existing developed association rules technique, previously applied for extracting patterns.[14,42]

The purpose of using this technique, in this paper, is to confirm the elements that are found together and then to confirm or refute the discovered patterns by the DBN in the patterns level. It is used to validate the patterns already extracted by the DBN technique. Combining DBN with association rules can be considered as a hybrid approach for automatically manipulating patterns *before* and *after* their extraction.

As shown in Fig. 13, extracted patterns (obtained by applying DBN tool) and medical data (cited in the previous section) form the learning datasets of the association rules technique in order to generate a set of rules.

Our proposal of the automatic pattern analysis process is based on association rules mining technique. The objective is to analyze and explore patterns by discovering hidden and significant rules that are useful for fighting against the nosocomial infections. By employing AR for patterns analysis, we aim to determine *the most relevant information from the information considered a priori as useful.* Accordingly, the user can gain more and more optimized knowledge. Based on the extracted rules he/she can discover the factors, which cause the NI.

The rules are of the form: "If variable(s) X then being Infected or Not infected in time T".[43,44] A variable can be an antibiotic, act or infectious examination. The condition of the rule can be a conjunction of variables. An example of rule is the following: "If Artificial Ventilation then probability of NI in 8 days".

The strength of an association rule is measured by its support and confidence indices. We define the support of the rule as the probability of observing both the premise X and the conclusion $Y : P\ (X \cap Y)$ and the confidence as $P\ (Y/X)$.

We used the temporal version of the Apriori algorithm as explained in Ref. 45. For each patient, we treat the list of transactions at every day as a subset and we eliminate the temporal factors (day). Then we determine the list of frequent itemsets (Lk) that consists of the frequent subsets having support greater than the min_support. Finally, after the generation of temporal association rules using Lk and adding the temporal factor, we calculate the confidence values. The algorithm allows discovering the rule sets that satisfy minimum support and confidence thresholds in the database.

Actually, the values of minimum support and confidence (respectively 20% and 5%) are obtained after several experiments in which we analyzed the obtained temporal association rules importance. In our research team, a specific group collected and prepared the 165 patients' data that were reported in the relational database format. Each record includes the following attributes: folder number, day,

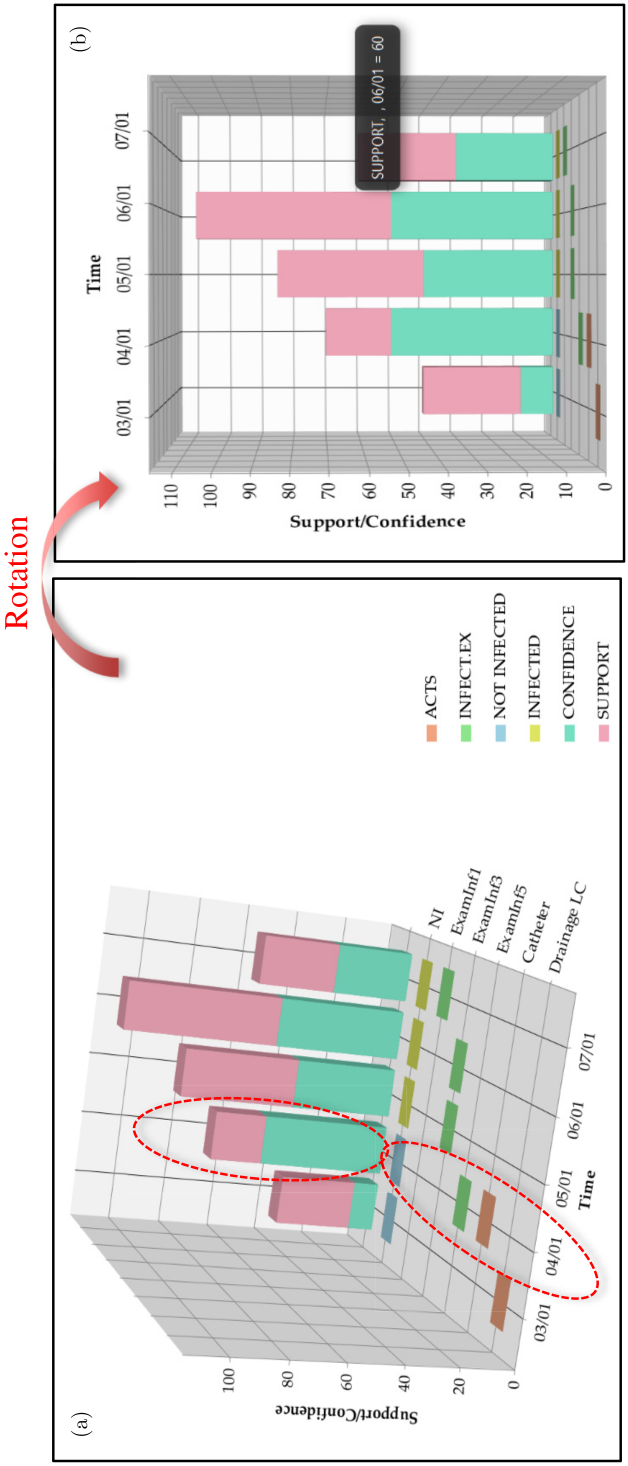

Fig. 13. Association rules user interface for patterns validation.

acts (act_1, $\text{act}_2, \ldots, \text{act}_n$), given antibiotics ($\text{ant}_1$, $\text{ant}_2, \ldots,$ ant_{10}), infectious examinations (ie_1, $\text{ie}_2, \ldots, \text{ie}_{30}$)[c] and the attribute NI (Nosocomial Infection).[d]

In addition, we have developed the 3D visualization technique to complete the VIDSS platform. The development of this technique required the consideration of three main dimensions: Items, Time and Metrics (Support and Confidence). The value of a temporal variable (e.g., act, antibiotic or infectious examination) at a time t is expressed by the intersection of the X-axis and the Y-axis in a 2D matrix.

Each box in the matrix represents a rule. The metrics (Support and confidence) are represented at the bottom of the matrix, and their sizes are proportional to their values (cf. Fig. 13(a)). We use these two metrics for the automatic exploration and analysis. Using interaction techniques like rotation, labeling and zoom in/out/to-fit, the analyst can choose the adequate view to analyze (cf. Fig. 13(b)).

The VIDSS prototype calculates these two metrics for each extracted pattern to check its relevance. A minimum value for these two metrics is presented to the physician (i.e., decision-maker) to ensure the validity of the pattern in question (cf. Fig. 13).

The example presented in Fig. 13 shows the rule: "If Arterial Catheter and examinf5 then Not Infected in day 04/01 with support = 20% and confidence = 50%".

As shown, the Association Rules method enables the physician to analyze extracted patterns thoroughly. The goal is to discover hidden relationships between all the stored variables (including transformed patterns) of interest to the doctor in order to accomplish his or her task. Thus, as a complement to Fig. 10, this representation explains, in a simple and interactive manner, the factors such as the acts taken and the given antibiotics causing such situation (being infected or not infected). The evolution of the patient state must be controlled daily. For this reason, it is necessary to support decision-maker in data analysis by offering the possibility to have daily and overall view to make the right decision.

The support and confidence values[e] are above the minimum thresholds (min support = 20% and min confidence = 5%), which ensure the rule's validity. Once the automatic analysis has confirmed the relevance of the extracted pattern, it comes to question its visual analysis. To do so, we explain following the application of its cognitive activities.

The visual interface (cf. Fig. 10) is a graphic representation that structures and explores causal relationships between data parts. It shows an example of the application of the encoding scheme of several node attributes (acts, antibiotics and infectious examinations) in the force-directed graph. It displays temporal data that influenced the NI probability at a specific day of the hospitalization period.

[c] Domain experts (i.e., physicians) have identified 30 infectious exams.

[d] It is the calculated probability of the NI occurrence prediction.

[e] Support and confidence are evaluation criteria of association rules.[17] The support is the indicator of the rule *reliability* while the confidence is the indicator of the rule *precision*.

The nodes' colors encode the case urgency of the temporal variables. The fill color of the node encodes a continuous variable while referring to the legend in the lower right corner of the main canvas. The colors become stronger towards the nodes of risk variables. At the bottom, the bar chart below the force-directed graph shows the evolution of the NI probabilities during the patient's hospitalization. Physicians may want to study this evolution and determine how to minimize the probability of NI occurrence. The physician can recognize the visual elements of the user interface.

The interaction mechanisms (zoom in, zoom out, filtering and node labeling) support the flexibility of the visualization, allow physicians to highlight a part of the force-directed graph following user attention and show in-depth information only on demand (cf. Fig. 14). These mechanisms aim at keeping the overall visualization experience from over-crowdedness. To understand the displayed pattern, the physician can repeat the application of the interaction mechanisms as needed, which can catch his/her attention. In fact, he/she dynamically interplays between global and local views of the different data displayed on the visual tool.

The physician can click over nodes to display related information (labeling mechanism) and filter out variables. Moreover, the physician interacts with the visual tool: (1) to acquire knowledge related to the NI probability (2) to retrieve data (acts, antibiotics and infectious examinations) associated with the displayed patterns from the database using the labeling technique, and (3) to visually interpret the differences and/or similarities between these related data each day during the patient hospitalization.

In addition, it is possible to allow physicians to move a certain number of nodes by drag-and-drop technique. However, such displacement interaction is not possible for rigid representation such as bar chart. Nevertheless, the user can change the layout of the bar chart to a curve (LineChart 3D). Another example is the zoom, which is a necessary mechanism that makes visualization in an unlimited area where some nodes can be pushed to a distant location. Figure 14 shows a box that appears when the user needs to get a detailed view of the infection examinations that had been carried out. In fact, he/she can see if the germs are resistant to the antibiotics given for each exam (positive-Green or negative-Red). All these examples of interactivity assist the physician to understand the force-directed, bar chart and curve graphs.

The physician can take different positions of viewing while the visualization can reveal further significant information. In addition, we allow physicians to visually inspect the impact of temporal variables on the NI appearance by navigating in the timeline and dynamically adding/deleting nodes in the network.

Such visual analysis facilitates the understanding of the critical variables influencing the patient's condition and then exploring building trust for visually creating knowledge about the NI occurrence, its causes and its evolution. The physician, looking at the dynamically displayed force-directed, bar chart and curve graphs, can analyze the displayed information using his/her visual reasoning skills.

Based on the calculated metrics for the automatic analysis and the visual knowledge generated by the visual analysis, the physician validates the NI

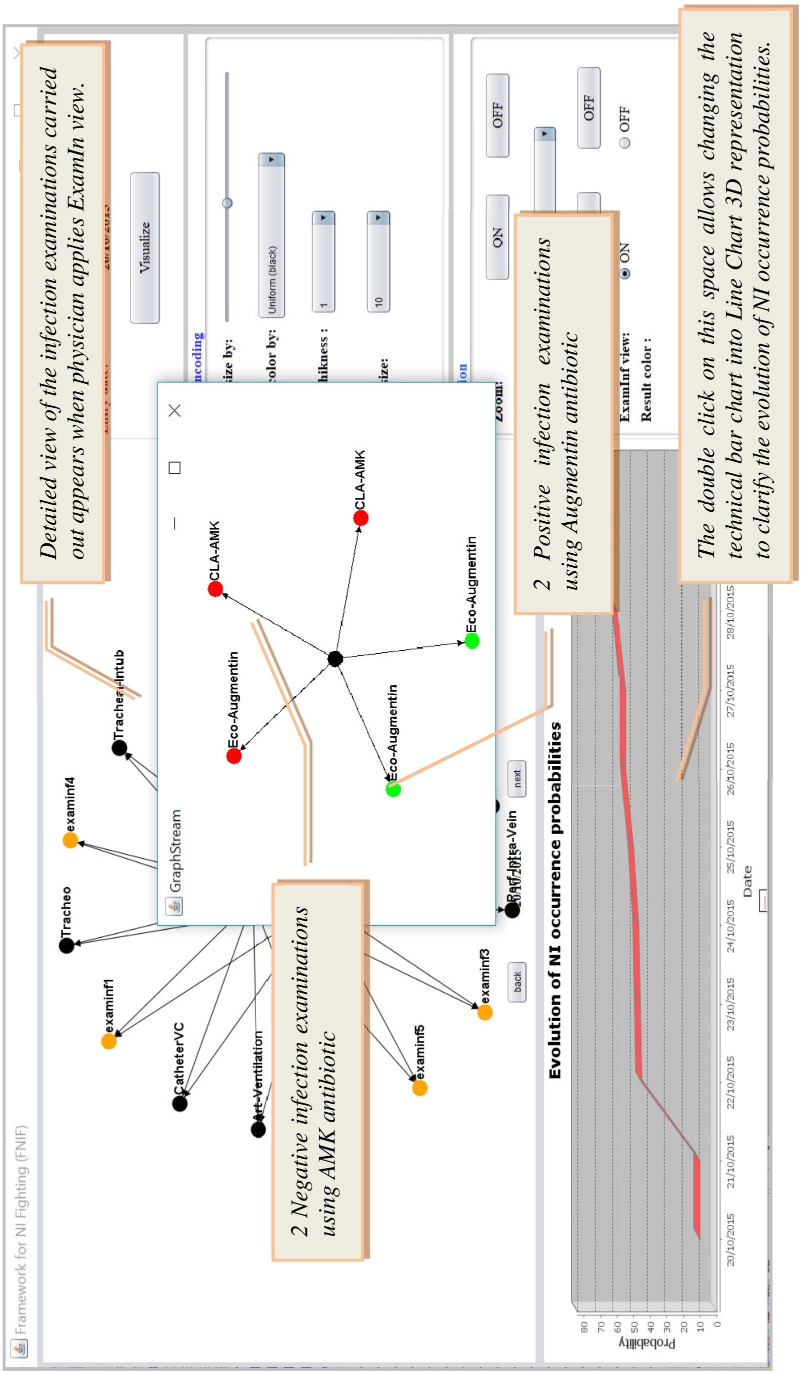

Fig. 14. Interaction mechanisms application.

probability at the current day of hospitalization (the 6th day of hospitalization for the example presented in Fig. 13). He/She understands the reasons why probability had this specific value.

4.2.3. *Knowledge level*

After acquiring knowledge on the NI occurrence, the physician builds new knowledge through the synergy between the explicit knowledge generated by the VIDSS (through the analysis level and corresponding to the NI occurrence probabilities during the ICU hospitalization stay), and his/her tacit knowledge[f] (corresponding to the history of the decisions taken based on the previous values of NI occurrence probabilities).

There is constant back and forth between tacit and explicit modes. Thus, appears this virtuous circle: All extracted and validated knowledge is at first explicit, it then becomes tacit to become explicit and to become tacit once again.

Based on the explicit knowledge at day_i, a set of possible recommendations will be displayed to the physician, who can select a solution or propose another one. It is the main purpose of the performed automatic and visual analysis. These recommendations are generated automatically by the VIDSS based on the following reasoning:

```
If (probability> 50% and probability <70%) then
  Solution 1: New PTD Sampling
  Solution 2: New HC Sampling
  Solution 3: New ECBU Sampling
  Solution 4: Rx Exploration
If not
  If (Probability> 70%) then
    Solution 1: New PTD Sampling
    Solution 2: New HC Sampling
    Solution 3: New ECBU Sampling
    Solution 4: Antibiotic change
    Solution 5: If Surgical Patient Then Surgery
  End if
Else
    The situation is non-urgent
  End if
End if
```

According to physicians, experts in nosocomial infections in the Teaching Hospital Habib Bourguiba — Sfax, Tunisia, if the probability of its occurrence is higher than

[f]Tacit knowledge is intrinsic to each of us and cannot be explicit.

50%, three possible sampling are always recommended based on the patient state (i.e., PTD Sampling, HC Sampling and ECBU Sampling) for accurate diagnosis. Subsequently, it is important to verify if the probability is lower than 70%, where an Rx Exploration is recommended. If greater than 70% then two other solutions are recommended (antibiotic change and Surgery).

After validating one or more solution by the physician (decision-maker), the choice will be stored in the database as a historical data for future decision-making task.

5. Evaluation and Results

The evaluation is the key factor for a successful research work. For this reason, we introduce in this section the theoretical validation of the proposed visual analytics process and the practical validation of the developed prototype using such process.

5.1. *Theoretical validation of the contribution*

The main contribution of this work is the proposed holistic cognitive visual analytics process to design and develop visual intelligent DSS. It is an extension of the existing framework of Keim,[8] aspiring to assist decision-makers in transforming extracted patterns (by data mining algorithm(s)) to knowledge and then decision. Usually, in such systems, users think about the efficiency of the data mining results, rather than about their transformation into knowledge/decision.

In this paper, we propose to design a VIDSS following three levels: (1) patterns level to treat data and apply data mining algorithm(s), (2) analysis level that combines automatic and visual analysis to discover validated and appropriate[g] knowledge, and (3) Knowledge Level to integrate it in the decision-making process. These three levels endeavor to facilitate the whole decisional process in a comprehensive manner. It views such process as cognitive transformation of patterns, evaluation and improvement of resulting knowledge to resolve a decisional problem (Sec. 3).

To show that the proposed process contributes to the literature, we classify it in relation to related works, which are (1) the data science,[15] (2) the Generic Visual Analytics model by Van Wijk,[11] (3) the Conventional Visual Analytics Model by Keim *et al.*,[8] (4) the knowledge generation model by Sacha *et al.*,[9] (5) the knowledge-assisted visual analytics by Federico *et al.*,[10] and (6) model building by Andrienko *et al.*[5] (cf. Table 1).

The classification is based on a set of criteria related to the knowledge generation. These criteria are grouped in three classes according to their focus on systems, interaction, or human aspects.[9] The information presented in Table 1 was extracted from the classifications made by Refs. 5 and 9 compared to the basic models of visual analytics. As introduced in Secs. 3 and 4, our approach deals with all concepts.

[g] "Appropriate" means fitting to the purpose.

Table 1. Classification of our contribution to related works.

	Systems				Interaction	Human aspects		
	Data	Knowledge	Decision	System	Interaction	Human Cognition	Reasoning	Trust Building
Data science[15]	X	X	X	X	X			
Generic Visual Analytics model of Ref. 11	X	X			X	X	X	
Conventional Visual Analytics Model of Ref. 8	X	X			X	X	X	
Knowledge generation model of Ref. 9	X	X		X	X	X	X	
Knowledge-assisted visual analytics of Ref. 10	X	X		X	X	X	X	
Model building of Ref. 5	X	X			X	X		
Our visual analytics process	X	X	X	X	X	X	X	X

Based on the classification visible in Table 1, we can identify that our cognitive visual analytics model provides new perspectives to categorize some related works. It sheds a light on specific interesting aspects of guiding the designing process of VIDSS. It takes into account basic visual analytics concepts presented by Keim[8] and adds additional features related to decisional aspects (the whole path from data to decision), cognitive reasoning and trust building (cf. Table 1). It gives more accurate results than existing approaches because its ability to automatically and visually analyze patterns already extracted by data mining application in order to generate knowledge, which improves the final decision quality.

In our paper, we applied the proposed model for the development of a DSS for the fight against nosocomial infections. The result of the prediction has been improved compared with existing tools (cf. Sec. 5.2.1.1), which proves that our VIDSS is more robust.

It is a holistic perspective of the Visual Analytics/VIDSS process including knowledge level. It attempts to propose an overarching framework that explains the visual analytics process for decision-making tasks. It aspires to be of great value to guide future research studies in various application domains.

This study suggests new perspectives on visual analytic process. Our proposed model underlines that patterns' extraction, their automatic and visual analysis and the integration of the discovered knowledge in decision-making are complementary levels in the knowledge generation process using visual analytics. Indeed, our model integrates human cognition aspects while applying the visual analysis components.

Most related visual analytics works (cited in Table 1) do not fully cover all aspects required by our model because it includes the holistic cognitive knowledge generation process that involves Systems, Interaction and Human aspects. Our model similarly identifies how levels are closely related to knowledge visualization, visual analytics and human cognition sub-processes and how interaction between each level can be influenced by reasoning and trust building processes.

Our model is significant for researchers as it grants more explicit discussions on specific automatic and visual analysis functions and their impacts on knowledge discovery and decision-making processes during the entire path from data (in the level of patterns) to the decision (in the level of knowledge). It also defines human concepts and introduces four stages of reasoning (perception, recognition, comprehension and reasoning).

Researchers can use our cognitive model to evaluate and improve existing visual analytics systems in terms of functions and analytical outputs.

5.2. *Practical validation of the contribution*

The evaluation of our VIDSS prototype is divided into two parts: (1) evaluation of its utility, which concerns the prediction results and the sensitivity analysis of the DBN and, (2) the evaluation of its usability, which concerns the user satisfaction of the VIDSS Human–Computer Interaction.

5.2.1. *Utility evaluation*

5.2.1.1. DBN prediction ability evaluation

We have applied the confusion matrix technique[46] to assess the prediction ability of our DBN (cf. Table 2) compared to the three designed and developed versions during

Table 2. Confusion matrix.

Predicted / Observed	IDSS[38]			Cognitive IDSS[39]			VIDSS[20]			Adapted VIDSS		
	No	Yes	Total	No	Yes	Total	No	Yes	Total	No	Yes	Total
No	34	7	41	34	8	42	46	4	50	113	8	121
Yes	8	9	17	4	10	14	4	10	14	9	35	44
Total	42	16	58	38	18	56	50	14	64	122	43	165
The accuracy rate		74.14%			78.6%			87.5%			89.69%	
The negative capacity of prediction		83%			80.9%			92%			93.38%	
The positive capacity of prediction		53%			71.4%			71.43%			79.54%	

preceding works in collaboration with Intensive Care Unit physicians of the Teaching Hospital Habib Bourguiba — Sfax, Tunisia.[20,38,39]

The results, obtained by the confusion matrix, show that from 165 instances (i.e., patients), 148 are correctly classified, which is equivalent to an accuracy rate of 89,69%. This percentage of precision is interesting for the ICU physicians. In addition, Table 2 shows that the performance rates of this current DBN prototype are better than those obtained by its three previous versions.[20,38,39]

5.2.1.2. DBN sensibility analysis

What asking experts and how assessing their responses accuracy is the main challenge in implementing a DBN. Inaccuracy of the posterior output is a result of the use of incomplete and sensitive appreciations. Consequently, understanding the certainty of deduction drawn from that model is fundamental when implementing a DBN model. Sensitivity analysis is a way to gain this understanding since it allows an evaluation of DBN outcomes.[47]

The accuracy of DBN is defined as the comparison between the output robustness and the changes in the probability values of the inputs. Furthermore, the probability values of the proofs and hypotheses in the DBN intended for the NI occurrence prediction are mainly discrete. Therefore, the sensitivity function and the sensitivity value can be used to assess the DBN by computing the related sensitivity analysis.

Sensitivity Function[47]: it is a function through the point $(x_0,\ h_0)$ limited by 2 rectangular hyperbolas, which are $i(x)$ (cf. Eq. (2)) and $d(x)$ (cf. Eq. (3)).

$$i(x) = \frac{h_0(1 - x_0)x}{(h_0 - x_0)x + (1 - n_0)x_0}, \tag{2}$$

$$d(x) = \frac{h_0 \cdot x_0(1 - x)}{(1 - h_0 - x_0) \cdot x + h_0 \cdot x_0}. \tag{3}$$

A sensitivity function $f(x)$ with $f(x_0) = h_0$ is bounded as presented by Eq. (4).

$$\min\{i(x_j), d(x_j)\} \preceq f(x_j) \preceq \max\{i(x_j), d(x_j)\}, \tag{4}$$

where x_j belongs in [0,1].

The intersection point of the bounds defines the sensitivity. It is growing when this point is oncoming zero.

Sensitivity Value[47]: it is obtained by applying the partial derivative of the hypothesis output regarding the probability of a well-defined proof state. Knowing that a hypothesis θ is evident as a function of a probabilistic probability x, the sensitivity function $f(x)$ for θ is equivalent to the posterior probability $P(\theta|e)\ (x)$ that is equal to the quotient of two linear functions of X. Equation (5) presents the sensitivity function.

$$f(x) = P(\theta|e)(x) = \frac{P(\theta \wedge e)(x)}{P(e)(x)} = \frac{a \cdot x + b}{c \cdot x + d}. \tag{5}$$

The coefficients (a, b, c and d) are calculated from the initial DBN variables. The sensitivity of the probability value consists of the absolute value of the sensitivity function at the original likelihood value as presented by Eq. (6).

$$\left|\frac{a \cdot d - b \cdot c^2}{(c \cdot x + d)}\right|. \tag{6}$$

It explicates the change in the hypothesis output for small changes in the evidence probability under study. *The higher the sensitivity value*, *the less robust the hypothesis output.*[47]

DBN for the NI occurrence prediction[47]:

In this section, we present the application of the different sensitivity analysis measurements, to evaluate the robustness of the DBN applied for the NI occurrence prediction cases in the ICU of the Teaching Hospital Habib Bourguiba — Sfax, Tunisia. Constructing a DBN starts with the establishment of the important hypothesis to be resolved. The hypothesis H is that *the patient was hospitalized in the ICU with a previously calculated NI probability* to predict the NI occurrence at each day during the patient hospitalization.

Hypothesis H represents the DBN's root, which is the ancestor of the remaining nodes of the network. Unconditional probabilities are: $P(H = \text{Yes}) = 0.5$ and $P(H = \text{No}) = 0.5$. The main hypothesis H directly influences five other dependent sub-hypotheses that are events triggered following the hospitalization of the patient in question. The sub-hypotheses (Yes/No states) are:

- $H1$: **The linkage between** the hospitalization at day $i-1$, with a NI occurrence probability Prob $i-1$, **and** the infectious examinations at the day i.
- $H2$: **The linkage between** the hospitalization at day $i-1$, with a NI occurrence probability Prob $i-1$, **and** act carried out at the day i.
- $H3$: **The linkage between** the infectious examinations at the day I, with a NI occurrence probability Prob $i-1$, **and** act carried out at the day i.
- $H4$: **The linkage between** the hospitalization at day $i-1$, with a NI occurrence probability Prob $i-1$, **and** Antibiotic taken at day i.
- $H5$: **The linkage between** act carried out at the day i**and** Antibiotic taken at day i.

Table 3 describes the digital evidence DEi (states: Yes, No and Uncertain) related to the five sub-hypotheses.

As there are no occurrences of the five sub-hypotheses, common approaches are not sufficient to predict their conditional probability values. For this purpose, an expert, who has more than 15 years of experience, was invited to subjectively assign the probability values produced by this study (cf. Table 4).

Table 5 shows the conditional probability values of the DE given the related sub-hypotheses.

Table 3. Sub-hypotheses and the related evidence.

Sub-hypotheses	Evidences	Description
$H1$	DE1	Patient hospitalized at date $i-1$, with a NI occurrence probability Prob $i-1$, has performed infectious examinations at the day i.
$H2$	DE2	Patient hospitalized at date $i-1$, with a NI occurrence probability Prob $i-1$, has carried out acts at the day i.
$H3$	DE3	Patient performed infectious examinations at the day i has carried out acts at the day i.
$H4$	DE4	Patient hospitalized at date $i-1$, with a NI occurrence probability Prob $i-1$, has taken antibiotic at day i.
$H5$	DE5	Patient carried out acts at the day i has taken antibiotic at day i.

Table 4. Likelihood of $H1, \ldots, H5$ given H.

H	$H1$, $H2$, $H3$		$H3$, $H5$	
	Y	N	Y	N
Y	0.7	0.3	0.6	0.4
N	0.3	0.7	0.4	0.6

The technique of sensitivity value analysis is demonstrated by evaluating the sensitivity of sub-hypothesis H1 (the link connecting the hospitalization at day $i-1$ and the infectious examinations at the day i) to the likelihood value of evidence DE1 (Patient hospitalized at date $i-1$ has performed infectious examinations at the day i).

The analysis of sensitivity value assesses the probability of interest, $P(H_1|\mathrm{DE}_1)P(H_1|\mathrm{DE}_1)$, for a variation in the likelihood value of $P(\mathrm{DE}_1|H_1)$. This needs a sensitivity function, which defines $P(H_1|\mathrm{DE}_1)$ in terms of $x = P(H_1|\mathrm{DE}_1)$ (cf. Eq. (7)).

$$P(H_1|\mathrm{DE}_1)(x) = \frac{P(\mathrm{DE}_1\backslash H_1)P(H_1)}{P(\mathrm{DE}_1)}. \tag{7}$$

If, $P(\mathrm{DE}_1\backslash H_1)P(H_1) = P(H_1)x + 0$, then the coefficient values a $= P(H_1)$ and $b = 0$.

Table 5. Probabilities of DE1, ..., DE5 given *Hi*.

Hi	$H1$, DE1			$H2$, DE2			$H3$, DE3			$H4$, DE4			$H5$, DE5		
	Y	N	U	Y	N	U	Y	N	U	Y	N	U	Y	N	U
	0.8	0.2	0.00	0.75	0.15	0.1	0.8	0.15	0.05	0.7	0.25	0.05	0.10	0.85	0.05
YN	0.2	0.8	0.00	0.15	0.75	0.1	0.15	0.8	0.05	0.25	0.7	0.05	0.05	0.9	0.05

Table 6. Sensitivity values and effects on posterior outputs.

Evidences	Elicited values	Sensitivity values	Change value
ED1	0.8	0.2	0.6
ED2	0.75	0.18	0.57
ED3	0.8	0.07	0.73
ED4	0.7	0.27	0.43
ED5	0.1	0.16	0.06

If, $P(\mathrm{DE}_1) = P(\mathrm{DE}_1 \backslash H_1)P(H_1) + P(\mathrm{DE}_1 \backslash \bar{H}_1)P(\bar{H}_1) = P(H_1)x + P(\mathrm{DE}_1 \backslash \bar{H}_1) P(\bar{H}_1)$.

Then the coefficient values $c = P(H_1)$ and $d = P(\mathrm{DE}_1 \backslash \bar{H}_1)P(\bar{H}_1)$.

Since $P(H_1) = 0.5$ and $P(\mathrm{DE}_1 \backslash \bar{H}_1) = 0.2$ (from Table 5), the coefficients of the sensitivity function are: $a = 0.5$, $b = 0$, $c = 0.5$ and $d = 0.2 * 0.5 = 0.1$.

The application of Eq. (6), gives the sensitivity value of $P(H1|\mathrm{DE1}), \ldots, P(H5|\mathrm{DE5})$ against $P(\mathrm{DE1}|H1), \ldots, P(\mathrm{DE5}|H5)$ visible in Table 6.

As presented by Ref. 47, if the sensitivity value is less than 1, then a small change in the probability value has a negligible consequence on the hypothesis posterior output. Table 6 describes sensitivity values showing the consequences of small changes in evidence likelihood values on the sub-hypotheses posterior outputs. It is clear that all the sensitivity values are less than 1. Hence, we can conclude that our DBN is robust to small variations in the evidence likelihood values in the elicited conditional probabilities.

Major headings should be typeset in boldface with the first letter of important words capitalized.

5.2.2. *Usability evaluation*

Usability evaluation becomes increasingly crucial in the visualization literature.[48] To measure our visual tool usability, we have conducted a usability test with 30 participants. In this study, we have designated three groups of participants: novice, knowledge-intermittent and expert. Table 7 shows the summary of user profile involved in the evaluation task.

Table 7. Participants profile.

Types of participants	Number	Age	Skill
Novice	**G1**: 10 PhD students in medicine	25–30	Limited experience in using computer
Knowledge-intermittent	**G2**: 10 Health Informatics professionals	32–38	Expert in using computer
Expert	**G3**: 10 physicians	35–45	Good experience in using computer

We have conducted this evaluation in three phases:

Phase 1: general feedback

We have received a general feedback on our tool from the 30 participants. It concerns the fundamental principles of the visual analytics design. Their main suggestions concerned a more clearly graphical representation of edge directionality as well as more simple view transition abilities. We have revised our tool based on these suggestions by making nodes interactive in presenting more information about orientation proposal.

Phase 2: experts' feedback

We have planned a specific interview session integrating the 10 experts. Based on their experience in participating in decisional systems development and taking care of patients, we were expecting to get constructive comments on our tool from an expert's perspective.

The experts confirmed that: (1) our interactive visual tool provides insight into the evolution of the patient's state in the fight against nosocomial infection, and (2) it would represent a rewarding increment if it were situated as a visual decision-making. They emphasized that there is an increasing request for decisional systems in the medical domain to be improved by automatic and visual analysis, particularly given the complexity of decision-making issues and the wide range of data to be analyzed. The provided experts' feedback revealed additional assurance of the practical value of our visual tool.

Phase 3: user study

In this final evaluation phase, we have conducted a user study. We have adopted the value-driven evaluation approach,[49] which is applied in DSS and information visualization literature.[50,51] This approach aims at assessing whether a tool was successfully developed and guaranteed integrated fundamental values. We have considered that the participant's verbal response is a part of our tool evaluation. It is a common way to validate our tool's value.[52]

This user study integrates the participants with the three profiles (cf. Table 8). In this context, we have developed: (1) specific tasks that articulate several goals of several visual representations, and (2) post-use surveys to evaluate our tool usability in a quantitative way. We have generated a set of questions for assessing our VIDSS tasks' performance based on the evaluation approach of Refs. 49 and 53. Questions are visible in Table 8.

Table 8 presents the tasks that our participants were asked to achieve using our VIDSS prototype and their interaction techniques. We have developed four sets of tasks labeled from T1 to T4. Each set of tasks is relative to the goal of a specific level of our Visual analytics approach.

T1 required managing the data of the patient, automatically applying the DBN algorithm and generating their visual representations. It is designed to be sure that participants understand the VIDSS structure and objective as well as the visual data

Table 8. Tasks' performance.

Task set	Sub-Tasks	Average score by group[a]		
		G1	G2	G3
T1	**Patterns Level:**			
	(1) Add a new patient (fixed and temporal data).	10.0	9.5	10.0
	(2) Apply the DBN algorithm on a new patient, each day during his/her hospitalization period.	9.0	9.2	9.3
	(3) Apply the visual mapping to generate the graphical representation of the DBN application result.	9.33	9.0	9.8
	(4) Give the signification of each node in this network.	10.0	9.8	10.0
	(5) What is the hospitalization period of the concerned patient by this network.	10.0	10.0	10.0
	(6) Move to the next stage for analyzing the NI occurrence pattern.	9.6	9.0	9.7
T2	**Analysis Level — Automatic Analysis:**			
	(1) For a specific day of patient hospitalization, calculate the support and confidence metrics of the NI probability associated.	5.6	5.0	6.0
	(2) Determine the associated temporal variables.	7.4	7.0	8.0
	(3) Generate the minimum values of the support and confidence metrics.	7.7	7.9	8.0
	(4) Compare the different metrics values to judge the NI probability relevance.	7.5	7.0	7.3
T3	**Analysis Level — Visual Analysis:**			
	(1) Give the taken antibiotics of the patient during his/her hospitalization.	7.8	7.5	8.0
	(2) Give the carried out acts of the patient during his/her hospitalization.	7.8	7.6	8.0
	(3) Give the infectious exams of the patient during his/her hospitalization.	7.8	7.6	8.0
	(4) Apply the interaction modes of the prototype (Navigating in time, Focus and context, labelling and colours adjustment).	7.4	7.6	7.0
	(5) Interpret the patient'scondition.	6.1	5.8	6.0
T4	**Knowledge Level:**			
	(1) Based on the calculated probability, generate the possible recommendation.	6.8	6.5	7.0
	(2) Validate the best recommendation.	4.0	4.0	4.0
T5	Use and explore the VIDSS freely and then report back on what insights you can find.			

[a]To evaluate a task, a participant can attribute a score between [0,10]. Table presents the average of the scores given by the participants of each group.

mining application. Most participants achieved correctly the T1 subtasks (the score is between 9 and 10). They were able to understand and identify the relationships in the force-directed and bar chart graphs.

Each of T2, T3 and T4 subtasks attempted to assess the utility of the generated interactive visual representations. Some participants failed at reading confidence and support metrics for the automatic analysis (T2(1)). This is due to the difficulty of nondata mining experts face in understanding such measures in quantifying the importance of the analysis association. As a matter of fact, it requires several attempts for users to easily assimilate and interpret them.

The scores for T3(5) and T4(2), show that several participants did not seem to understand how to perform the task based on their tacit knowledge. The reason the scores' value is pretty low is due to the fact that the majority of our participants are not experts in the fight against nosocomial infection (for the three groups). In fact, interpreting the patient's condition or selecting the best decision requires, in addition to our proposed visual and automatic analysis, a specific background and experience in this decisional domain in order to be able to control and question the recommendations generated by the system. Since few of our participants have a good idea on nosocomial infections, the scores for these two tasks are low. Perspectives related to the user experience are planned in future work.

Finally, T5 requested participants to freely use and explore the VIDSS. We have received a set of comments. In general, the physicians thought that: (1) the visual association rules technique is well selected to give an idea about the NI probability relevance, (2) the force-directed and bar chart graphs indicate clearly the temporal data relationships and simplify the visual analysis of the discovered patterns. By inspecting these visualizations, physicians can easily make comparisons to interpret the evolution of temporal data and patterns and can intuitively detect the recommended solution to fight nosocomial infections (based on his/her tacit knowledge).

Furthermore, they appreciated the use of interaction modes with the visualization interfaces to focus on what they thought was interesting. While one physician indicated that he/she was not sure about the bar chart graph usefulness, the rest of participants said that this was an interesting visual representation and they liked it.

A final comment provided by two physicians, who were not sure about using the current VIDSS indicating that they were familiar and satisfied with the traditional system used for 6 years (which allows automatic analysis using Bayesian Networks but not visual analysis).[38]

The others thought that it would positively save time compared to the traditional system. After the evaluation of the tasks' performance, participants have gone to the value-driven evaluation for a post-use survey. They were asked to answer 8 questions based on 5-point Likert scale (1 for "Strongly Disagree" and 5 for "Strongly Agree").

According to the results presented in Table 9, Participants assigned relatively high scores to VIDSS usability, generated insight about temporal data and tasks completion (Q1, Q3 and Q7). The mean scores to questions Q2, Q4, Q5 and Q6 are between [3.2–3.8], which are all above the middle of the scale. Q8 asked participants to rate the VIDSS. Most physicians gave high scores. The rest of them thought they would not be able to attribute a precise score without using intensively the proposed VIDSS.

Generally, our VIDSS was very well accepted by users and their feedback suggested that we have a practical basis for deploying this system into real-world settings. Especially in the medical field and due to the fact that one error can cause

Table 9. Value-driven evaluation.

Code	Question	Min	Max	Mean
Q1	The VIDSS was easy to use.	3	5	4.2
Q2	The VIDSS was easy to learn.	2	5	3.6
Q3	The VIDSS enables discovering insights about the temporal data.	3	5	3.9
Q4	The VIDSS enables asking insightful questions about the temporal data.	2	5	3.2
Q5	The VIDSS helps in generating knowledge about the data.	2	5	3.4
Q6	The VIDSS helps in completing the given tasks quickly and save time compared to standard systems.	3	5	3.8
Q7	The VIDSS helps in completing the given tasks effectively.	3	5	3.9
Q8	On a scale of 1–5, how would you rate the VIDSS?	3	5	3.8

death, it was vital to combine the expert capability with the automatic analysis.[19,24,54,55] Accordingly, we present in this paper the visual analytics process to exhibit the cognitive activities exerted for knowledge generation.

6. Conclusion

DSS involve data mining and visualization techniques to combine human intelligence with computational intelligence in order to enhance decision-making quality. Data mining produces automatic patterns extracted from prepared data. Several research works introduced systems for visualizing data, data mining algorithm and extracted patterns.

Due to this fact, we introduced an adapted visual analytics model for acquiring knowledge behind these patterns to finally generate actionable recommendations for making appropriate decisions. It is a generic design framework that can be applied to different domains of application and to a large class of decision-makers. The proposed process of knowledge generation occurs on three main levels: patterns, analysis and knowledge. It allows to automatically and visually studying the displayed data mining patterns to generated associated knowledge.

We have applied this process to fight against nosocomial infections in the Intensive Care Unit of the Teaching Hospital Habib Bourguiba — Sfax, Tunisia. We have developed the Dynamic Bayesian Network (DBN) technique to extract patterns from temporal medical data. These patterns are displayed using interactive force-directed and bar chart graphs to be automatically analyzed (using the association rules technique) and visually interpreted (perceived, recognized, comprehended and reasoned) in obtaining associated knowledge.

We have conducted two evaluation studies: (1) utility evaluation to assess the VIDSS prediction ability and (2) usability evaluation based on three phases (general feedback, experts' feedback and user study). These studies were designed to provide valuable feedback from selected experts. The evaluation results confirm positively the value of the developed VIDSS. Such evaluation reflected the feasibility of the suggested visual analytics process.

From a managerial perspective, the developed VIDSS suggests several levers of action for ICU physicians who wish to ensure the management of medical files, to improve the continuous monitoring of their patients as well as to minimize the risk of nosocomial infections. Physicians, decision-makers and experts in nosocomial infections, can indeed recommend one or more solutions generated by the VIDSS after intelligent and visual analysis of patients' data which would save time and make urgent decisions in real time. This system aims at minimizing the mortality risk of patients caused by these infections. In consequence, patients in ICU are better handled and the reanimation quality is improved.

From a policy perspective, by using the developed VIDSS, physicians can influence ICU policy making in three ways: (1) they can predict NI mortality risk and thus identify critical problems, (2) analyze the cost–benefit of the action execution and facilitate the development of cost effective action plans, and (3) actively participate in the ICU policy process through the real-time decision-making.

Indeed, our adapted visual analytics model grants knowledge generation for intelligent decision-making. However, our research can be improved by considering the collaboration that must exist between the domain expert and the visual analytics expert. In fact, without domain knowledge, visual analytics experts are able to generate findings and information about the data, not the domain. Domain experts are responsible for formulating problem hypotheses, detecting and interpreting patterns. They must be familiar with visual analytics methods and systems. Likewise, visual analytics experts have to learn about the problem domain. Another limitation is related to history tracking.

Our model can be enhanced by automatically recording the knowledge exploration process. A possible approach is to capture the actions of the user in order to provide a history. The user can revisit the history for recovery and reversal operations. All these limitations will be considered, in future research, for improving our VIDSS.

An immediate extension of our study would be to improve our K2 algorithm by proposing a new node-ordering algorithm and introducing a new search method for causality detection. We aim also to apply the proposed visual analytics process to other data mining techniques (such as Neural Network and Fuzzy Logic) and then provide a comparative study between these techniques and our DBN. Another extension would be to develop and integrate other advanced visual representations and interactions in our VIDSS prototype. In addition, we can improve the ARN technique[41] to produce direct pattern visualization for exhibiting more the relationships between items.

We also plan to improve our VIDSS by studying its users. It aims at understanding how users think and feel, what they need and want, and why. We propose to use that information to analyze VIDSS users' behavior and experience in order to enhance their training. Lastly, our current prototype analyzes the problem of ICU nosocomial infections. A future study could expand this case study by integrating various hospital services.

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