Contribution to the design and evaluation of visual intelligent Decision Support Systems, application to the healthcare domain

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Doctor in Engineering of Computer Systems

Contribution to the design and evaluation of visual intelligent Decision Support Systems, application to the healthcare domain

Approved in 19/12/2016 by the Examination Committee composed of

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M.	**Mounir BEN AYED**	*Examiner*

Acknowledgements

Many people contributed to my career in so many ways that I could write pages and pages of acknowledgments: family, teachers, colleagues, students, and friends, without whom it would be impossible to get here: *my sincere thanks to all of them*.

First of all, I would like to thank Pr. Mounir Ben Ayed. With him I learned everything that I know: to perform research, to work in-group and to supervise students. Thanks for the first co-supervision opportunity, which resulted in a great evolution in my career.

During this HDR, I had the pleasure of working with Pr. Christophe Kolski. Special thanks for his support and enthusiasm that makes this work very stimulating and challenging.

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I would like to take the opportunity to thank Pr. Faiez Gargouri for having accepted to judge this work and to be president of the jury.

Undoubtedly, thank you very much to the professors Faouzi Moussa and Bertrand David for their precious time spent in reading this document and writing the evaluation report.

Finally, I deeply thank all my students, without them the work presented in this report would not be completed.

Abstract

Title of the manuscript: Contribution to the design and evaluation of visual intelligent Decision Support Systems, application to the healthcare domain.

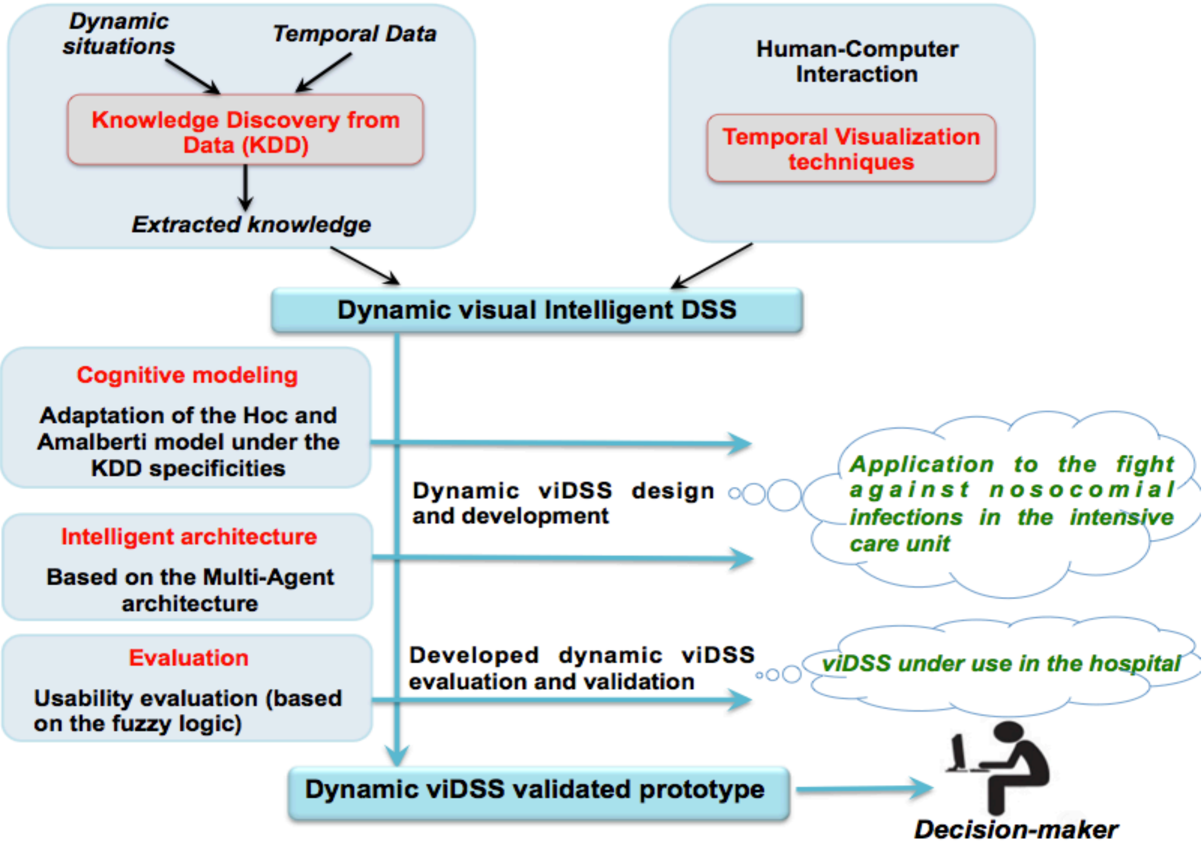
Keywords of the research work: decision support systems, data mining, Knowledge Discovery from Data, visualization, cognitive modeling, multi-agent architecture, fuzzy logic based usability evaluation.

This manuscript presents my postdoctoral work I conducted since 2012 on the theme of the modeling and evaluation of Decision Support Systems, based on the data mining and visualization technologies, in dynamic situations. Healthcare domain is a very important application area for these 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 applying the data mining process have become more and more difficult. To overcome this problem, we propose to integrate visualization techniques in order to use human pattern recognition capabilities and then to increase confidence and improve the comprehensibility of the temporal data and knowledge. To design such complex and real-time systems, two modeling contributions are suggested:

- The first consists in integrating appropriate temporal visualizations in the intelligent DSS modules and designing the resulting dynamic visual intelligent DSS (viDSS) using a cognitive model. This kind of modeling allows understanding the human behavior 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 cognitive model 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 dynamic viDSS modules has to be associated with an adapted HCI.
- The second consists in proposing a new architecture based on the Multi-agent technology in the real-time environment. A set of intelligent agents is involved in each visual intelligent DSS module. They play the main role in assisting a user in dynamic decision-making; more they are given the authority to communicate with each other to achieve the decisional objective of the visual intelligent DSS.

We have applied the cognitive modeling approach based on the Multi-agent architecture to design and develop a dynamic viDSS 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 usability dimension. A new proposed evaluation method based on the fuzzy logic technique was introduced. As an outcome, this evaluation has shown satisfactory results.

Graphical Abstract



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Part I. Detailed Curriculum Vitae

Overview

TEACHER-RESEARCHER IN THE FIELD OF COMPUTER SCIENCE

Date and place of birth: 23 November 1981 in Fériana, Kasserine (Tunisia)
Nationality: Tunisian
Civil Status: Married
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Faculté des Sciences et Techniques de Sidi Bouzid
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Actual situation

- **Assistant professor** recruited by the Ministry of Higher Education and Scientific Research in 2013 following a promotion session.
- **Teacher-Researcher** in the field of computer science since March 2006. Currently a teacher in the Faculty of Computer Sciences and Techniques of Sidi Bouzid, department of Mathematics and Computer Science.
- Research activities in the laboratory **REGIM-Lab** (REsearch Groups in Intelligent Machines) and within the **iDSS** (intelligent Decision Support Systems) research group.

Memberships

Since 2012	IEEE Member
Since 2012	IEEE Engineering in Medicine and Biology Society Member
2009 - 2011	IEEE Computer Society Member
2009 - 2011	Member of the research laboratory LAMIH-UMR CNRS, University of Valenciennes and Hainaut-Cambrésis (France) *Research group*: Automatic Reasoning and Human-Computer Interaction (http://www.univ-valenciennes.fr/LAMIH/)
2008 - 2011	Student member of Institute of Electric and Electronic Engineering
Since 2006	Member of the Research Groups in Intelligent Machines (REGIM-Lab), National Engineering School, University of Sfax (Tunisia) (http://www.regim.org).

Diplomas and qualifications

- **September 2013**: qualification to the functions of Assistant Professor by the Ministry of Higher Education and Scientific Research after a promotion session of teachers.
- **July 2011**: graduated with a jointly supervised Ph.D. diploma with a "Right Honorable" mention.
  - *Title*: User-centered approach for the design of decision support systems based on knowledge discovery in databases process, application to the fight against nosocomial infections.
  - *Institutions awarding the diploma*:
    - National Engineering School, University of Sfax, Tunisia (Specialty: Computing System engineering specialty).
    - University of Valenciennes and Hainaut-Cambrésis, France (Specialty: Automatic and Computer Science of Industrial and Human Systems, Computer Science mention).
  - *Laboratories where the thesis was prepared:*
    - REGIM-Lab: Research Groups in Intelligent Machines, SFAX, Tunisia.
    - LAMIH-UMR CNRS 8201: Laboratory of Industrial and Human-Automation Control, Mechanical engineering and Computer Science, Valenciennes, France.
  - *Mention:* Right Honorable
  - *Thesis Supervisors*
    - Pr. Mohamed Adel Alimi, Professor, University of Sfax, REGIM-lab, Tunisia
    - Pr. Christophe Kolski, Professor, University of Valenciennes and Hainaut-Cambrésis, LAMIH-UMR CNRS Laboratory.
  - *Thesis Co-Supervisor*: Dr. Mounir Ben Ayed, University of Sfax, REGIM-Lab
  - *Jury*:

President	David Bertrand - Professor, Central Institute, Lyon, France
Reviewers	Faouzi Moussa - Associate Professor, University of Tunis, Tunisia
	Patrick Girard - Professor, University of Poitiers, France
Examiner	Pierre Morizet-Mahoudeaux - Professor, University of Technology, Compiègne, France

- **September 2010**: qualification to the functions of Assistant by the Ministry of Higher Education and Scientific Research after a recruitment session of assistant teachers in Computer Science specialty.
- **April 2007**: graduated with a Master diploma in the specialty of new technologies of dedicated computer systems - highest honor mention.

- *Title*: Towards a development approach of decision support system based on data mining
- *Supervisor*: Dr. Mounir Ben Ayed, University of Sfax, REGIM-Lab

- **September 2005**: qualification to the functions of common trunk professor by the Ministry of Higher Education and Scientific Research.
- **June 2005**: success in the national contest of aptitude to the professorship of the secondary education: CAPES (Tunisia)
- **June 2004**: graduated with the Four-year University Degree on Computer Science applied to the management at the Superior institute of Management of Tunis, University of Tunis (Tunisia)
- **June 2000:** graduated with the Baccalaureate diploma on mathematics - March 2, 1934, secondary school, Sidi Bouzid (Tunisia).

Research activities

I summarize in this section the master and Ph.D. supervision activities that I have conducted in the REGIM-Lab.

Supervision of master students

I supervised five masters to validate the research Master 2 courses:

1. Supervision of the master of Emna Ben Mohamed defended on February 2014. Master on Information system and new technologies, Faculty of Economics and Management of Sfax.

   Title: «*Using visualization techniques in the knowledge extraction process for decision-making*».

   Publications:

   a. Ltifi H., Ben Mohamed E. and Ben Ayed M. (2015), Interactive visual KDD based temporal Decision Support System, *Information Visualization*, Vol. 14, no. 1, pp. 1-20.

   b. Ben Mohamed E., Ltifi H., Ben Ayed M. (2014), Integration of temporal data visualization techniques in a KDD-based DSS, *Journal of Network and Innovative Computing (JNIC)*, Vol 2 (1), pp. 061 - 070.

   c. Ben Mohamed E., Ltifi H., Ben Ayed M. (2013), Using visualization techniques in knowledge discovery process for decision making, *The 13th International Conference on Hybrid Intelligent Systems (HIS 2013)*, Hammamet, Tunisie, pp 94-99.

2. Supervision of the master of Awatef Brahmi, defended on December 2014. Master on Computer science, Higher Institute of Computer Science and Multimedia of Sfax.

   Title: «*Towards an evaluation approach of visual representations of a DSS based on KDD*».

   Publications:

   a. Brahmi A., Ltifi H., Ben Ayed M. (2014), Approach for the evaluation of a KDD based DSS visual representations, *2014 Middle East Conference on Biomedical Engineering (MECBME)*, Qatar, 2014, pp. 338-341.

   b. Brahmi A., Ltifi H., Ben Ayed M. (2013), *Evaluating clinical DSS temporal visualizations, International Conference for Engineering Sciences for Biology and Medicine, ESBM 2013*, Mahdia, Tunisie, November 29-December 1, 2013, pp.33-48, 2013.

3. Supervision of the master of Randa Ben Ammar, defended on December 2015. Master on.

   Title: «*Visual and cognitive Contribution to the Knowledge Evaluation in a DSS based on a KDD process: Medical Application* ».

Currently, I supervise two masters:

1. The master of Safa Mohamed started on January 2016. Master on Computer science, Faculty of Sciences of Gafsa.

   Title: «*Visual and cognitive contribution for the temporal data mining*»

2. The master of Ibtissem Brahmi started on January 2016. Master on Computer science, Faculty of Sciences of Gafsa.

   Title: « *Implementing a machine learning algorithm for the evaluation of medical visualizations* »

Co-Supervision of Ph.D. students

- **Thesis in progress**

1. Co-supervision of the thesis of Hamdi Ellouzi since September 2011 to propose a Multi-Agent architecture for the design of a viDSS for the fight against nosocomial infections.

   Title: « *A Visual Intelligent Decision Support Systems based on Multi Agent Systems, application in Medical Field* »

   Supervisor: Mounir Ben Ayed

   Planned date of Ph.D. defense: December 2016

   Publications:

   a. Ellouzi H., Ltifi H., Ben Ayed M. (2015), New Multi-agent architecture of visual intelligent Decision Support Systems: Application in the medical field, *The 12th ACS/IEEE International Conference on Computer Systems and Applications*, accepted paper, Marrakech, Morocco, November 2015.

   b. Ellouzi H., Ltifi H., Ben Ayed M. (2015), Multi-agents based visual intelligent decision support system in the real-time environment, *IETE Journal of Research* (paper under revision).

2. Co-supervision of the thesis of Emna Ben Mohamed since September 2014 to propose cognitive modeling activities of a viDSS, application to the fight against nosocomial infections.

   Title: «Cognitive modeling of a DSS based on visual data mining process in dynamic situations»

   Supervisor: Mounir Ben Ayed

   Publication: Ben Mohamed E., Ltifi H., Ben Ayed M. (2015), Using Bloom's taxonomy to enhance interactive concentric circles representation, *The 12th ACS/IEEE International Conference on Computer Systems and Applications*, accepted paper, Marrakech, Morocco, November 2015.

3. Co-supervision of the thesis of Afef Ben Jemmaa since September 2014 to propose a Multi-Agent architecture of a visual Remote Healthcare Monitoring system.

   Title: « multi-agent approach for the development of a Remote Healthcare Monitoring system based on Visual Data Mining »

   Supervisor: Mounir Ben Ayed

Publication: Ben Jemmaa A., Ltifi H., Ben Ayed M. (2015), Multi-Agent architecture for Visual Intelligent Remote Healthcare Monitoring System, *The 15th International Conference on Hybrid Intelligent Systems* (HIS 2015) in Seoul, South Korea, November 2015, pp. 211-221.

4. Co-supervision of the thesis of Jihed Elouni since September 2014 to propose a visualization framework of extracted patterns by a Dynamic Bayesian Network technique.

   Title: «Knowledge visualization model of a data mining based dynamic decision support system »

   Supervisor: Mounir Ben Ayed and Mohamed Masmoudi

   Publication: Elouni J., Ltifi H., Ben Ayed M. (2015), Knowledge visualization model for intelligent dynamic decision-making, *The 15th International Conference on Hybrid Intelligent Systems (HIS 2015)* in Seoul, South Korea, November 2015, pp. 223-235.

5. Co-supervision of the thesis of Saber Amri since September 2014 to propose an evaluation method of visualizations generated by a viDSS.

   Title: «An intelligent methodology for evaluating visualizations generated by a DSS based on Visual Data Mining»

   Supervisor: Mounir Ben Ayed

   Publication: Amri S., Ltifi H., Ben Ayed M. (2015), Towards an intelligent evaluation method of medical data visualizations, *The 15th International Conference on Intelligent Systems Design and Applications (ISDA)*, in Marrakech, Morocco, accepted paper, December 2015.

Collective responsibility activity

This section provides information on the different activities in collective responsibilities that I supported. They allow attesting my involvement in the research community.

Organization of the workshop WIMTA 2015

I organized the WIMTA Workshop (Workshop on Intelligent Machines: Theory & Applications) in its 25th edition. This workshop offers the opportunity for latest Ph.D. student research results discussion and for innovation in machine intelligence and linked data presentation. I was, in particular, responsible for the scientific part of the workshop by organizing the plenary talks, practical sessions, Ph.D. student presentations (oral, poster and demo) and exhibition of developed applications.

Member of the iData-iDSS group

Since 2012, I belong to the iData-iDSS group. In particular, I contributed to the implementation of the interactive decision support system for the fight against nosocomial infections under use in Intensive Care Unit of the Habib Bourguiba Hospital of Sfax, Tunisia. It is the initial prototype on which the group researchers contribute.

Participation in the review committees

I am a member of the following review committees:

- **The Decision Support Systems** journal since 2015
- **The Workshop WIMTA** (Workshop on Intelligent Machines: Theory & Applications) since 2012
- **The Symposium on Machine Intelligence** (ICALT-SIMTA'2013), which was held in Sousse-Tunisia from 29 to 31 May 2013.
- **The 6th International Conference on Soft Computing and pattern recognition** (SoCPaR 2014), which was held in Tunis, Tunisia from 11 to 14 August 2014.

Pedagogical administration

- I assured the C2i coordination activities within the Higher Institute of Arts and Crafts of Gafsa for three years from 2007 to 2010
- I participated in the graduation projects defenses as a supervisor, reviewer and president of the Jury since 2011
- I assured the pedagogical coordination activities of the students of the Fundamental license in Computer Science - Level 2 during the academic years 2012-2013 and 2013-2014.
- I assured the pedagogical coordination activities of the graduation projects of students of the Fundamental license in Computer Science - Level 3 during the academic years 2012-2013 and 2013-2014.
- I am a Member of the organization committee of the graduation projects in the Faculty of Sciences and Techniques of Sidi Bouzid (since 2015)
- I am the Chair of the “Computer Science license and Research Master preparation” habilitation committee in the faculty of Sciences and Techniques of Sidi Bouzid (since 2015).

Training activities

I assured the training activities to:

- The technicians in the University of Gafsa to introduce the computer maintenance and networks concepts as well as their applications.
- The students of the Basic Degree in Computer Science-Level 3 to explain how to prepare a graduation project and how to write a scientific report.

Teaching activities

This section provides information on the different teaching activities that I am conducting in parallel to my research activities described in detail in Part 2 of this document. These activities are divided into three establishments: the Higher Institute of Arts and Crafts of Gafsa, the Faculty of Sciences of Gafsa and the Faculty of Sciences and Techniques of Sidi Bouzid:

- The first phase (until August 2010) represents my teaching activities as a Professor Common Trunk.
- The second phase from September 2010 to August 2013 represents my teaching activity as an Assistant.
- The third phase from September 2013 represents my teaching activity an Assistant Professor.

Period 09/2005 - 08/2010

I, first of all, achieved five years of teaching (equivalent to 504 hours of tutorials per year) as a common trunk teacher at the Higher Institute of Arts and Crafts of Gafsa. My hourly volume is detailed as follows.

Table 1.1: hourly volume as a common trunk professor

Higher Institute of Arts and Crafts of Gafsa			
	Subject	**Charge**	**Section**
2008 - 2009	Computer graphics: Photoshop software	Integrated Course (Int. C.)	1st year interior decoration
2007 - 2010	C2i	Int. C.	1st year interior decoration
2005 - 2010	Computer Science: General concepts	Int. C.	1st year interior decoration
2005 - 2008	Computer-assisted Drawing	Int. C.	1st year interior decoration
2005 - 2006	Computer-assisted Music	Int. C.	1st year music and musical sciences

Period 09/2010 - 08/2013

I thereafter recruited as an assistant at the faculty of Sciences of Gafsa, where I achieved three years of teaching (equivalent to 336 hours of tutorials per year). My hourly volume is detailed as follows.

Table 1.2: hourly volume as an assistant

Faculty of Science of Gafsa			
	Subject	**Charge**	**Section**
2012 – 2013	Advanced Oriented-Object Design	Lecture, Tutorials	Fundamental License

2010 – 2012			in Computer Science - Level 3 (FLCS3)
	Human-Computer Interface	Lecture	FLCS3
	Object-oriented design methodology	Lect., Tut.	FLCS2
	Supervising graduation projects		FLCS3

Period Since 2013

At 2013, I promoted to an assistant professor in the faculty of Sciences of Gafsa. After a year, I switched to the faculty of Sciences and Techniques of Sidi Bouzid where I achieved two years of teaching (equivalent to 266 hours of tutorials per year). I also teach master's students in computer science for two years (equivalent to 392 hours of tutorials in total). My hourly volume is detailed as follows.

Table 1.3: hourly volume as an assistant professor

Faculty of Science of Gafsa			
	Subject	**Charge**	**Section**
2013-2014	Advanced Oriented-Object Design	Lect., Tut.	FLCS3
	Human-Computer Interface	Lecture	FLCS3
	Object-oriented design methodology	Lect., Tut.	FLCS2
	Supervising graduation projects		FLCS3
2014-2016	Advanced architectures and systems	Lect., Tut.	Computer Science Master – Level 1
Faculty of Science and Techniques of Sidi Bouzid			
	Subject	**Charge**	**Section**
2014-2015	Software engineering	Lect., Tut.	FLCS2
	Object-oriented design methodology	Tut.	FLCS2
	Computer Architecture	Tut.	FLCS1
2015-2016	Advanced Oriented-Object Design	Int. C.	FLCS3
	Human-Computer Interface	Lecture	FLCS3
	Object-oriented design methodology	Lect., Tut.	FLCS2
	Introduction to Business Intelligence systems	Int. C.	FLCS3
	Project management	Int. C.	FLCS3
	Supervising graduation projects		FLCS3

Publications

The publications I have written in the context of my research activities are listed in the following tables.

International journal papers

Table 1.4: journal papers

Title	Interactive visual KDD based temporal Decision Support System
Abstract	The paper aims to present a generic interactive visual analytics solution that provides temporal decision support using Knowledge Discovery in Data (KDD) modules together with interactive visual representations. It bases its design decisions on the classification of visual representation techniques according to the criteria of temporal data type, periodicity and dimensionality. The design proposal is applied to an existing medical KDD-based decision support system aiming at assisting physicians in the fight against nosocomial infections in the intensive care units. Our solution is fully implemented and evaluated.
Journal name	Information Visualization [IF=0.541]
Reference	**Ltifi H., Ben Mohamed E. and Ben Ayed M. (2016)**, Interactive visual KDD based temporal Decision Support System, *Information Visualization*, Vol. 15, no. 1, pp. 31-50.
Title	Combination of cognitive and HCI modeling for the design of KDD-based DSS used in dynamic situations
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 behaviors 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.
Journal name	Decision Support Systems [IF=2.313]
Reference	**Ltifi H., Kolski C., Ben Ayed M. (2015).** Combination of cognitive and HCI modeling for the design of KDD-based DSS used in dynamic situations. *Decision Support Systems,* vol. 78, pp. 51-64.
Title	Integration of temporal data visualization techniques in a KDD-based DSS
Abstract	This paper addresses the interactive temporal Decision Support System (DSS) based on Knowledge discovery in Databases (KDD). Our goal is to propose an approach to improve decision-making process by integrating visualization techniques in the different KDD stages for producing visual interpretations in order to combine potential computational capabilities of the machine with the human judgment. Our application context is the fight against the Nosocomial infections.
Journal name	Journal of Network and Innovative Computing

Reference	**Ben Mohamed E., Ltifi H., Ben Ayed M. (2014),** Integration of temporal data visualization techniques in a KDD-based DSS, *Journal of Network and Innovative Computing (JNIC)*, Vol 2 (1), pp. 061 - 070.
Title	Perspective wall technique for visualizing and interpreting medical data
Abstract	Increasing the improvement of confidence and comprehensibility of medical data as well as the possibility of using the human capacities in medical pattern recognition is a significant interest for the coming years. In this context, we have created a visual knowledge discovery from databases application. It has been developed to efficiently and accurately understands a large collection of fixed and temporal patients' data in the Intensive Care Unit in order to prevent the nosocomial infection occurrence. It is based on data visualization technique, which is the perspective wall. Its application is a good example of the usefulness of data visualization techniques in the medical domain.
Journal name	International Journal of Knowledge Discovery in Bioinformatics
Reference	**Ltifi H., Ben Ayed M., Trabelsi G., Adel M. Alimi, (2012),** Perspective wall technique for visualizing and interpreting medical data, *International Journal of Knowledge Discovery in Bioinformatics*, vol. 3(2), pp. 45-61.
Title	Dynamic Decision Support System Based on Bayesian Networks, application to fight against the Nosocomial Infections.
Abstract	The improvement of medical care quality is a significant interest for the future years. The fight against nosocomial infections (NI) in the intensive care units (ICU) is a good example. We will focus on a set of observations, which reflect the dynamic aspect of the decision, the result of the application of a Medical Decision Support System (MDSS). This system has to make a dynamic decision on temporal data. We use dynamic Bayesian network (DBN) to model this dynamic process. It is a temporal reasoning within a real-time environment; we are interested in the Dynamic Decision Support Systems in healthcare domain (MDDSS)
Journal name	International Journal of Advanced Research in Artificial Intelligence
Reference	**Ltifi H., Trabelsi G., Ben Ayed M., Alimi A. (2012),** Dynamic Decision Support System Based on Bayesian Networks, application to fight against the Nosocomial Infections, *International Journal of Advanced Research in Artificial Intelligence (IJARAI)*, vol 1(1), pp. 22-29.

International Conference papers

Table 1.5: conferences papers

Title	Visual Intelligent Remote Healthcare Monitoring System using Multi-agent Technology
Abstract	For a good use of health care resources to reflect the increasing numbers of elderly and dependent persons, Remote Healthcare Monitoring Systems (RHMS) are becoming more and more requested. Such systems are built around signs and home environmental sensors to collect data and to get vital signs results to transmit any valuable information to patients and physicians. The process of extracting, analyzing and interpreting this data combines several techniques: data mining, decision-making, visualization and detection of damage. In This context, our works is integrates to introduce a visual intelligent RHMS using the technology of multi-agent coordination.

Conference name	The international conference on Advanced Technologies for Signal & Image Processing (ATSIP)
Reference	**Ben Jemmaa A., Ltifi H., Ben Ayed M. (2016),** Visual Intelligent Remote Healthcare Monitoring System using Multi-agent technology, *The international conference on Advanced Technologies for Signal & Image Processing ATSIP 2016*, March 21-24, 2016, Monastir-Tunisia, accepted paper.
Title	Towards an intelligent evaluation method of medical data visualizations
Abstract	In this paper we evaluate interactive visualizations generated by existing medical tool used to visualize patients' fixed and temporal data. It has been developed to better understand a large collection of patients' data in the Intensive Care Unit in order to daily prevent the nosocomial infection occurrence. Existing visualization evaluation studies introduce a variety of classical and novel evaluation methods but we need to integrate more intelligent techniques for the evaluation of visual analytics tasks of medical data. The proposed method consists of interpreting and analyzing initial evaluation results using fuzzy logic technique. Such technique allows intelligent analysis of the evaluation results. Our contribution tends to propose a more novel and interesting method to reach high performance in evaluation procedure.
Conference name	The 15th International Conference on Intelligent Systems Design and Applications (ISDA) [class C]
Reference	**Amri S., Ltifi H., Ben Ayed M. (2015)**, Towards an intelligent evaluation method of medical data visualizations, *The 15th International Conference on Intelligent Systems Design and Applications (ISDA)*, in Marrakech, Morocco, acceped paper, december 2015.
Title	Knowledge visualization model for intelligent dynamic decision-making
Abstract	Decision Support Systems frequently involve data mining techniques for automatic discovery of useful patterns. Using appropriate visualization techniques for displaying temporal extracted knowledge integrates users in the decision-making process. In this context, our work consists in proposing a model that supports the knowledge visualization for decision-making. Such model allows the decision-maker to quickly recognize, gain insight and interpret the knowledge in the temporal patterns representation. This proposition was applied to fight against nosocomial infections in the intensive care units to prove the viability of the proposed model.
Conference name	The 15th International Conference on Hybrid Intelligent Systems (HIS 2015) [class C]
Reference	**Elouni J., Ltifi H., Ben Ayed M. (2015)**, Knowledge visualization model for intelligent dynamic decision-making, *The 15th International Conference on Hybrid Intelligent Systems* (HIS 2015) in Seoul, South Korea, November 2015, pp. 223-235.
Title	Multi-Agent architecture for Visual Intelligent Remote Healthcare Monitoring System
Abstract	The growing numbers of elderly and dependent people leads to utilize Remote Healthcare Monitoring Systems (RHMS). RHMS are decision support systems where data collected from vital signs and home environmental sensors need to be analyzed using data mining techniques. Visualization allows gaining insight into these data and the extracted knowledge. The aim

	of this paper is to introduce a visual intelligent RHMS. To design such real-time, complex and distributed system, we propose to employ the Multi-Agent coordination technology. The proposed approach is illustrated and evaluated to assess the developed RHMS ability to improve the monitoring performance.
Conference name	The 15th International Conference on Hybrid Intelligent Systems (HIS 2015) [class C]
Reference	**Ben Jemmaa A., Ltifi H., Ben Ayed M. (2015)**, Multi-Agent architecture for Visual Intelligent Remote Healthcare Monitoring System, *The 15th International Conference on Hybrid Intelligent Systems* (HIS 2015) in Seoul, South Korea, November 2015, pp. 211-221.
Title	Using Bloom's taxonomy to enhance interactive concentric circles representation
Abstract	Concentric circles representation has been developed for visualizing the periodic character of a temporal data set. It is particularly useful for visually interpreting periodic time-oriented patterns extracted by data mining techniques. However, this requires a cognitive study to support the transformation into the closest mental representation to reality. In this paper, the proposed information visualization tool is enhanced taking into account key human factors for temporal patterns perception and cognition. This allows facilitating visual analysis of data space to make the right decision by exerting a minimum of cognitive load. We based our work on the taxonomy proposed by Bloom of the cognitive domain to improve the concentric circles technique.
Conference name	The 12th ACS/IEEE International Conference on Computer Systems and Applications [class C]
Reference	**Ben Mohamed E., Ltifi H., Ben Ayed M. (2015),** Using Bloom's taxonomy to enhance interactive concentric circles representation, *The 12th ACS/IEEE International Conference on Computer Systems and Applications*, accepted paper, Marrakech, Morocco, November 2015.
Title	New Multi-agent architecture of visual intelligent Decision Support Systems, *Application in the medical field*
Abstract	Currently, Decision support systems in dynamic and complex environment involves the use of visual data mining technology for interactive data analysis and visualization. This paper presents a new architecture for designing such systems. The envisaged architectures based on the Multi-Agent Systems to improve coordination and communication between the different system modules to generate the appropriate solution for a specific problem. In this work, we have applied the proposed architecture to develop visual intelligent clinical decision support systems to fight against nosocomial infections. The developed prototype was evaluated to show the new architecture applicability.
Conference name	The 12th ACS/IEEE International Conference on Computer Systems and Applications [class C]
Reference	**Ellouzi H., Ltifi H., Ben Ayed M. (2015),** New Multi-agent architecture of visual intelligent Decision Support Systems: Application in the medical field, *The 12th ACS/IEEE International Conference on Computer Systems and Applications*, accepted paper, Marrakech, Morocco, November 2015.
Title	Approach for the evaluation of a KDD based DSS visual representations
Abstract	Due to the progressing growth of temporal data, data analysis and exploration

	become more and more difficult task; particularly in the medical domain. For this reason, it seems important to use Decision Support System (DSS) based on the decisional tool Knowledge Discovery in Data (KDD) and the visualization techniques for assisting the user to get and understand information. Our research is based on the visual representations of an existing KDD based DSS for the fight against nosocomial infections. In this paper, we are interested in proposing a method, focusing on the user evaluation of this system.
Conference name	Middle East Conference on Biomedical Engineering
Reference	**Brahmi A., Ltifi H., Ben Ayed M. (2014),** Approach for the evaluation of a KDD based DSS visual representations, *2014 Middle East Conference on Biomedical Engineering (MECBME)*, Qatar, 2014, pp. 338-341.
Title	Using visualization techniques in knowledge discovery process for decision making
Abstract	The presence of large quantities of temporal data requires interactive analysis for decision-making. Interactive decision support system (DSS) based on knowledge discovery in databases (KDD) process proves to be useful. Temporal data visualization techniques are used in the KDD stages to increase the user participation as well as its confidence in the result in order to improve the decision support quality. Our applicative context is the fight against nosocomial infections in the intensive care unit.
Conference name	The 13th International Conference on Hybrid Intelligent Systems [class C]
Reference	**Ben Mohamed E., Ltifi H., Ben Ayed M. (2013)**, Using visualization techniques in knowledge discovery process for decision making, *The 13th International Conference on Hybrid Intelligent Systems (HIS 2013)*, Hammamet, Tunisie, pp 94-99.
Title	Evaluating clinical DSS temporal visualizations
Abstract	Clinical decision support systems involve frequently time-oriented data visualizations. These representations support users in the decision-making process. In this context, our work consists in proposing a method focusing on the evaluation of the temporal visual representations of an existing clinical DSS for the fight against nosocomial infections.
Conference name	International Conference for Engineering Sciences for Biology and Medicine
Reference	**Brahmi A., Ltifi H., Ben Ayed M. (2013),** Evaluating clinical DSS temporal visualizations, *International Conference for Engineering Sciences for Biology and Medicine, ESBM 2013,* Mahdia, Tunisie, November 29- December 1, 2013, pp.33-48, 2013.

International Workshop

Table 1.6: workshop papers

Title	Using perspective wall to visualize medical data in the Intensive Care Unit
Abstract	Due to the progressing growth of temporal data, data analysis and exploration become more and more difficult task; particularly in the medical domain. For this reason, it seems important to use Decision Support System (DSS) based on the decisional tool Knowledge Discovery in Data (KDD) and the

	visualization techniques for assisting the user to get and understand information. Our research is based on the visual representations of an existing KDD based DSS for the fight against nosocomial infections. In this paper, we are interested in proposing a method, focusing on the user evaluation of this system.
Conference name	IEEE 12t^h International Conference on Data Mining [class A*]. Workshop: Workshop on Biological Data Mining and its Applications in Healthcare
Reference	**Ltifi H., Ben Ayed M., Trabelsi G., Alimi A-M. (2012)**. Using perspective wall to visualize medical data in the Intensive Care Unit. *IEEE 12t^h International Conference on Data Mining Workshops: Workshop on Biological Data Mining and its Applications in Healthcare*, IEEE Computer Society, Brussels, Belgium, December 10 - 13. pp. 72-78.

Book chapter

Table 1.7: Book chapter

Title	Visual Intelligent Decision Support Systems in the medical field: design and evaluation
Abstract	Tendency for visual data mining application in the medical field is increasing, because it is rich with temporal information, furthermore visual data mining is becoming a necessity for intelligent analysis and graphical interpretation. Such use of interactive machine learning allows to improve the quality of medical decision-making process by effectively integrating and visualizing discovered important patterns and/or rules. This chapter provides a survey of visual intelligent decision support systems in the medical field. First, we highlight the benefits of combining potential computational capabilities of data mining with human judgment of visualization techniques for medical decision-making. Second, we introduce the principal challenges of such decision systems, including the design, development and evaluation. In addition, we study how these methods were applied in medical domain. Finally, we discuss some open questions and future challenges
Book name	Machine Learning for Health Informatics
Reference	**Ltifi H. and Ben Ayed M., (2016),** Visual Intelligent Decision Support Systems in the medical field: design and evaluation, *Machine Learning for Health Informatics*, LNCS Springer, in press

Part II. Contribution to the design and evaluation of visual intelligent DSS

Chapter 1 : Introduction

It is with great pleasure that I write a summary of four years of post-doctoral work in a single document. It is not easy to do so. The difficulty lay not in the writing itself, but in the selection of works that will be mentioned. To make this selection, I mainly based on the work proved by publications.

1.1. Theoretical context

The general theme of research I am working on is the decision support systems based on data mining and visualization in dynamic situations.

Decision Support Systems (abbreviated DSS) are interactive computerized systems that help people making appropriate decisions. The decision process is a collection of linked tasks, which include: collecting data, analysing them, identifying scenarios, choosing among possible alternatives, implementing and finally evaluating the selected choice. Nowadays, most of the exploited data are temporal. Hence, the decision-making process is dynamic and requires a series of decisions, where the decisions are not independent. These dynamic DSS provide accurate information at the appropriate time, and adequately assisting the decision-making process. The dynamic decisions must be taken in real-time, thus making time constraints an important issue of decision support.

To provide an efficient and optimal dynamic decision making, the collected data must be accurate and understandable. These properties require some kind of intelligence: *Intelligent DSS (iDSS)*. Currently, such systems arise from the combination of the data mining techniques and the fundamental DSS function models (data mining based DSS). DSS and data mining are complementary to provide intelligent decision support by discovering and representing relevant patterns and knowledge for the quality improvement of the decision process.

As the dynamic iDSS are highly interactive, it is thus significant to understand the role of the user who can also be seen as a decision-maker in the data mining and Dynamic DSS processes. In fact, the human knowledge, creativity and flexibility are joint with the huge storage capacity and computing power of computers in dynamic situations. Hence, the idea is to combine traditional data mining algorithms with information visualization techniques. Coupling them showed interested visual analytics results in many application areas. Generating overviews and exploring real-time data space allow visually extracting potentially useful information. We are so interested in visual data mining based Dynamic DSS: *visual iDSS (viDSS)*. The decision-maker in charge of this kind of systems is required to simultaneously manage a set of visualization, data mining and decision tasks dynamically.

Our research is in this context; it outlines the integration of the data mining and visualization technologies in the dynamic decision support activities. It aims to assist organizations to make important decisions faster with higher confidence level and lowers the uncertainty in the decision process.

1.2. Application context

To apply our research propositions in the context of viDSS in dynamic situations, we work in collaboration with physicians of the Intensive Care Unit of the Teaching Hospital Habib Bourguiba Sfax. The aim of our work is the fight against nosocomial infections.

Nosocomial Infections are considered as a real challenge for health authorities. An infection is considered as nosocomial if it is acquired in a hospital, that appears 48 hours or more after the hospital admission. The frequency and the gravity of the nosocomial infections are important indicators for assessing the health system development status in a given country. Our application context considers this problem in the Habib Bourguiba Hospital of Sfax, Tunisia where the nosocomial infections prevalence for 2008 was estimated at 9.8%. According to the hospital professionals, the prevalence was the most frequent (42.1%) in the Intensive Care Unit, then the dermatology (18.5%), rheumatology (17.9%) and nephrology (16.7%) services [Fki et al. 2008]. Thus, the daily nosocomial infection surveillance is essential to constantly promote prevention and to control patients' state during their hospitalization.

1.3. Motivation

The business intelligence has seen exceptional growth since the early 90s. The organizations that need to be up-to-date to remain competitive and at the cutting edge of the technology, are expected to adopt one or several business intelligence tools. Especially as the world in which exist these organizations is becoming more complex and decisions must be made quickly in a dynamic way. Decision-making and its execution are the fundamental goals of all decision-makers. The successful functioning of an organization depends structurally on decisions taken by the "decision makers".

Most organizations store increasingly more information; to the extent that new data storage structures have emerged including Data warehouses. To exploit this great mass of data, techniques have been proposed such as OLAP (On Line Analytical Processing), ERP (Enterprise Resource Planning) and Dashboards. But the technique that has most attracted experts is the Data Mining (Intelligent DSS). Numerous of nowadays application domains of intelligent DSS provide huge sets of time-oriented data such as medicine, science, etc. Visualization techniques are required to represent and analyze them (Visual Intelligent DSS).

Moreover, time is increasingly taken into account in the implementation of information systems such as those for decision support. It becomes a very important dimension in decision-making. Indeed, the expert makes a decision after analysis. The decision leads to a result, which influences the data, another decision must be taken, and so on ... In reality, the world is dynamic, DSS should be too. We therefore naturally interested in Dynamic DSS.

In my work, I am interested in conducting research in the fields of dynamic Decision Support Systems (DSS), on the data mining and the visualization. I supervised several Masters and co-supervised one Ph.D. thesis whose subjects were related to these axes. Currently, I co-supervise four Ph.D. theses.

1.4. Report organization

This document is organized in three chapters besides this introduction.

- Chapter 2 presents briefly the basic concepts of decision support systems based on knowledge discovery and visualization. The goal of this chapter is not to provide a state of the art about the subject, but to introduce the main concepts that will be used in the following chapters.
- Chapter 3 presents the research I have been working on in the area of visual knowledge discovery based decision support systems since the conclusion of my Doctor degree. Although the research of my Masters and of my Doctoral degrees was the basis of this HDR research.
- Chapter 4 presents my conclusions summarizing the main contributions in the domain and research perspectives.

Chapter 2 : Visual Intelligent Decision Support Systems

2.1. Introduction

In this chapter I present my three main research areas namely: Decision Support Systems (DSS), Knowledge Discovery from Databases (KDD) and visualization.

Decision support in real-life tasks is usually dynamic and automatic due to the intuitive processing [Norwawi et al. 2005]. Dynamic decision support systems are interactive decisional systems that use temporal data and models to solve problems. Taking into account the temporal dimension of data, DSS remains largely open to both domains: knowledge discovery from data (KDD) and Human-Computer Interaction (HCI).

In fact, within the general framework of decision support, the KDD has become a research topic that has already amply demonstrated its scientific and economic importance and appears now as a strategic area. Both KDD and DSS are highly interactive [Ltifi et al. 2008] [Ltifi et al. 2009a] [Aigner et al. 2011]. It is therefore important to understand the user and join the human creativity; flexibility and knowledge with the huge storage capacity and computing power of computers in the KDD based dynamic DSS: dynamic Intelligent DSS (iDSS) [Keim 2002].

Data visualization is an emerging HCI area allowing data graphical display. It aims to make data sense (data analysis) and user communication [Heer et al. 2014] [Kim et al. 2013] [Batagelj et al. 2011]. Our research work explores temporal data visualization by designing and developing appropriate synergetic visualization techniques for the visual temporal data and knowledge interpretation and analysis for dynamic decision-making. Our idea is to integrate these techniques in the iDSS modules to support the user in the knowledge discovery and decision-making tasks: visual iDSS (viDSS).

One of the essential issues of our work concerns the choice of the appropriate visualization techniques in each module in the KDD process. Indeed, a significant set of research studies has been devoted to the classification of visualization techniques [Ltifi et al. 2009b]. In this study we focus only on the temporal data visualization techniques. Our work consists in integrating them in the different modules of an iDSS to improve the HCI (viDSS).

The goal of the integrated dynamic iDSS process is to identify the key information necessary for temporal data analysis. The data in individual steps have their own unique features. To design visualization tools for such data, we should emphasize such features and align them with temporal concerns. This methodological proposal of integration will be concretized in an existing medical iDSS aiming at assisting physicians in the fight against nosocomial infections in the intensive care units (cf. chapter 3).

This chapter is organized into three sections. Section 2.2 and section 2.3 focus on the research background and related work on dynamic decision support, knowledge Discovery from data and data visualization. Section 2.4 shows how the appropriate visualization techniques can be integrated in the dynamic intelligent DSS modules.

2.2. Research context

2.2.1 Dynamic intelligent DSS

Decision Support Systems (DSS) are defined as interactive, flexible and adaptable computer-based information system. They are specifically developed to assist decision makers in the resolution of a decision problem [Turban 1993] [Turban et al. 2008].

Supporting large volumes of temporal data is an inherent characteristic of modern database applications [Augusto et al. 2005]. The decision makers are brought to create and analyze these quantities of temporal data. They (DSS) consist in determining the nature of the relationships among features rather than analyzing the singular features values [Kusiak 2002]. As the world is becoming data-driven [Kusiak 2002], the complexity of decision-making is rapidly increasing. To cope with this complexity, real knowledge of the application domain is required, which refers to an approach of Knowledge Discovery from Data (KDD). This approach allows extraction of interesting, non-trivial, implicit, previously unknown and potentially useful information from large databases. This discovery takes place through an iterative and interactive process [Fayyad et al. 1996] [Fayyad et al. 2002] [Fayyad et al. 2003]. The KDD process of focus to this chapter is presented by figure 2.1:

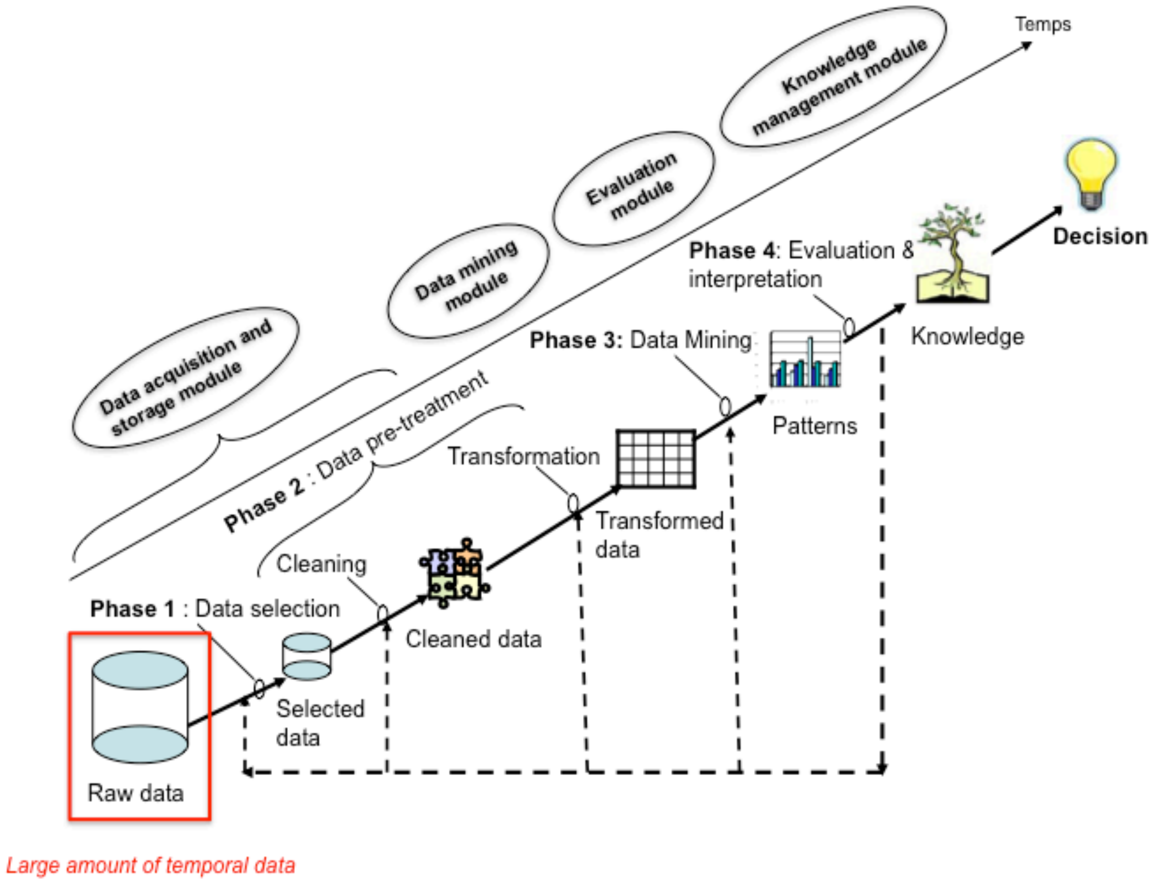

Figure 2.1: the KDD process [Ltifi et al. 2013]

This process proceeds according to four modules: (1) preparation of data relevant to the requested analysis (data selection, cleaning and transformation); (2) applying one or more data mining techniques to extract interesting patterns, (3) evaluation of the discovered models (patterns). Once the knowledge is extracted, it has to be integrated into the decision-making system (4) [Ltifi et al. 2013].

The majority of the research works in the field of KDD are focused on developing efficient automatic algorithms. Currently, the role of the user gradually becomes a major concern [Chevrin et al. 2007] [Ltifi et al. 2009b] [Ben Mohamed et al. 2013] [Holzinger 2013]. Then it seems necessary to include the user in the KDD based decision-making process in order to combine human judgment with potential computational capabilities of the machine. In this context, the field of the Human-Computer Interaction (HCI) is highlighted.

2.2.2 HCI and visualization techniques

Within the framework of the iDSS, one of the stakes is to be able to detect the strategies to solve a decision problem by means of Data Mining techniques. In the KDD process, the needs analysis of the decision makers, the various activities carried out in connection with the preparation, the handling of the relevant data and the visualization of the results constitute very important actions. The acceptance or the rejection by the end-user of the decision-making support tool often depends on the HCI [Ltifi et al. 2009b]. Consequently adapted HCI makes it possible to guide the users throughout the stages of KDD; it is also important to adjust as better as possible the HCI to each class of decision maker and/or each decision maker [Ltifi et al. 2010] [Ben Ayed et al. 2010].

The mental representation construction of temporal data evolution is a difficult task for end user. In fact, the user is forced to make a data comparison; hence the rise of the user cognitive load. For this reason, it is necessary to design an appropriate visual representation for viewing data. Thus, good visual representations facilitate temporal data understanding, interpreting and knowledge extracting [Mackinlay et al. 2007].

An emerged HCI area allowing these representations is the data visualization. Since the turn of the 21st century, this field has been popularized [Few 2013] and proposed many visualization techniques developed in order to exploit the human visual system characteristics and facilitate the handling and interpretation of the data. In our context, we are interested in temporal data. Temporal visualization techniques allow producing graphical representations reflecting the evolution of data over time using graphic objects (circle, segment or rectangle). These techniques are designed to help users to perform their tasks handling temporal data [Daassi et al. 2004].

2.3. Related work on viDSS

2.3.1 Intelligent DSS

Decision-making has become a critical part of many information structures. A DSS allows users to always have access to updated information that interests them. DSS should not be limited to information retrieval. The challenge is to be able to use the available information in order to gain a better understanding of the past, and predict the future through better decision-making. Data mining [Fayyad et al. 1996] technology responds to this challenge.

Data mining based DSS, commonly named intelligent DSS, is a rapidly expanding activity that represents analytical information technologies spectrum. In fact, data mining methods: (1) extend the data analysis possibilities by exploiting richer model representations, such as decision rules or decision trees, than traditional statistical methods and (2) making analysis results more comprehensible especially to the non-technically users [Nemati et al. 2002].

This interdisciplinary field of intelligent DSS includes statistical, machine learning and pattern recognition tools to support interesting patterns discovery for facilitating decision-making [Heinrichs et al. 2003]. There are examples of intelligent DSS in the literature that have already been designed and developed. Bose and Sugumaran (1999) presented the Intelligent Data Miner (IDM) decision support system. It is a Web-based application system enabling predefined and ad-hoc data mining model creation. It provides data mining phases and necessary parameters for used algorithms. It allows also connection to external data mining software tool for data mining model creation. Polese et al. (2002) proposed an intelligent DSS that uses association rules as data mining technique to support decisions of a basketball coach by proposing tactical solutions based on the data of the past games. Lee and Park (2003) introduced Customized Sampling Decision Support System (CSDSS) which is a web-based system enabling the autonomous generation of available customized sampling methods by using clustering data mining technique. Ltifi et al. (2013) introduced an intelligent DSS that aims to generate possible solutions for the fight against nosocomial infections in the intensive care units. It allows using the dynamic Bayesian networks as data mining technique for calculating daily nosocomial infections occurrence probability.

While intelligent DSS are used to improve data analysis and decision problems resolving, decision makers could easily understand the relationships of related data for decisions. Several visualization techniques in the context of intelligent DSS have been developed to help people gain more value from significant data collections. Related literature in information visualization and intelligent DSS presents different roles that visualization techniques could play in data mining for decision support. In fact, various research works integrate a set of visual data mining techniques. For classification purpose using association rules visualization, interactive mosaic plots [Hofmann et al. 2000], rule polygons [Han et al. 2000], parallel coordinates [Bruzzese et al. 2002] [Zhao et al. 2001] [Zhao et al. 2004], 3D graph [Blanchard et al. 2003] and CrystalClear with grid view [Ong et al. 2002] are proposed. Ma et al. [Ma et al. 1999] study consists in ordering categorical data to improve the visualization clutter. An opportunity Map visualization framework was proposed to identify actionable knowledge [Zhao et al. 2005]. Other types of visualization show useful results in the knowledge discovery from Databases process for decision-making [Ltifi et al. 2016].

Numerous of nowadays application domains of intelligent DSS provide huge sets of temporal data such as medicine, science, etc. Temporal visualization techniques are required to represent and analyze them [Aigner et al. 2011]. We briefly present intelligent DSS temporal visualization (dynamic viDSS) tools in the next sub-section.

2.3.2 Dynamic viDSS tools

Several temporal visualization tools have been proposed in the last years due to the need of intelligent decisional applications to analyze the large amount of temporal data. Items that have a start and finish state and overlapping intervals characterize it. Temporal visualizations represent all events before, after, or during specific time period.

Recently, various temporal visualization tools are developed for visual analytics to support decision-making. Ankerst et al. (2008) introduced a CalendarView as visualization tool integrated in a temporal data mining architecture called DataJewel. Munaga et al. (2009) developed a novel tool called CAST (Clustering And visualizing Spatio-Temporal data) as a solution for studying and analyzing the moving entities (users, vehicales, etc.) navigating. Ramírez-Ramírez et al. (2013) discussed a tool called SIMID providing medical decision makers with effective spatio-temporal visualization of infectious disease spread. Mittelstädt et al. (2014) introduced a visual intelligent DSS for adverse drug event detection. Fischer et al. (2014) proposed a visual analytics tool called NVisAware aiming at compressing data streams for visually identifying events to solve the Kronos Incident problem. Mittelstädt et al. (2015) presented a visual analytics tools to support response in crisis situations. They introduced specific temporal visualizations for mobile devices and control rooms.

2.3.3 Motivation and purpose

Our mission is to support human intelligence with machine intelligence by bringing two fields together: Knowledge Discovery from Data (KDD) and visualization. We believe that their combination is an interesting topic.

Several data visualization systems and tools are available such as: XGobi [Swayne et al. 1998], XGvis [Buja et al. 2001] and GGobi [Swayne et al. 2003], Cytoscape [Shannon et al. 2003], Vis5D, Cave5D, and VisAD [Hibbard 2005], GUESS [Adar 2008], Gephi [Bastian 2009], CGV [Tominski et al. 2009], Tulip [Auber et al. 2012], InfoVis Toolkit [Fekete 2004], Xmdvtool [Ward 1994], Prefuse [Heer et al. 2005] and Protovis [Bostock et al. 2009]. This list of systems is not exhaustive but representative. These are generic frameworks, generally freely downloaded and allow handling a very large data set, analyzing and visualizing high-dimensional data, graphs and networks. However, they do not take into account the temporal dimension and the technical specificities (type of data and decisional tasks) of each stage of the KDD process. Our work consists in integrating appropriate temporal visualization tools in the different KDD modules (cf. Fig. 2.2) in order to better visualize and interpret temporal data and facilitate navigation in time. In fact, the literature underlines the need for using several views (i.e. several techniques of visualization) [Jonathan 2000] [Wang et al. 2000] [North 2001] of the same space of temporal data.

The main objective of this chapter is to integrate in each dynamic iDSS module, an appropriate temporal visualization technique(s) (cf. Fig. 2.2). Integrated interactive visualization in the KDD modules tools assist decision-makers to visually extract and interpret knowledge that supports him/her to take the best decision: viDSS.

Many visualization techniques have been designed and developed to meet the growing mass of temporal data [Daassi et al. 2004] [Rind et al. 2013] [Kriglstein et al. 2014], but a few works were devoted to the classification of these techniques [Aigner et al. 2007] [Daassi et al. 2006] [Muller et al. 2003] [Adjanor et al. 2010]. We base our choice on the taxonomies made by Daassi [Daassi et al. 2006] and Adjanor [Adjanor et al. 2010] taking into account the criteria of temporal and structural dimensions of data and user tasks.

A set of studied visualization techniques by these taxonomies concerns the Timeline [Freeman 1997], perspective wall [Robertson et al. 1991], diagram [Daassi et al. 2004], tabular representation [Daassi et al. 2004], star representation [Daassi et al. 2004], spiral representation [Daassi et al. 2004] [Tominski et al. 2008], concentric circles (CCT) [Daassi et al. 2004] and Life Lines [Plaisant et al. 1996] techniques, etc. A wider coverage of visualization methods for temporal data is presented in [Aigner et al. 2011].

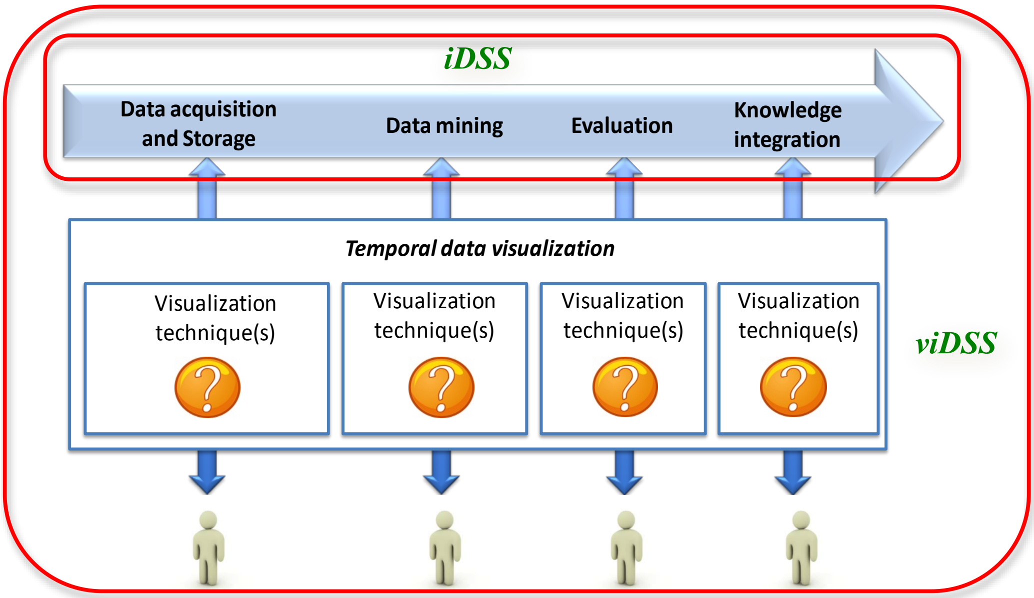

Figure 2.2: The integration of temporal visualization techniques in the iDSS modules

Many studies are focusing on the design of temporal visualization techniques to assist users to visually analyze and explore temporal data ([Aigner et al. 2007] [Mackinlay et al. 2007] [Mackay et al. 2009] [Shneiderman 2013] [Kriglstein et al. 2014]) for decision-making purposes. Our research is within this avenue but in relation with the KDD specificities and modules.

2.4. Temporal visualization techniques integration in the iDSS modules

Dynamic viDSS uses visualization techniques to exhibit deep informational component contained in the raw data and to facilitate the process of knowledge discovery associate in its analysis and interpretation by the users. A synergetic combination of visualization techniques can make users active players in the KDD process and discover the knowledge they need for decision support. The choice of the appropriate visualization technique to integrate in each module is a critical issue that will be treated in this section.

2.4.1 Selection criteria

A time series is a series of values of some feature or events that are recorded over time. They are characterized by a unique "identifier" (ID). To this basic characteristic, we can add other features that allow to better defining the temporal data [Brockwell et al. 1986]; for example: periodicity, data value, description, etc.

Temporal data are defined as a sequence of couple <T, v> where: (1) T is the temporal value dimension (moment, duration, time interval). It indicates the moment of observation; and (2) v is the structural dimension (numerical value, title of an event, image, etc). It is the value of the data at this moment [Daassi et al. 2004].

To transform temporal data from its raw format to visual elements, Daassi et al. [Daassi et al. 2004] proposed the temporal data visualization process visible in Fig. 2.3. Indeed, the temporal data is an association of a structural dimension and a temporal dimension. The visualization process of a temporal data is an association of two visualization processes: one of the structural dimension and the other of the temporal dimension when several points of contact between the two processes are possible (cf. Fig. 2.3).

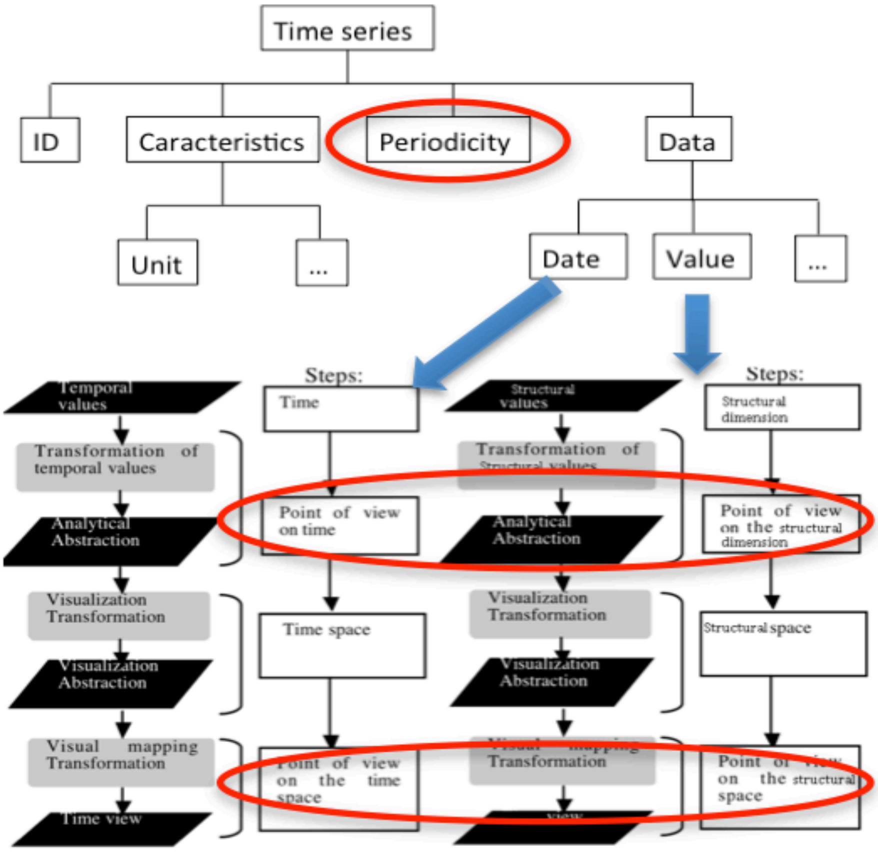

Figure 2.3: The visualization processes of (a) temporal dimension and (b) structural dimension [Daassi et al. 2004]

The steps of the two processes presented in the figure 2.3 are defined as follows:

- Step 1: represents the time (a) /structural (b) values to be visualized
- Step 2: defined by the transformation of the time (a) / structural (b) values to the appropriate representation.
- Step 3: Displayable space of the time (a) / structural (b) values is defined
- Step 4: It refers to the perceptible rendering of the temporal (a) / structural (b) dimension. At this step, the perceptible forms or representations are defined. These representations must be studied according to the human perception of time.

We propose to consider design choices of visualization in each step of the KDD process from the perspective presented by figure 1.3. In fact, the choice of appropriate visualization techniques translating the data values does not depend on the application domain but on the characteristics of the data to be displayed. In this context, we propose the following selection criteria:

- **Data periodicity** (point of view on time): the choice of the visualization technique is influenced by the point of view on time. This step allows identifying the characteristics of the temporal values to be represented: linear or periodic. Some of temporal data visualization techniques can rely simultaneously on the two forms of time. Indeed, at the point of view on time step, two time perceptions can be considered: (1) The linear perception of time can be used in the design of the temporal space by the perspective wall, timeline or the two techniques combined together as a navigation mode [Ltifi et al. 2012b], (2) while the periodic perception can be used in the design of the structural space by the star, spiral representation, concentric circles techniques, etc.

- **Data type** (point of view on structural value): structural values are defined by a type that characterizes them. They can be quantitative (continuous, numeric data) or qualitative (categorical data) [Morgan et al. 1980]. Depending on the data type, some graphics are naturally more appropriate than others.
- **Data dimensionality** (point of view on time and structural spaces): concerns the number of dimensions of the graphical space that are mostly defined with respect to both data structural and temporal dimensions. The number of dimensions of data to be displayed is not always equivalent to the number of dimensions of the representation space. A hierarchical or temporal data may be represented in two-dimensional (2D) or three-dimensional (3D). The characteristics of the representation space depend on the characteristics of the structural and temporal dimensions and the user tasks to consider.

2.4.2 Visualization techniques integration

The temporal visualization techniques integration in the dynamic iDSS modules aims to increase the user involvement in the data preprocessing, mining algorithm, evaluating and interpreting extracted patterns. In this section, we are interested in defining what temporal visualization techniques are appropriate in each module.

2.4.2.1 Data acquisition and storage module

The temporal data can be located on different sites. They can be stored in various architectures: relational databases, data warehouse, web or specialized databases (images, digital libraries or bookstores, genome database). They can be structured or unstructured in different types: tabular or textual data, images, sounds or video clips. In dynamic iDSS, we must have a well-defined problem (objectives, informational and technological resources, etc.). All available and accessible temporal data are certainly not useful in their entirety.

The acquisition module aims to target the data space that will be explored. It implements ad hoc queries to repatriate potentially useful data according to the point of view of the expert. Data cleaning task is typically used to clean the retrieved data that can probably be marred by uncertainty and imprecision. These data can be of different types: texts, images, quantitative recordings or video clips. The transformation task is to standardize the data and arrange them in rows/column table. In other cases, they are in a tabular structure but require a transformation such as centering relative to the average or normalization. The expert should therefore choose a canvas to represent data and possibly perform a series of transformations to obtain data suitable for mining methods.

After the acquisition phase, the analyst (the module user) is, a priori, in possession of a stock of data potentially containing information or knowledge to find. This module handles large amounts of complex linear or periodic data. Temporal data in its raw state have neither shape nor size, or color [Hervouet 2011]. Then applying temporal visualization, such data will be graphed to provide quantitative and qualitative understanding (cf. Table 2.1).

We begin with two-dimensional data. To visualize them in the data acquisition and storage module, we propose to study the graphical elements based techniques. Each entity is represented by a graphical object where one or more retinal variables (shape, size, orientation, etc.) are varied [Mackinlay 1986].

If data are quantitative and linear, appropriate visualization techniques to select, clean and transform temporal data are tabular representations. In fact, data preparation especially affects data tables. The tabular representation techniques are motivated by the particular nature of handled tables. It can be applied in this module for managing, visualizing and making sense of large quantity of temporal data. It allows giving an overview about the data headlines by focusing on the tables and attributes names. It supports navigation around data space, isolation and investigation of interesting temporal features.

Graphical representations have to be incorporated in the tabular representation because of their ability in showing cell values. Using this kind of representation improves the effectiveness with which patterns and features can be spotted in the graphical rendering of the temporal data table.

Diagrams are also recommended for the quantitative linear data visualization because they present a treelike structure with branches demonstrating temporal relationships.

If data are qualitative and linear: (1) diagrams and semantic network diagrams [Weitzman 1999] are suitable visualization techniques because of their ability to compare categorical temporal data. It is very visual and allows comparing classes of data (eg. presenting and interacting with tables to select or to transform) and (2) pie charts, bar charts, scatter plots [Wilkinson 2005], LifeLines [Plaisant et al. 1996] and Lifeflow representation [Wongsuphasawat et al. 2011] can be used to represent qualitative data. Each zone of the selected technique represents the relative frequency of class in a data category. They are simple to construct yet are very effective [Miles et al. 1994].

If data are quantitative and periodic (likewise for periodic qualitative data): we proposed to use the cyclic representation techniques for selecting and cleaning temporal data. In the literature, we distinguish between different types of cyclic representation of time such as spiral, star and circular representations. These techniques are similar in principle and analytic results. In fact, cyclic techniques generate displays for visualizing periodic character of a data set where periodic aspects are encoded in the cycles of the chosen technique. They are principally useful for spotting cyclic patterns in temporal data.

Among the possible uses of cyclical techniques in this module, we can cite the missing or outlier structural data that can be easily detected in cyclic drawings. It allows user to clean these data by directly interacting with these drawings.

In the case of multidimensional quantitative or qualitative data sets, we propose to integrate pixel-oriented visualization techniques [Ankerst 2001] where each entity in the data space is represented by a pixel whose color translates the value of an attribute. Using pixels allows viewing a large data space. An example is the circle-Segments Technique [Ankerst et al. 1996].

We have proposed a set of appropriate temporal visualization techniques to visualize structural data of the first dynamic iDSS module. The navigation task is carried out by the timeline technique. An overview on the module data can be represented by the perspective wall technique [Ltifi et al. 2012b]. Every wall integrates other visualization technique combined with timeline to facilitate navigation in time.

2.4.2.2 Data mining module

The second module in the dynamic iDSS process uses multiple methods from statistics, machine learning, or pattern recognition for the detection, interpretation, and prediction of patterns in temporal qualitative and/ or quantitative data. The data mining methods aims at discovering what contain these data as useful models.

The quantity of the quantitative and/or qualitative data mining input variables is large. The appropriate visualization technique to use must support this large quantity of temporal data, give a visual summary of the figures and allow in a single sight to grasp the general trend. In this context, we can propose to apply the tabular representation technique in order to present input variables as attributes and visualize the progress of the data mining algorithm to explore patterns and investigate various explanatory models.

To visualize the output result(s) which is/are the discovered pattern(s), we have to refer to the three selection criteria as follows:

- If results are quantitative and linear: we recommend the use of the tabular representation.
- If results are quantitative and periodic: cyclic representations are appropriate
- If results are qualitative (linear or periodic): a technique called the Spectrum facilitates interpretation and analysis of this kind of results at a glance [Collins et al. 2002].
- If results are multidimensional: pixel-oriented visualization techniques are recommended.

The selected visualization technique can be incorporated in the perspective wall combined with timeline for navigation to provide a global view of the module.

2.4.2.3 Evaluation module

Extracted model(s) cannot be used directly in all reliability for making decision. We must evaluate it i.e. submit it to the test of reality and appreciate its accuracy. The usual method is to estimate the model error rates. Thus, the user decides whether to apply the prediction model. The error rate is usually calculated using the confusion matrix. Indeed, two generated temporal data have to be represented in this module:

(1) The temporal output patterns are in most cases transformed to probabilities for prediction. The visualization of this two-dimensional quantitative information should be used to interpret its evolution in time. The amount of data to be displayed in this stage is not large. For this reason, we propose to use the diagram representation technique in order to facilitate the visual comparison of the discovered pattern(s). The navigation task is carried out by the timeline technique in the framework of the perspective wall. It is only after this stage that the learned data (output discovered pattern) becomes extracted knowledge.

(2) The Confusion matrix for the evaluation of the extracted knowledge. It is a table to be visualized; thus tabular representation is an adequate technique to apply in this stage of the dynamic iDSS module.

2.4.2.4 Knowledge integration module

Once the discovered patterns are interpreted and evaluated, the question will be to generate the possible solutions of the decision problem based on the extracted knowledge. In fact, these solutions are in general qualitative linear data (possible solutions = categorical classes).

Integrating visualizations in this module means representing possible solutions and validate the appropriate one according to the decision maker. The visualization has to represent the solutions taken during time (we can talk about histories). Lifelines technique is then the proposed temporal visualization technique to use for the visual knowledge integration (cf. Table 2.1).

Table 2.1: Possible visualization techniques for dynamic iDSS modules

<table>
<tr><th rowspan="3"></th><th colspan="4">Two-dimensional</th><th rowspan="3">Multi-dimensional</th></tr>
<tr><th colspan="2">Quantitative data</th><th colspan="2">Qualitative data</th></tr>
<tr><th>Linear</th><th>Periodic</th><th>Linear</th><th>Periodic</th></tr>
<tr><td rowspan="2">Data acquisition and storage</td><td>Tabular representation
Diagram</td><td>Cyclic representations (concentric circles, star, etc.)</td><td>Diagram, semantic network diagrams, pie charts, bar charts, scatter plots, LifeLines and Lifeflow</td><td>Cyclic representations</td><td>Pixel-oriented visualizations</td></tr>
<tr><td colspan="4">Temporal data Global view (TDGV): perspective wall
Temporal dimension (TD): Timeline</td><td>TD: Timeline</td></tr>
<tr><td rowspan="2">Data mining</td><td>Tabular representation</td><td>Cyclic representations</td><td>Spectrum display</td><td>Spectrum display</td><td>Pixel-oriented visualizations</td></tr>
<tr><td colspan="4">TDGV: perspective wall
TD: Timeline</td><td>TD: Timeline</td></tr>
<tr><td rowspan="2">Evaluation</td><td>Tabular representation
Diagram</td><td rowspan="2"></td><td rowspan="2"></td><td rowspan="2"></td><td rowspan="2"></td></tr>
<tr><td>TDGV: perspective wall
TD: Timeline</td></tr>
<tr><td rowspan="2">Knowledge integration</td><td rowspan="2"></td><td rowspan="2"></td><td>LifeLines, Lifeflow</td><td rowspan="2"></td><td rowspan="2"></td></tr>
<tr><td>TDGV: perspective wall
TD: Timeline</td></tr>
</table>

The presented temporal visualization techniques are selected to improve interaction with the temporal data and/or patterns in each dynamic iDSS module. May be there are other appropriate techniques that can be applied in these modules. It will be the subject of future research.

2.4.3 Visualization techniques interaction

Table 2.2 presents a set of interaction principles that we propose to be considered in the design and implementation of the selected temporal visualization technique (cf. Table 2.1). Indeed, the user is particularly able to extract information from an environment that he/she actively and directly controls [Hascoët et al. 2001].

Table 2.2: interactive data exploration principles

Interaction mode	Brief description
Navigating in time	Concerns how to browse in time. Severel methods can be used. For example: 1. Using the mouse to clic directly on the date in the timeline 2. Using the keyboard to press UP or DOWN keys for moving one time step forward or backward in time. To browse in the perspective walls, users can clic on the concerned buttons, use PAGE UP and PAGE DOWN keys or also the mouse wheel.
Focus and context	It is a key principle of interactive data visualization. It consists in [Card et al. 1999]: - Focus : viewing selected regions in greater detail - Context: displaying global view at reduced detail - No occlusion : all data is visible simultaneously This principle include those cited by [Hascoët et al. 2001] such as interactive filtering and interactive zooming.
Labeling	Clicking on visualization cells allows automatically providing corresponding labels to show their data values in textual form [Tominski et al. 2008].
Colors adjustment	It concernes the methods devoted to adapt the color coding to the user needs. In fact according to [Silva et al. 2007] : "*the way of how colors are used affects what can be seen from the visualization*".
Settings panel	For each visualization tool, it seems important to create a panel for all adjustable parameters which can be encapsulated in groups. The design of this panel depends on the technical specificities of each visualization technique such as the number of cycles to view in a spiral representation [Tominski et al. 2008].

Interactive principles (table 2.2) to take into account in the temporal visualization techniques development aim at adding the user enormous capacities of pattern recognition to the dynamic iDSS tasks: interactive temporal visualization techniques.

This research was subject of different publications (**[Benmohamed et al. 2013] [Benmohamed et al. 2014] [Ltifi et al. 2016]**).

2.5. Conclusion

In this chapter, I presented my research area: visual intelligent DSS in dynamic situations. Our first contribution consists in integrating selected interactive visualization techniques in the dynamic iDSS modules to assist the user in his/her approach of knowledge discovery from temporal data to improve the decision-making process: **visual iDSS**. In the following chapter, I present my contributions for the design and evaluation of viDSS.

Chapter 3 : Contribution to the design and evaluation of visual intelligent DSS

3.1. Introduction

The contribution of this manuscript is to illustrate how to design, develop and evaluate a complex and real-time viDSS. Such complexity is generated by the multi-disciplinary of the related integrated technologies (data mining and temporal visualization techniques). I begin this chapter by presenting the key research findings that have been introduced during my doctoral experience and the transition to the post-doctoral at the REGIM-lab.

Thesis Work: September 2007 - July 2011: in this work, we focused on the design, development and evaluation of Interactive Decision Support Systems based on the data mining technology (iDSS). We found that there is no specific user centered design approach that is appropriate to this kind of system. For this reason, we have proposed an approach called **E**xtended **U**nified **P**rocess (ExUP).

The originality of the proposed approach is based on the methodological aspects of three research fields, which seem complementary: Software Engineering, Human-Computer Interaction and Data mining. In fact, our proposal was based on a global methodological framework, issued from the Software Engineering field, which is the unified process. This approach consists of extending the Unified Process activities under: (1) Human-Computer Interaction elements, and (2) the technical specificities of the knowledge extraction. This approach has been applied in the medical field in order to validate its founder principles. The developed dynamic iDSS aims to fight against nosocomial infections in the Intensive care unit of a hospital situated in Sfax, Tunisia. For the knowledge extraction and prediction tasks, we have selected and developed the Dynamic Bayesian Networks algorithm (dynamic data mining). We have performed a global evaluation of the proposed ExUP approach based on the developed system. We have conducted utility (prediction results of the data mining algorithm) and usability evaluation studies. These studies have allowed validating the overall principles incorporated in the ExUP.

In the Ph.D. thesis, the user-centered design was the principal contribution. However, we believe that the future of Human-Computer Interaction is in the direction of the information visualization for visual display and visual analysis purposes. In this context comes our Post-doc work.

Post-doc Work: September 2011 - September 2015: I began my Post-doc work with many perspectives related to the decision support systems, data mining and visualization. I aim with my research group to conduct innovative research in this context. In fact, based on the decision-maker (potential user) behavior understanding, our research contributes to the cognitive modeling of visual intelligent DSS taking into account the data mining and visual specificities. The architecture of such systems is addressed by applying the Multi-agent technology because of the complexity and real-time nature of the viDSS.

Since developed the system by applying the cognitive modeling and the multi-agent architecture, it must be evaluated on the utility and usability dimension. Concerning the utility evaluation, we investigate the ability of data mining algorithm (i.e. Dynamic Bayesian Network) to daily predict the nosocomial infections occurrence probability. For the usability evaluation we believe that the intelligent analysis of the evaluation results given by the user is interesting. For this reason, we have contributed to the usability evaluation by proposing an intelligent method based on the Fuzzy Logic technique.

Following, the chapter (section 3.2) shows the different contributions previously introduced: (1) the cognitive modeling approach, (2) the Multi-Agent architecture, and (3) the intelligent usability evaluation. Thereafter, I provide the software development (section 3.3) that was necessary to validate these scientific contributions using our proposed usability evaluation method.

3.2. Contribution to the design and development of viDSS

My experience as a PhD and post-doc student allowed me to focus, initially, on the issues of the data mining based dynamic decision-making support and to consider the medical applicative context for the fight against nosocomial infections in intensive care units. Thus, by integrating visualization, I had the opportunity to consider these same issues in dealing with visual aspects. My research could thus be extended to the new environment while considering the issues that are fundamental to my work: cognitive modeling, multi-agent architecture and the comprehensive evaluation framework.

3.2.1 Contribution to the cognitive modeling

Initially, I was interested in proposing a cognitive model that enables decision-makers to reason about their visual dynamic decision process based on the discovered knowledge from data. In fact, dynamic DSS are designed and developed in the literature using: (1) classical design methods (issued from Software Engineering field), (2) system dynamics approach (system modeling and simulation tool) [Chan 2011] or (3) cognitive modeling methods. Few works are devoted to the development of iDSS (e.g. my master and Ph.D. works presented in [Ben Ayed et al. 2010] (based on the Unified Process/U model) and [Ltifi et al. 2013] (an extended version of the Unified Process)). However, to the best of our knowledge, there is no approach proposed in the literature for dynamic viDSS cognitive modeling. Consequently, in this section, we try to answer the following interrogations: (1) "which cognitive modeling approach should be applied to build a dynamic viDSS?" and (2) "Is it possible to take advantage of existing cognitive modeling approaches?"

First, I present the theoretical foundations of the cognitive modeling field. Then I introduce a discussion about the proposed approach that models decision-making in the context of viDSS.

3.2.1.1 Cognitive modeling

Cognitive modeling is a domain, which deals with the simulation of human problem solving and mental task processes in a computerized model [John 1998] [Hoc et al. 2007]. Such modeling 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 [Wang et al. 2007], neural networks [Perlovsky 2009], robotics [Wang 2010], virtual reality applications [Saânchez et al. 2000], and (2) in the Human-Computer Interaction (HCI) field such as human factors engineering, user interface design and visualization [Card et al. 1983] [Holzinger 2013].

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 [Gray et al. 1993]. The ultimate potential for cognitive modeling in HCI is that it provides the science base needed for predictive decisional situations analysis and methodologies [Card et al. 1983]. Most cases of these situations are dynamic owing to the temporal data allowing monitoring and analysis of variations over time using displays representing the 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 [Rasmussen 1980] [Rasmussen 1983] [Rasmussen 1986]; a synthesis of his works is available in [Le Coze 2015]. 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 [Hoc et al. 1998]: 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. 3.1).

This model has disadvantages as well [Hoc et al. 1998]. 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 [Vicente 1999] [Sanderson 2003]. We are particularly interested in the Hoc and Amalberti work. Indeed, to overcome the disadvantages of the Rasmussen model, Hoc and Amalberti [Hoc et al. 1995] 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 [Hoc et al. 1998] 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 [Hoc et al. 2007]. 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 [Neyns 2011]. In addition, this DSM model does not take into account the visual representations specificities of visual dynamic situations of decision support based on the data mining process. Hence, in the following section, we propose to adapt the Hoc and Amalberti model according to these specificities.

3.2.1.2 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. However, to the best of our knowledge, there is no model that takes into account the technical specificities of visual data mining process. Thus, the aim pursued in this research work is to understand how the decision-maker gets the dynamic situations of visual intelligent decision-making under control.

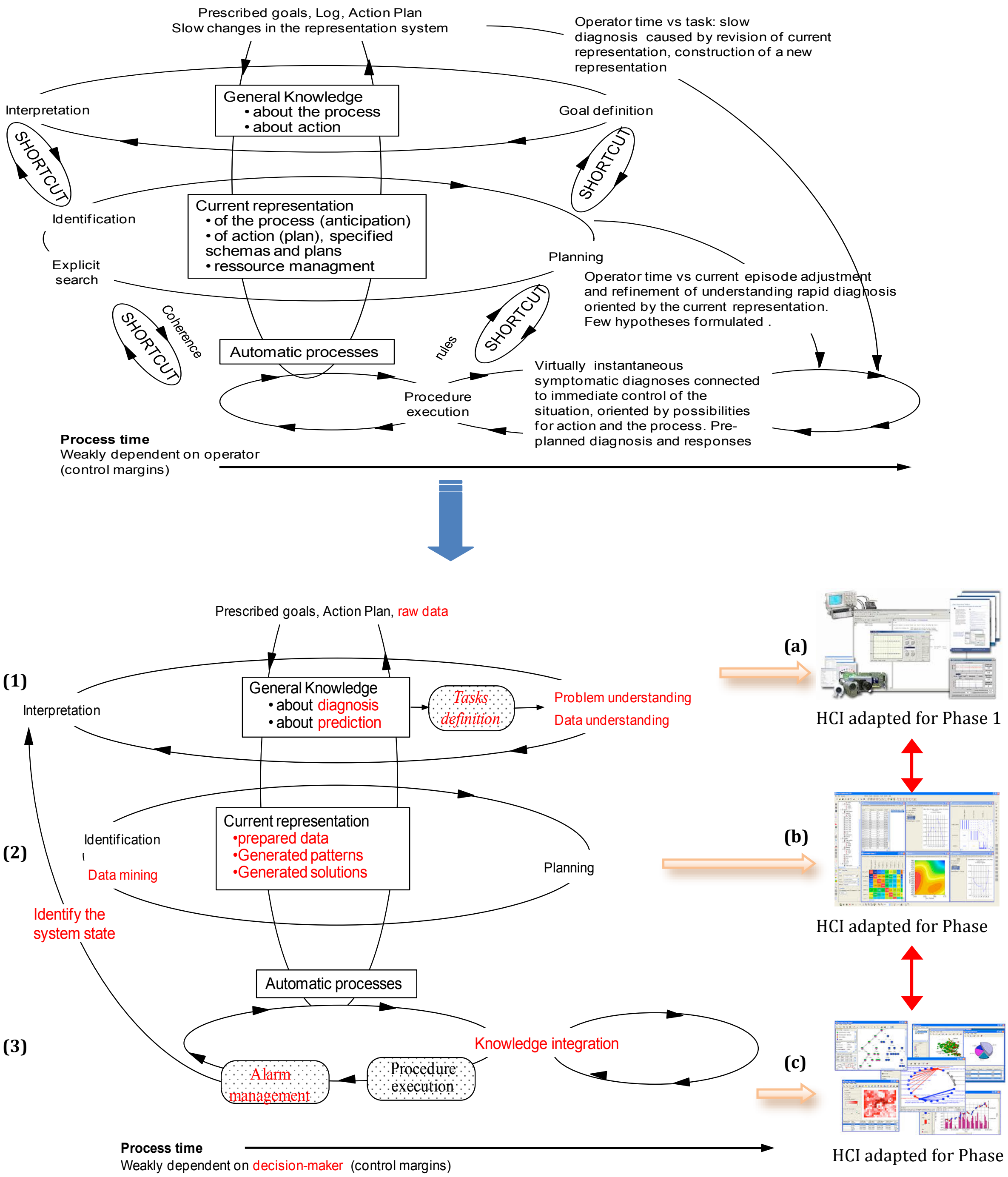

Figure 3.1: From the multi-level diagnosis architecture (Hoc & Amalberti, 1995, p. 96) to the visual data mining based diagnosis architecture

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

(1) Phase 1: data acquisition

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. [Wilson et al. 2005]. It is designed to provide a structured framework for 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 [Clark et al. 2007].

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 Dynamic viDSS 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.

(2) Phase 2: data analysis

Data analysis phase investigates cognitive processes and physical actions of Dynamic viDSS 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 [Miller et al. 2009] [Olson et al. 2012]. 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 [Ben Mohamed et al. 2013] [Heer et al. 2014]. 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 [Holzinger 2012]. 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 [Kolski 1997] [Kolski 2011]). 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) Phase 3: decision-making

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 [Carreras et al. 2008] [Morel et al. 2008]. 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 Dynamic viDSS.
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 an 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 and provides the decision-maker with a deterministic behavior 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.

This research was subject the publication of **[Ltifi et al. 2015]**.

The architecture of the viDSS will be investigated in the following contribution taking into account the three cognitive modeling phases presented above.

3.2.2 Contribution to the Multi-agent design

The intelligent agent concepts have been applied in DSS and iDSS to automate decision-making process [Bose et al. 1999] [Rahwan et al. 2004]. To the best of our knowledge, there is no literature presenting the application of intelligent multi-agent architecture for viDSS especially, in the real-time environment. In fact, viDSS integrates several disciplines, which makes its architecture more complex. One solution to overcome such complexity is the multi-agent technology. In this context comes my second contribution addressing the using of this technology for the viDSS architecture modeling.

In this section, we present the Multi-Agent System (MAS) and how we have applied it to the proposition of intelligent viDSS architecture.

3.2.2.1 Multi-Agent technology

The intelligent agents are software or hardware entities that perform a set of tasks on behalf of a user or another program with some degree of autonomy [Barley et al. 2005]. They apply artificial intelligence techniques (e.g. machine learning, inductive or deductive reasoning) to reveal their intelligent behaviors. Nowadays, several research works on intelligent agents and MAS focused on applications in various areas including decision support systems, database and knowledge-base systems, information retrieval, and distributed computing [Godoy et al. 2004].

Intelligent agents are categorized into two main classes based on their degree of perceived intelligence and capability: (1) the *reactive agents* that act only in response to signal, stimuli or perception and have a knowledge base containing a set of <condition, action> rules, and (2) the cognitive agents that may act by itself, taking action according to its objectives and cognitive knowledge [Barley et al. 2005].

The Agent technology in a DSS performs numerous of the essential decision support tasks previously considered as entirely human activities. Delegating decisional tasks to intelligent agents allows: (1) automating the repetitive tasks, (2) extracting and filtering information from complex data and (3) learning and making recommendations to users concerning a particular action course by employing some knowledge of the user's purposes or desires [Barley et al. 2005].

A MAS is characterized by the ability of its agents to work together as a coherent team. They act autonomously, communicate, cooperate, and coordinate in order to achieve the system collective goal. In DSS, the agents' coordination is attained, for example, by exchanging data, generating partial decision solution plans, and managing constraints between the different agents.

3.2.2.2 MAS based viDSS architecture

(1) Involved agents:

The involved viDSS agents are cognitive agents. They are identified to perform the decision support, data mining and visualization tasks referring to the three phases of the viDSS presented in the previous section (£ 3.2.1.2). We propose the following intelligent cognitive agents:

The **User interface agent** divided into two types of user: (1) decision-maker providing the high-level problem objectives and, (2) data-miner providing specific details about the visual data mining approach. Each one has its own interface agent to interact with the DSS. In general, the user interface agent learns the user preferences, receives the user specifications and delivers the results.

The user interface agent provides a dynamic interface for the visual user interaction, the problem definition, the inputs and output of the data preparation process, the input data-mining parameters and the visual mapping of temporal raw data, extracted models and generated solutions of the decision problem. The user interface agent communicates the input to the DSS coordinator agent.

The **Coordinator (Supervisor) agent** coordinates the different tasks to be executed in each viDSS module. Once the user input is received from the user agent, the supervisor agent controls the tasks and delegates appropriate actions to the other agents. It may demand services from the other agents and also generate reports.

The **local agents** that represent a set of agents assigned to achieve tasks of KDD stages. In each module, local agents cooperate together in order to generate a relevant result. We propose the following local agents:

1. **Data preparation agent:** it resolves the existing invalid and missing values in the temporal data. It applies scripts and methods for cleaning, pre-processing and transformation of the temporal data to be prepared for data mining algorithms. To do so, it communicates with the data-mining agent to take into account the specific characteristics of the used algorithm(s).
2. **Data mining agent:** it is responsible for applying data mining algorithms to efficiently describe the past and predict the future. It takes prepared temporal data as an input and produces predictive models or patterns as an output. It communicates with other agents to take input parameters, transfer output models and visually interact with the user.
3. **Visualization agent:** it is responsible for identifying insights in temporal data and extracted models. It provides visual data summarization through graphic representations. It allows also visually identifying important trends in data. It cooperates with the coordinator and database agents (to have access to temporal data and models to visualize).
4. **Evaluation agent**: it automatically and visually assesses the quality of the extracted model (the output provided by the data mining agent). It describes if the output model should be used and integrated into the decision process. It interprets the model and produces new knowledge to be integrated. It communicates the model to the database agent for its storing and the knowledge integration agent for generating possible alternatives.
5. **Knowledge integration agent:** it uses the evaluated and interpreted model by the evaluation agent to integrate this new knowledge in the model management module to generate the possible solutions. It communicates the proposed decision solutions to the database agent for their storage and to the user interface agent for their presentation to the decision-maker.
6. **Database agent:** it provides access to the database and keeps track of the stored temporal data and validated models. It maintains database local and global schema. It also allows retrieving the requested data by the other agents for visual data mining tasks. It ensures the execution of the requested queries and communicates back their results to the coordinator and visualization agents.

(2) Multi-Agent based viDSS architecture

Our proposed architecture for a multi-agent based visual intelligent DSS in the real-time environment is organized around the DSS modules visible in figure 3.2. It consists of: (1) *passive objects* including interface, data and models, and (2) *active agents* developed to perform tasks.

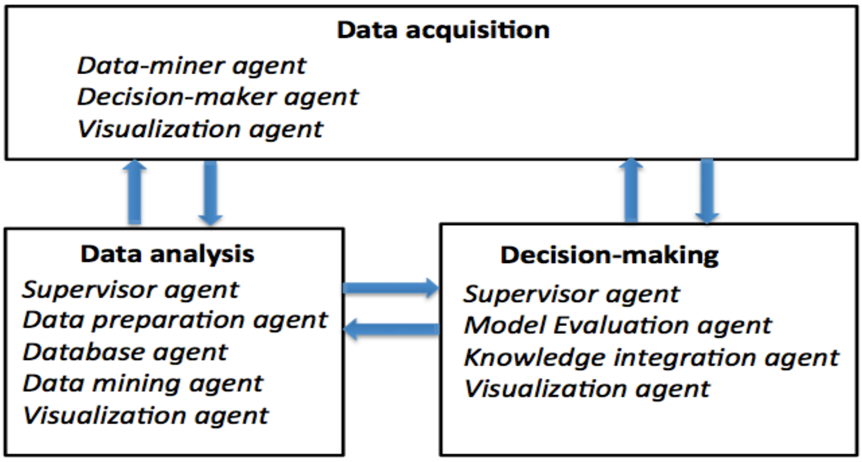

Figure 3.2: Involved agents in the viDSS

The entire architecture is presented in Figure 3.3. It consists of three layers assigned to the cognitive modeling phases (i.e. data acquisition, data analysis and decision-making): the data acquisition layer is visible to the other agents and the users (data-miner and decision-maker). It sets out mechanisms for visually interacting with agents and provides the inter-agent communication and cooperation. The data analysis layer is restricted to the agents manipulating and mining the temporal data. The visualization agent generates graphical representation of the data preparation and data mining inputs and outputs and transfers it to the data acquisition layer. The decision-making layer includes methods relevant to the problem solving. These methods implement knowledge integration services and computations in response to requests from agents and/or users. The visualization agent generates representations of the inputs and outputs of these methods.

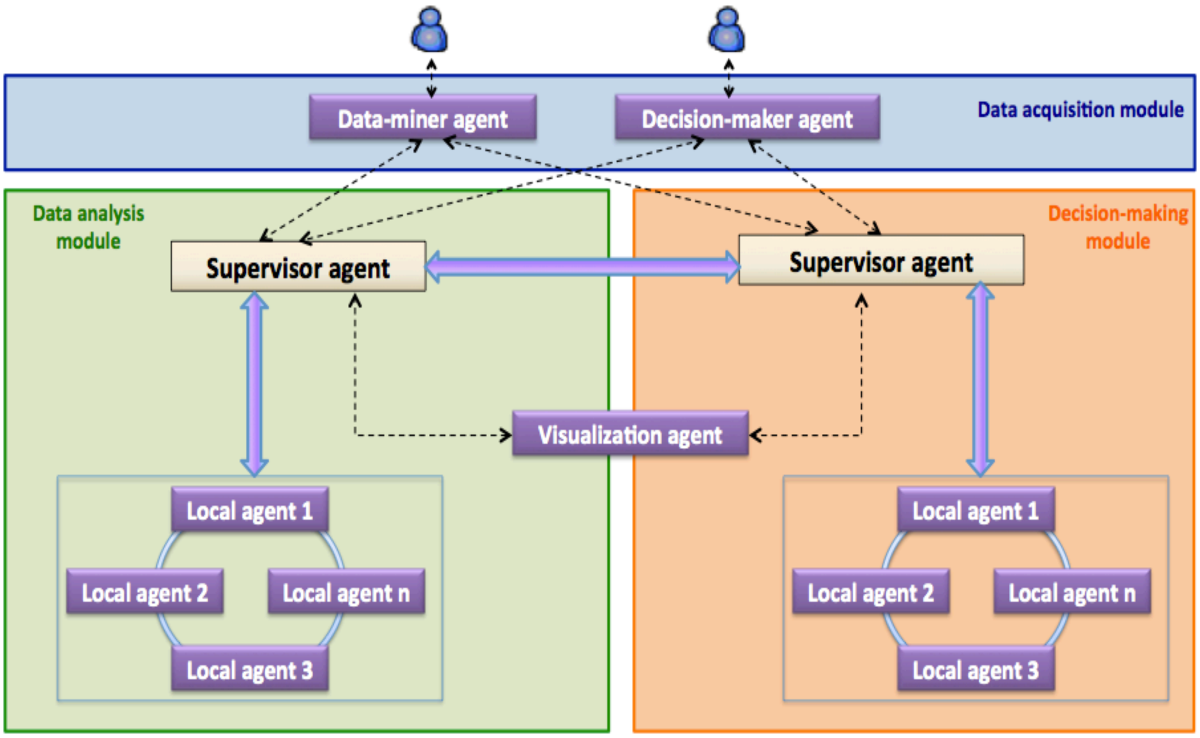

Figure 3.3: Multi-agent architecture of the viDSS

(3) Agent interactions scenarios

Our architecture is characterized by the ability of its agents to work together as a cohesive team. These agents act autonomously, communicate, cooperate and coordinate in order to achieve the collective objective of the system, which is the decision-making.

After having received a request from the user (decision maker or data-miner), the supervisor agent of the concerned module analyses the request and then specifies the local agent who will be responsible for its processing. This agent receives a request from the supervisor to ensure its availability.

Two possible cases:

1. First case (available agent): it informs the supervisor that it is available and is ready to receive the task. It receives the request and carries out the requested treatment. Then, it exchanges the treatment result with the other local agents belonging to the same module to complete the collective processing.
2. Second case (not available agent): it informs the supervisor that it is unavailable (another processing is running) and is not ready to receive a task to do at this time. The supervisor creates helper agent to assist the assigned agent in performing the requested task.

Finally, the supervisor collects the results of tasks performed by the local agents to generate a final result (cf. Figure 3.4).

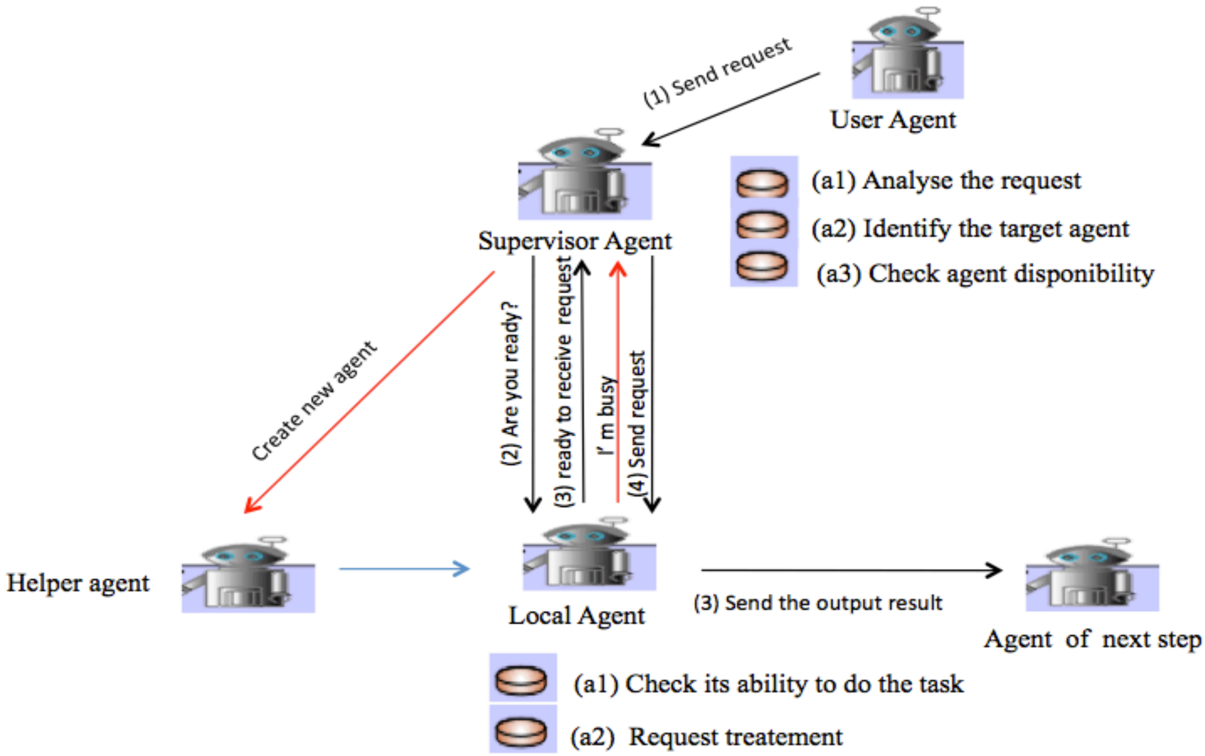

Figure 3.4: agent interactions scenarios

(4) MAS Communication process

In figure 3.5, we see the MAS communication process of the proposed architecture. The decision-maker agent interacts with the coordinator agent to apply automatic and visual analysis to gain visual knowledge from data for real-time decision-making. The temporal data stored by the database agent need to be cleaned, pre-processed and transformed before applying the data-mining agent. The data preparation agent derives appropriate temporal data representations for data mining. Then, the data-miner applies automatic methods of the data-mining agent to discover useful and previously unknown models. Once the model is discovered, the data-miner interactively evaluates and refines it by applying the evaluation agent code.

The visualization agent allows the data-miner interacting with the applied automatic techniques to modify input parameters and/or select other data mining algorithms. Visualizing the model at a time point allows evaluating it regarding the previously discovered models. Interaction modes in visual mapping are needed to dynamically manipulate insightful data and models (zooming, filtering, labeling, etc.) by considering areas and views on the displayed information. Since the discovered model is evaluated and validated, it will be integrated using the knowledge integration agent to generate possible solutions for the decision-maker.

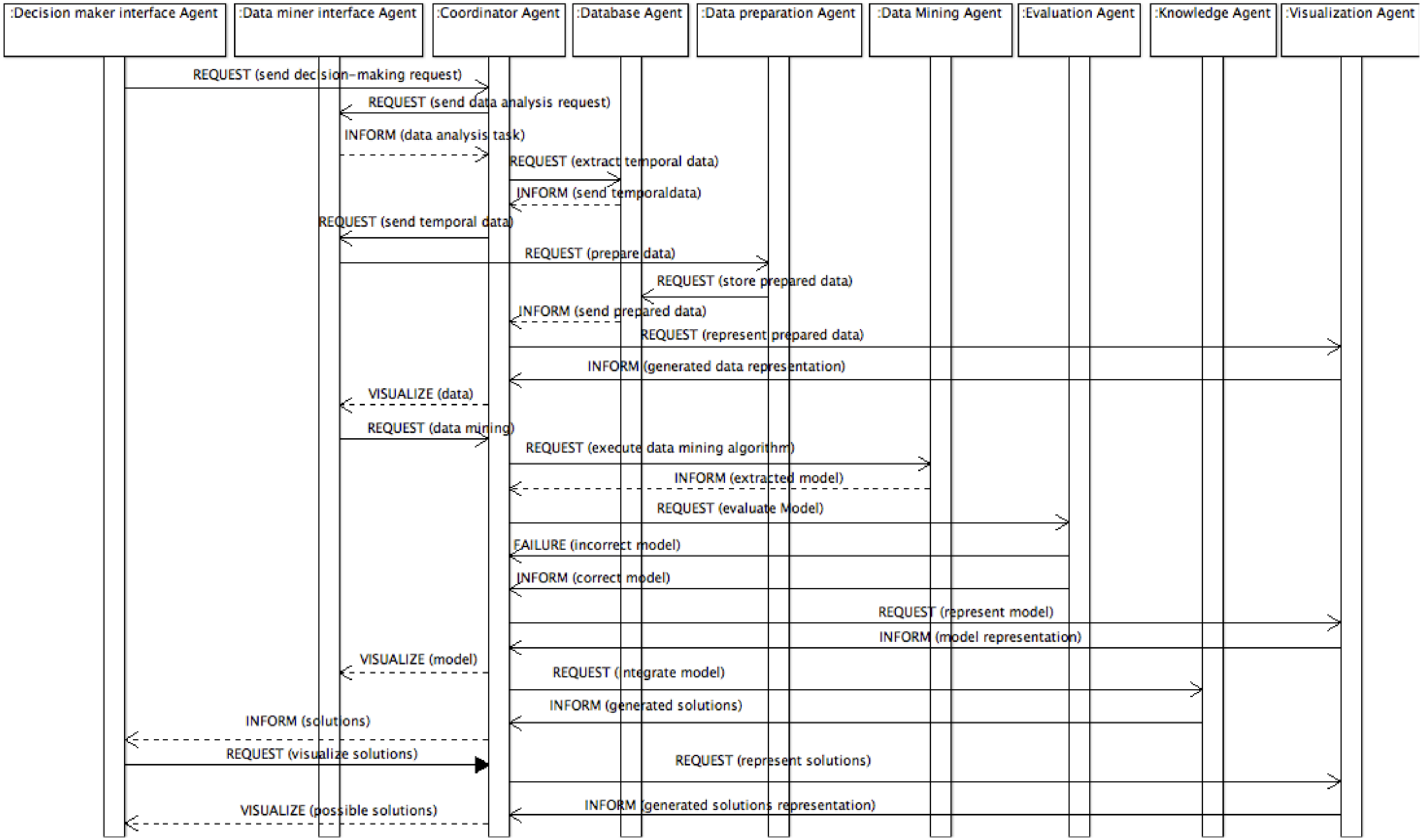

Figure 3.5: MAS communication process

This research was subject of the publication of **[Elouzi et al. 2015]**.

As detailed above, I have presented our two first design contributions considering the three phases of the viDSS (data acquisition, data analysis and decision making). In the following section, I will focus on the proposition of an evaluation method of such visual system.

3.2.3 Contribution to the evaluation

Existing evaluation methods use: (1) quantitative techniques such as surveys/questionnaires, pre/post tests and heuristic analysis, (2) qualitative techniques such as observations, interviews and focus Groups, or (3) "mixed-method" approaches that collect both quantitative and qualitative data. Visualization evaluation studies are either based on user tasks and data characteristics, either observational by learning about users. As far as we know, no study captured vagueness in the ordinal judgments obtained from users evaluation on the visualizations of intelligent DSS. For this reason, we propose the use of the fuzzy logic to analyze evaluation scores provided by these users and to determine the precise weights reflecting the importance of criteria for assessing the impact of visualization on the decision-making environment.

Our proposal is in this context; it outlines a proposed usability evaluation method to assess the temporal data visualizations generated by dynamic intelligent DSS. The proposed evaluation procedure occurs in two steps: (1) the first consists in answering a set of evaluation questions; and (2) the second applies the fuzzy logic to analyze the participants responses (cf. Figure 3.6).

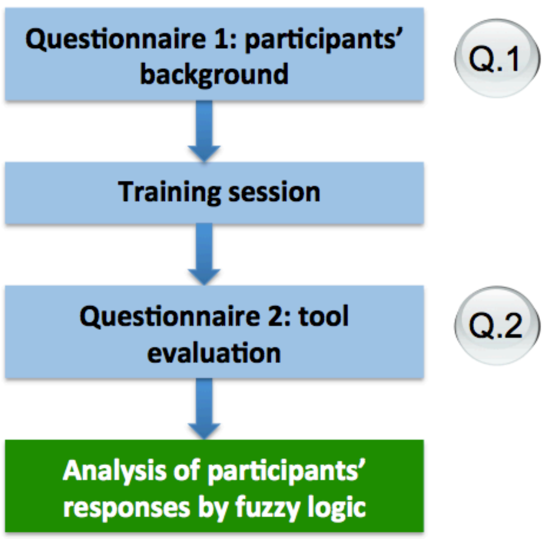

Figure 3.6: evaluation process

3.2.3.1 Step 1: usability evaluation questionnaire

For the first step, we adopt the questionnaire as a quantitative technique to gather evaluation data from a large number of users. It is considered as the most common and popular tool. A good questionnaire can be a powerful tool to inform the evaluation. The participants have to answer two sets of questions: (1) participants knowledge and experience, and (2) summary questions about the visualization tools usage after a training session.

SET Q.1: participant background

We have designed a 5-point Likert scale questionnaire to allow participant providing feedback on their background. Such information allow to determine if they have certain skills and/or background requirements, if they will be familiar with the evaluation tasks, or have experience with performing certain tasks.

This Likert scale questionnaire contains the following issues, where the participants attribute for each one a value from 1 (lack of knowledge) to 5 (expert):

1.1. Database concepts (classes, times series, etc.)
1.2. Databases Management System experience
1.3. Query language experience (SQL)
1.4. Visual data mining experience
1.5. Decision support systems experience

Training session: it consists of presenting: (1) the motivations behind the visualization tools in the context of dynamic and intelligent decision-making, (2) the detailed instructions of the tools usage and their interactivity (zooming, labeling, filtering, etc.) which includes tools demonstration. During this session, the participants have the opportunity to explore the tools by themselves and learn how to use them without any outside intervention.

The training session ends with answering a set of query questions relating to the data manipulation and analyze. For each one, participants have to complete the following survey: difficulty of the query question and the time to achieve it.

SET Q.2: evaluation variables

After the training session, the second set of questions aims to verify how a visualization tool supports the generation of actionable and relevant knowledge for decision-making. In particular, we evaluate visualization tool's ability to support visual analysis and reasoning about data. We introduce a new set of relevant metrics. They are all based on current usability studies and experts' recommendations for DSS, data mining as well as visualization aspects and characteristics. The participants have to reply to the questions associated to the following criteria (cf. Table 1). Users attribute a value between 1 and 10.

The evaluation criteria are grouped into three categories:

<u>Category 1: usability dimension (U)</u>

2.1. Comprehensibility (COM): important factor in visualizations for analytic purpose.
2.2. Ease to use (ETU): the way to use interactive options or execute actions for a visualization task.
2.3. Speed of use (SPU): the speed to use interactive options or execute actions for a visualization task.
2.4. Performance (PRF): concerns the speed of working and the information retrieval.

We propose this set of usability criteria to address in particular the performance and user subjective satisfaction about the visualization tool.

<u>Category 2: temporal data dimension (T)</u>

2.5. Navigating in time (NGT): ensure the navigation in the visualization tool.
2.6. Data comparison (DTC): comparing visual objects in terms of the variables that define the data.
2.7. Changes over time (CHT): assess the identification, tracking and understanding of the data changes.

2.8. Overview (OV): the ability of the visualization tool to provide an overview of the data.
2.9. Details (DET): the ability of the tool to explore data at different levels of detail [Keim 2002].

The proposed data manipulation criteria focus on the ability of the tool to incorporate and understand the data. Selected criteria are common in several visualization evaluation methods.

Category 3: patterns discovery dimension (P)

2.10. Data and knowledge quality (DKQ): it is the belief to which the tool provides the user with: helpful and important data to mine and knowledge to integrate in the decision-making process.
2.11. Causal dependencies (CD): verify the exploration of the causal relationships between variables.
2.12. Visual prediction (VP): measures the performance of the visualization tool in the prediction task.

We suggest this list of criteria for verifying the ability of the tool to visually provide knowledge on the displayed data.

Table 3.1 presents the possible linguistic variables associated to the evaluation questions. These evaluations do not imply any representative value. The solution for treating uncertainty in users' evaluations is to express them in fuzzy numbers form corresponding to the linguistic variables. The participants could end the set 2 by presenting suggestions for improvement and/or extensions.

Table 3.1: Evaluation criteria

Criterion	Linguistic Variables	Evaluation question
Comprehensibility	Very-low, low below-medium, medium, above- medium, high, very-high	To what degree do you consider the information is comprehensible?
Information retrieval	Very-low, low, below-medium, medium, above- medium, very-high, high	Evaluate the speed of working and the information retrieval.
Speed of use	Very-low, low, below-medium, medium, above- medium, high, very-high	Qualify the speed of information's loading.
Navigating in time	Very-low, low below-medium, medium, above-medium, high, very-high	Specify the degree to which you find the visualization tool's navigation simple and comprehensible
Data comparison	Very-clear, clear, below-medium, medium, above medium, unclear, very-unclear	To what degree do you consider the visual objects comparison is clear in terms of data variables?
Changes over time	Very-clear, clear, below-medium, medium, above-medium, unclear, very-unclear	Qualify the identification, tracking and understanding of the data changes about visualization tool use.
Data and knowledge quality	Very-low, low below-medium, medium, above-medium, high, very-high	To what degree do you believe the tool provides helpful and important data to mine and knowledge to integrate in the decision-making process?
Causal dependencies	Very-low, low below-medium, medium, above-medium, high, very-high	Verify the exploration clarity of the causal relationships between variables
Visual prediction	Very-low, low below-medium, medium, above-medium, high, very-high	To what degree the tool is preferment in the prediction task?
Overview	Very-low, low, below-medium, medium, above-medium, high, very-high	To what degree the visualization tool is able to provide an overview of the data?
Details	Very-clear, clear below-medium, medium, above-medium, unclear, very-unclear	To what degree the visualization tool is able to explore data at different levels of detail?

3.2.3.2 Step 2: fuzzy logic application

The application of fuzzy set theory [Zadeh 1965] on the participants' answers is a suitable approach since its use of linguistic variables (verbal values) and its ability to deal with limited and vague information. It provides a formal tool for representing and analyzing survey results issued from questionnaire.

The fuzzy logic application in processing visualizations evaluation is expected to represent the mechanisms of human thought processes capable of resolving the visualization tools evaluation problem. It allows handling numerical and symbolic knowledge using natural language, representing human knowledge and reasoning by linguistic variables. It is based on a set of rules for reasoning and organized in three steps (cf. Fig 3.7):

1. **Fuzzification**: translating numeric variables in linguistic variables with a membership function defined in the interval [0,1]:
   μ_A: X --> [0,1] : *quantifies the grade of membership of the element in X to the fuzzy set A*

   Where A is the fuzzy set and each element of X is mapped to a value between 0 and 1.
2. **Motor inference**: applying the rules of the fuzzy logic method to exploit the tolerance for imprecision and uncertainty. A fuzzy rule is a linguistic IF-THEN construction that has the following form:
   If <input variable is A> then < output variable is B >

   Where: A and B are descriptors of knowledge pieces containing linguistic variables and the fuzzy rule expresses a relationship between inputs and outputs variables.
3. **Defuzzification**: producing crisp results given the fuzzy sets and their corresponding membership degrees.

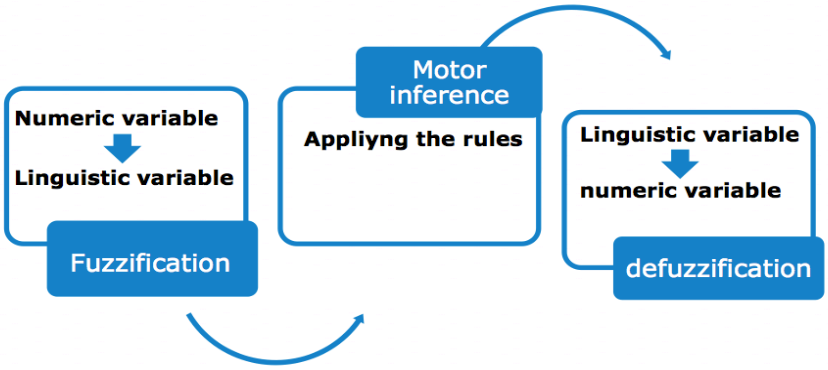

Figure 3.7: Fuzzy inference system

In the Fuzzy Logic method, we assign to each category linguistic variables using the membership function that allows the graphical representation of a fuzzy set. The figure 3.8 presents three examples of the fuzzy sets of the input variables of our method: usability, data manipulation and patterns discovery fuzzy sets. The x-axis denotes the universe of discourse and the y-axis denotes the membership degrees in the [0,1] interval.

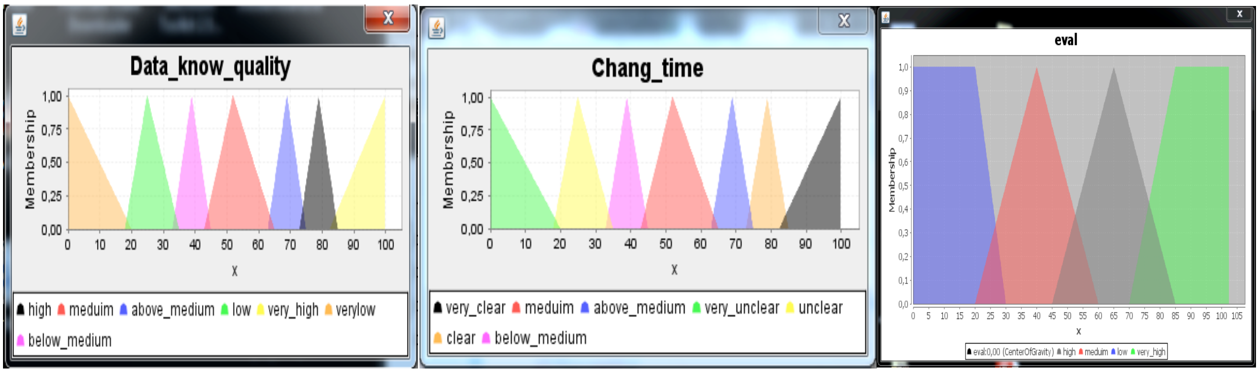

Figure 3.8: Three examples of fuzzy sets

In our context, we propose to use the Mamdani's fuzzy inference method [Zadeh 1965] that is the most frequently seen fuzzy approach. Mamdani's work was based on Zadeh's 1973 publication on fuzzy algorithms for complex systems and decision processes. The implication method (Mamdani's method) is:

$$\mu'_{conclusion}(y) = \mathrm{MIN}\,(\mu_{premise}(x_0),\ \mu_{conclusion}(y)) \qquad (1)$$

It integrates the most commonly defuzzification method, which is the centroid technique. It allows finding a point representing the Center of gravity (COG) of the output fuzzy set. It is the abscissa of the center of gravity of the area under the curve results:

$$\text{Output} = \int y.\mu(y).dy \Big/ \int \mu(y).dy \quad \text{with universe of discourse (all the considered output values)} \quad (2)$$

Rules base: the Fuzzy rules are generated from: (1) the experts reasoning and linguistic expressions and (2) the relationships between the variables. The fuzzy output is concluded by the degrees of realization and the consequent rules part. The rules should be aggregated to provide a membership of the output fuzzy variable to a consolidated fuzzy set. We consider that the rules are linked by an OR.

$$\mu_B(y) = \mathrm{MAX}\,[\mu_{Bi}(y)], \text{ where i belongs to indexes of enabled rules} \qquad (3)$$

Rule antecedent is created following sets of evaluations; however rule consequent is determined by evaluator (human expert) by assigning a linguistic value to linguistic variable usability of evaluated criteria. The evaluator chooses linguistic value of particular criterion according to the intersection of fuzzy number for the criterion with the membership functions of such criterion. Then, he/she defines a new fuzzy rule depending on linguistic value and his/her expert knowledge and experience. With each new evaluation a new fuzzy rule is added allowing learning to our inference module and more accurate results. Generating automatically a fuzzy rule base diminishes the subjectivity of establishing evaluation values of intelligent DSS visualization tools. The Figure 3.9 presents two examples of generated rules by our system.

```
RULEBLOCK

RULE 1: IF Comprehens IS verylow AND inf_retr IS verylow AND Speed IS verylow AND Navigation IS verylow AND Data_compar IS very_clear AND Chang_time IS verylow AND Data_know_quality IS verylow AND Causal_dependency IS verylow AND Visual_predic IS verylow THEN eval IS low;

.

.

.
```

```
RULE 29: IF Comprehens IS very_high AND inf_retr IS very_high AND Speed IS very_high AND Navigation IS very_high AND Data_compar IS very_unclear AND Chang_time IS very_high AND Data_know_quality IS very_high AND Causal_dependency IS very_high AND Visual_predic IS very_high THEN eval IS very_high;


END_FUNCTION_BLOCK
```

Figure 3.9: examples of generated rules

This research was subject of different publications (**[Brahmi et al. 2013] [Brahmiet al. 2014] [Amri et al. 2015]**).

In the following section, our presented methodological contributions (architectural and cognitive design as well as comprehensive evaluation approaches) were applied to a case study in the medical field.

3.3. Contributions validation

3.3.1 Medical application context

The importance of the medical decisions facing the vast volume of temporal data requires the use of viDSS [Augusto 2005]. Such system can be particularly useful in intensive care units for the fight against nosocomial infections. These infections are defined as being infections, which appear at least 48 hours after the patient admission at the hospital. They are considered as a public health problem, especially because of the increasing frequency of immunodeficiencies, the emergence of new microorganisms and the increasing bacterial resistance to some antibiotics. To detect these infections, the physician must follow the state of the patient according to the evolution of his/her data in time [Ltifi et al. 2012a].

This section is dedicated to introduce the design, development and evaluation of a dynamic viDSS for the fight against Nosocomial Infections (NI) in the ICU of Habib Bourguiba Hospital of Sfax, Tunisia based on the proposed cognitive model and MAS-based architecture. In fact, the NI topic has already been presented and discussed [Ben Ayed et al. 2010] and [Ltifi et al. 2013], 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. Since developed the system must be evaluated under the utility and usability dimensions. The utility evaluation assesses the predictive capability of the system. The usability evaluation aims to determine to what degree the Human Computer Interfaces (i.e. visualizations) are useful with respect to the user tasks. The usability evaluation is based on our third contribution (based on the fuzzy logic) aiming to determine how well visualizations generate insight to their users in reasonable time and with reasonable satisfaction [North 2005].

3.3.2 The viDSS design and development

We begin by presenting the way in which our viDSS has been implemented, building on: (1) the cognitive considerations (visible in Fig. 3.1) of the proposed visual KDD-based diagnosis architecture by following its three phases, and (2) the MAS-based architecture principles. Each phase allows the generation of a system prototype, as presented in Fig. 3.10:

- 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.

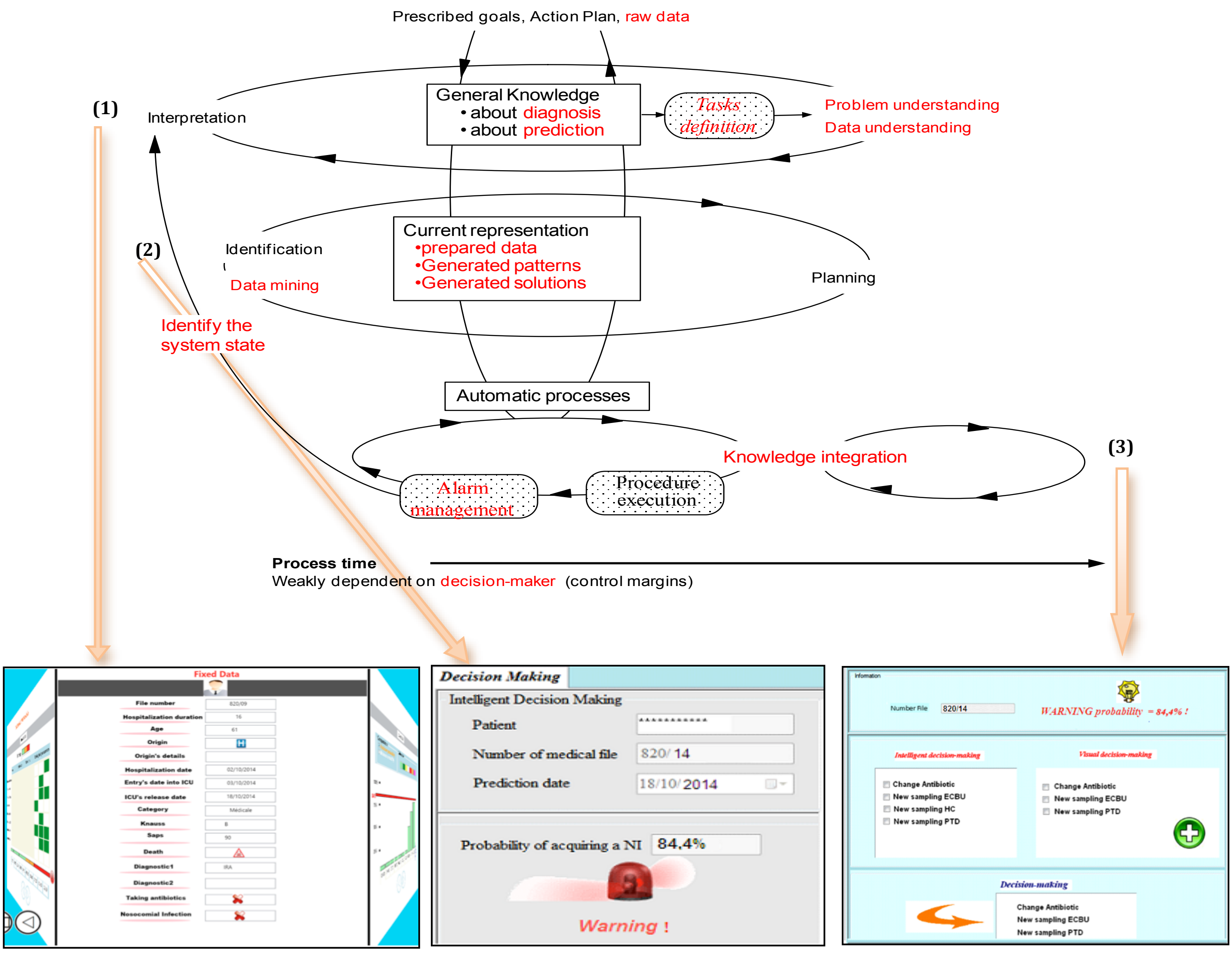

Figure 3.10: visual data mining based diagnosis architecture for the fight against nosocomial infections: each phase is associated with one or several adapted user interface (one in our case study)

The following tables describe the steps for applying cognitive and agent considerations to design interactive dynamic viDSS and develop its three prototypes.

3.3.2.1 Phase 1: data acquisition

Table 3.2 presents the different steps of phase 1 applied to our case study. This phase allows the application of relevant cognitive modeling considerations and the development of the correspondent agents 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 3.2: data acquisition

Cognitive modeling step	**Associated agent**	**Brief description**
Prescribed goals	*Coordinator agent* *Decision-maker interface*	- 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	*Coordinator agent* *Decision-maker interface agent*	- 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 [Keim 2002].
Raw data	*Coordinator agent* *Database agent*	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	*Coordinator agent* *Data miner interface agent*	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	*Coordinator agent* *Data miner interface agent* *Data preparation agent*	- 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 [Ltifi et al. 2012b], temporal data can be represented by the perspective wall technique [MacKinlay et al. 1991] [Ltifi et al. 2016]. This technique allows joining together temporal and structural

	Database agent *Visualization agent*	dimensions to present a global view (cf. Fig. 3.11). 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 on the walls. The timeline presented in Figure 3.11 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 into a wall with a temporal visualization technique: star, tabular and histograms.
Interpretation	*Coordinator agent* *Data miner interface agent* *Visualization agent*	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.

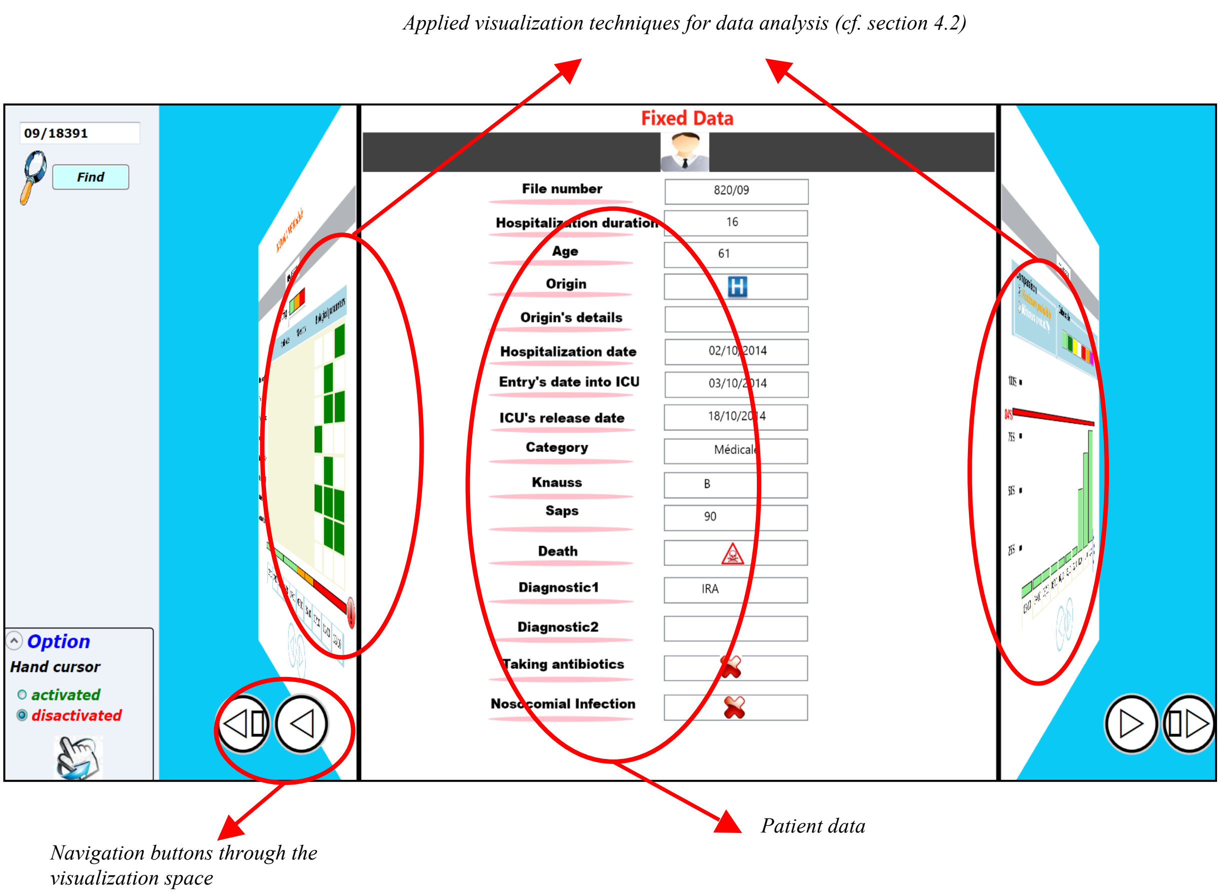

Figure 3.11: Perspective wall technique for patient data acquisition

3.3.2.2 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 3.3 presents the application of the different data analysis tasks performed by the associated agent.

Table 3.3: data analysis

Cognitive modeling step	**Associated agents**	**Brief description**
Current representation	*Coordinator agent* *Data-miner interface agent* *Database agent* *Visualization agent*	The following figures shows the star (cf. Fig. 3.12.(a)), tabular (cf. Fig. 3.12.(b)) and histograms (cf. Fig. 3.12.(c)) representations with the reusable component timeline. The data observed are represented in the form of a star (Fig. 3.12.(a)). This technique must have a timeline to navigate according to the temporal dimension of data [Daassi et al. 2004]. 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. 3.12.(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 (or biological parameters) over time through the observation of the change of the graphic objects color. 2. Compare acts (or biological parameters) over time. This comparison determines if a given act evolves differently beside another. 3. Identify concentration areas of acts (or biological parameters) and corresponding times. These acts were represented by specific color intensity. The histogram (cf. Fig. 3.12.(c)) allows the representation of quantitative data. It explicitly uses the relation of dependence between units of observation, by considering the data in two dimensions [Daassi et al. 2004]. 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	*Coordinator agent* *Data-miner interface agent*	The intelligent decision-making [Zhuang et al. 2013] 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 3.2). Each day, the decision on the patient depends on the NI probability.

	Database agent *Data mining agent* *Evaluation agent*	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) [Darwich 2001] [Murphy 2002]. The diagram of the DBN process is presented in Figure 3.13. More details on the design and implementation of this data mining technique are available in [Ltifi et al. 2012a]. The Figure 3.14 presents the result of DBN application of a patient registered in the ICU database. This result is presented in the form of a probability. To assess the quality of this result, the evaluation agent must be executed in order to validate or not the discovered model.
Planning	*Coordinator agent* *Data-miner interface agent*	Our dynamic viDSS 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.

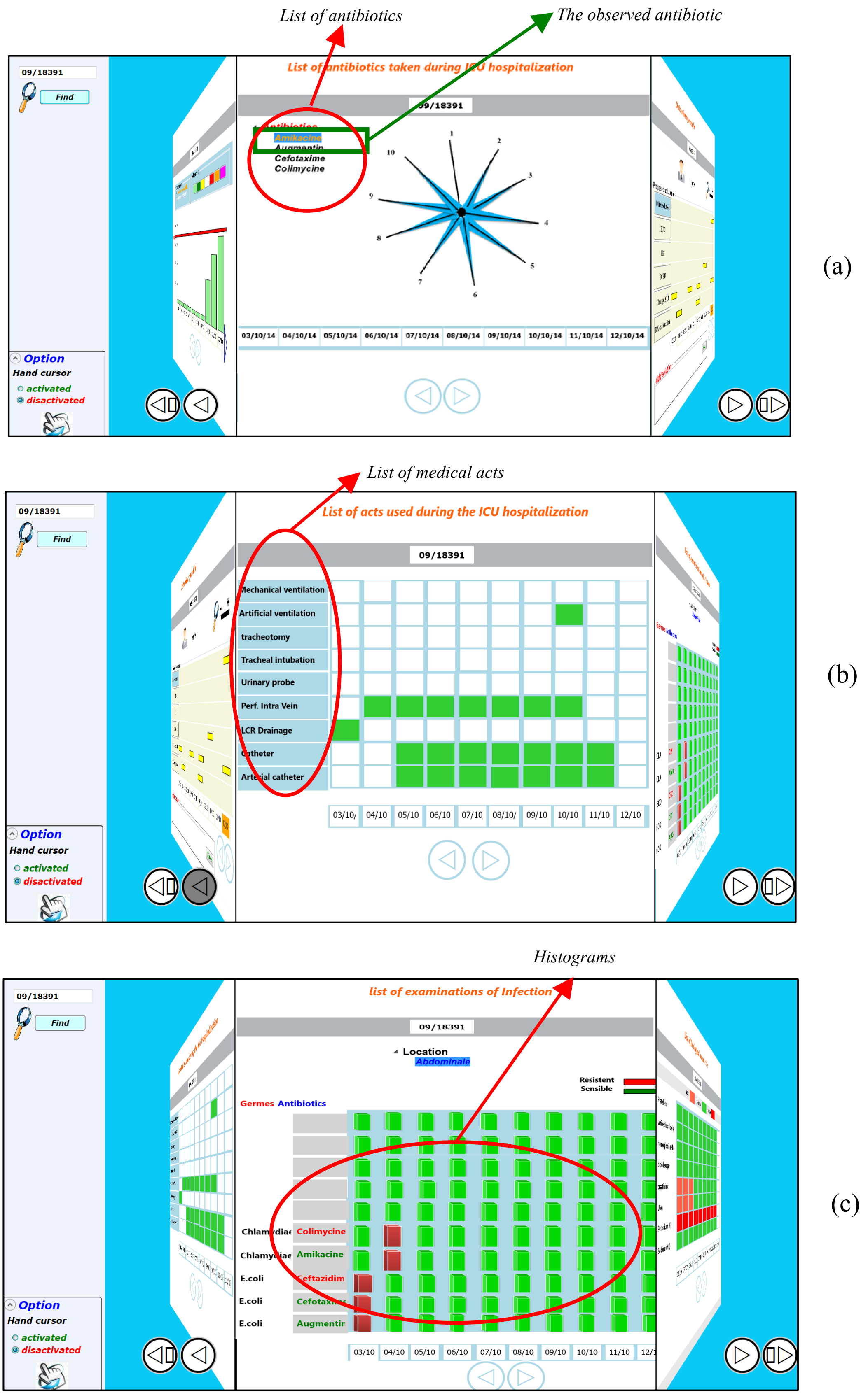

Figure 3.12: (a) Star representation for visualizing antibiotics catch, (b) The tabular representation for visualizing the acts, and (c) the Diagram for visualizing the infectious exams

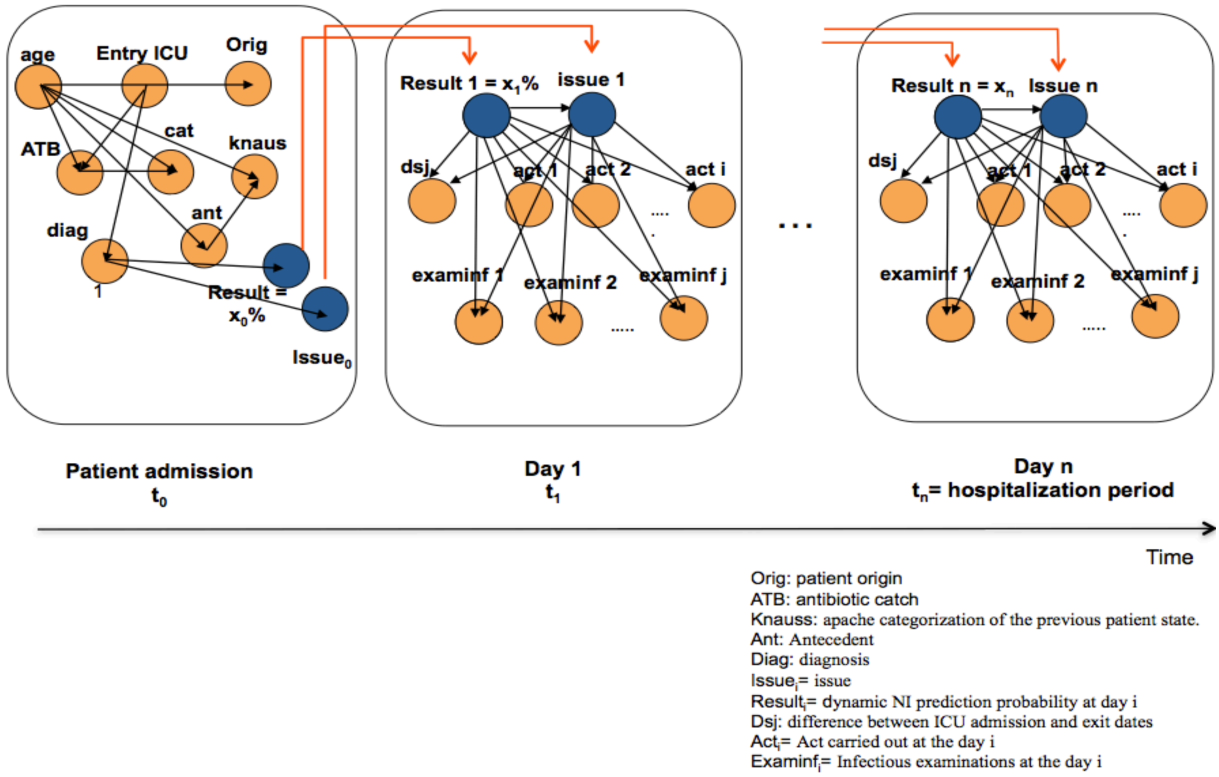

Figure 3.13: The DBN process diagram

3.3.2.3 Phase 3: decision-making

The first and second phases allow generating a set of possible solutions. Table 3.4 consists in identifying how agents integrate the best solution and how they incorporate the new information into the system knowledge base building on the cognitive considerations of phase 3.

Table 3.4: decision-making

Cognitive modeling step	**Associated agents**	**Brief description**
Automatic processes	*Coordinator agent* *Decision-maker interface agent* *Visualization agent*	The interpretation of the visual representations generates a set of possible solutions. For example, as shown in Figs. 3.12, the physicians extracted the following solutions: - In Figure 3.12.(a), 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 3.12.(c) helped the physician to decide on making new sampling PTD (diastolic pressure) and ECBU. These solutions are integrated into the iDSS in the visual decision-making panel visible in Figure 3.14. 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 3.14. 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	*Coordinator agent* *Decision-maker interface agent* *Knowledge integration agent*	The efficient running of the procedure execution allows knowledge integration; the executed solutions are incorporated in the knowledge base of the dynamic viDSS.
Alarm management	*Coordinator agent* *Decision-maker interface agent*	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.

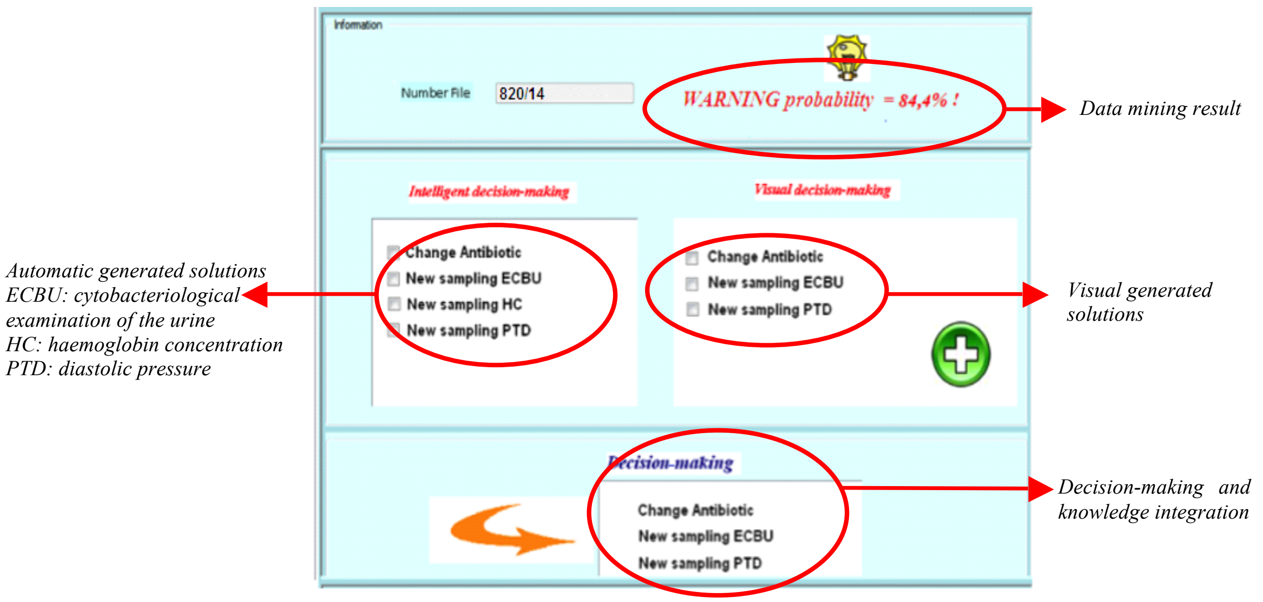

Figure 3.14: Decision-making and knowledge integration interface

In order to verify the effectiveness of the cognitive and multi-agent viDSS, we focus in the following section to its utility and fuzzy logic-based usability evaluation.

3.3.3 The viDSS evaluation

The objective of this section is to highlight the evaluation of the developed cognitive muli-agent viDSS. The interest, at this level, is in two traditional dimensions of evaluation in the HCI field: utility and usability [Nielsen 1993] [Ivory et al. 2001] [Sears et al. 2008] [Shibl et al. 2013] [Ben Ayed et al. 2013].

3.3.3.1 Utility evaluation

To evaluate the utility of our Dynamic viDSS, the verification of its predictive capability is investigated. We have generated the confusion matrix (cf. table 3.5) 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 3.5: confusion matrix

<table>
<tr><td colspan="2" rowspan="3"></td><td colspan="3">Predicted results</td></tr>
<tr><td colspan="3">Data Mining technique (DBN) results combined with visual interpretations</td></tr>
<tr><td>Yes</td><td>No</td><td>Total</td></tr>
<tr><td rowspan="3">Observed results</td><td>Yes</td><td>10 (a)</td><td>4 (b)</td><td>14</td></tr>
<tr><td>No</td><td>8 (c)</td><td>34 (d)</td><td>42</td></tr>
<tr><td>Total</td><td>18</td><td>38</td><td>56</td></tr>
</table>

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 Dynamic viDSS 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.

3.3.3.2 Usability evaluation

This section describes the process of Dynamic viDSS usability evaluation and presents the main results. It refers to the assessment of the User Interfaces, including the temporal visualization techniques by testing them with representative users. For this reason, we have applied our proposed evaluation method to evaluate the two developed visualizations: the perspective wall and the star representation. Participants are divided into two groups with 6 members. Each group is interested in evaluating a specific visualization.

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

1) Profile 1: no knowledge of 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 in the area; the users of this profile are physicians.

The number of participants in the evaluation process is twelve, whose characteristics are presented in Table 3.6.

Table 3.6: profile of the participants in the evaluation process

Users' characteristics	
Number of participants	12
Gender	7 men 5 women
Age	Average age: 39 years Minimum age: 20 years Maximum age: 57 years
Profile	4 with profile 1 4 with profile 2 4 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 Dynamic viDSS
7) Second interview for gathering user feedback on using the two visualizations of the viDSS. It consists in answering a 9-item questionnaire in which each question, with multiple choices, is evaluated by a note ranging between 0 and 10. We assigned six users per tool.
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 usability questionnaire was implemented to allow participants entering, for each item (criteria), a value from 1 to 10 and helping to calculate corresponding scores. Once all responses have been recorded, evaluation scores will automatically appear on the final user interface. Two conducted surveys are fulfilled to evaluate the perspective wall and the star representation tools.

A. **Perspective wall evaluation:** Table 3.7 shows the answers given by the first set of participants about the perspective wall tool. Average answers are positive since they are more than 6 in the 10-degrees scale.

Table 3.7: participants' responses to the questionnaire on the perspective wall evaluation

Participant	Results
	Perspective Wall Tool (1st group of participants)
Physician 1 G1	COM=7, ETU=7, SPU=7, PRF=8, NGT=8, DTC=6, CHT=6, OV=9, DET=7, DKQ=8, CD=6, and VP=5.

	Activated Rules: R26 and R27 E=7.48 ➔ projection: 28% Very High and 59% High
Physician 2 G1	COM=9, ETU=8, SPU=7, PRF=8, NGT=7, DTC=9, CHT=7, OV=7, DET=7, DKQ=8, CD=6, and VP=4. Activated Rules: R26 and R27 E= 7.24 ➔ projection: 10% Very High and 60% High
HI professional 1 G1	COM=6, ETU=7, SPU=6, PRF=7, NGT=8, DTC=5, CHT=6, OV=7, DET=8, DKQ=8, CD=5, and VP=6. Activated Rules: R14, R15, R17, R18, R23, R24, R26 and R27 E= 6.93 ➔ projection: 79% High
HI professional 2 G1	COM= 7,ETU = 9, SPU=7, PRF=6, NGT=8, DTC=6, CHT=7, OV=8, DET=7, DKQ=7, CD=4, and VP=6. Activated Rules: R26 and R27 E= 7.1 ➔ projection: 5% Very High and 70% High
Assistant 1 G1	COM=4, ETU=8, SPU=6, PRF=6, NGT=8, DTC=6, CHT=7, OV=6, DET=6, DKQ=8, CD=7, and VP=7. Activated Rules: R15, R18, R24 and R27 E=5.9 ➔ projection: 5% Meduim and 65% High
Assistant 2 G1	COM=7, ETU=8, SPU=6, PRF=6, NGT=7, DTC=5, CHT=6, OV=5, DET=8, DKQ=8, CD=7, and VP=8. Activated Rules: R15, R18, R24 and R27 E=5.5 ➔ projection: 25% Meduim and 50% High

In Figure 3.15 is visible an example of user interface presenting the answers of a physician on the perspective wall evaluation. According to the participant answers (cf. Fig. 3.13), the system activates two rules (R26 and R27). Applying the Mamdani method, the evaluation value obtained is 7.48 (cf. Figure 3.16). By projecting this value on the curve, we find that the evaluation is 59% high and 28% very high (cf. Figure 3.16).

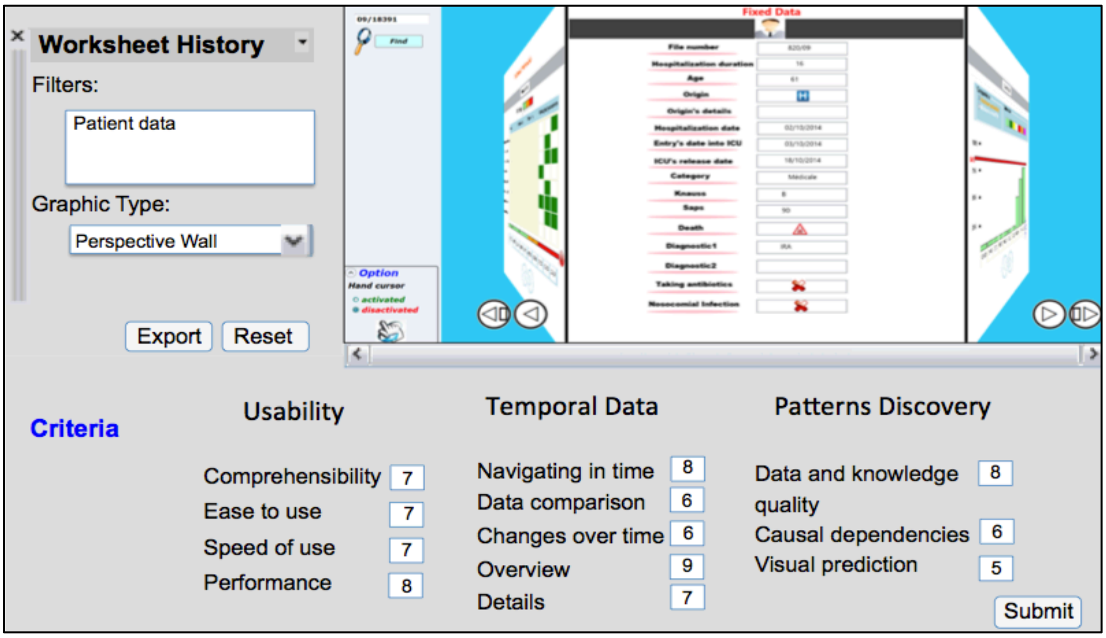

Figure 3.15: Questionnaire user interface of the perspective wall tool

Figure 3.16: Evaluation result of the perspective wall for the first physician

B. Star representation evaluation: Listed in the table 3.8 are the values given by the second set of participants for each criterion aggregated for the Lifelines tool.

Table 3.8: participants' responses to the questionnaire on the star representation evaluation

Participant	Results
	Star representation (2nd group of participants)
Physician 1 G2	COM= 8, ETU = 8, SPU=7, PRF=6, NGT=7, DTC=6, CHT=6, OV=7, DET=5, DKQ=8, CD=4, and VP=6. Activated Rules: R23, R24, R26 and R27 E=7,1 ➔ projection: 3% Very High and 68% High
Physician 2 G2	COM=9, ETU=7, SPU=7, PRF=6, NGT=6, DTC=6, CHT=7, OV=6, DET=4, DKQ=8, CD=5, and VP=4. Activated Rules: R23, R24, R26 and R27 E=5.59 ➔ projection: 18% Meduim and 52% High
HI professional 1 G2	COM=7, ETU=7, SPU=6, PRF=5, NGT=7, DTC=5, CHT=6, OV=7, DET=3, DKQ=7, CD=5, and VP=6. Activated Rules: R14, R15, R17, R18, R23, R24, R26 and R27 E=5.7 ➔ projection: 16% medium and 60% high
HI professional 2 G2	COM= 8,ETU = 8, SPU=7, PRF=6, NGT=7, DTC=6, CHT=5, OV=7, DET=6, DKQ=8, CD=4, and VP=5. Activated Rules: R23, R24, R26 and R27 E=5.01 ➔ projection: 45% Meduim and 25% High
Assistant 1 G2	COM= 7, ETU = 8, SPU=6, PRF=5, NGT=8, DTC=6, CHT=7, OV=6, DET=6, DKQ=7, CD=6, and VP=7. Activated Rules: R14, R15, R17, R18, R23, R24, R26 and R27 E= 7.1 ➔ projection: 3% High and 72% Very High
Assistant 2 G2	COM= 7,ETU = 8, SPU=6, PRF=6, NGT=7, DTC=5, CHT=6, OV=7, DET=5, DKQ=8, CD=6, and VP=6. Activated Rules: R14, R15, R17, R18, R23, R24, R26 and R27 E=5.25 ➔ projection: 35% Meduim and 34% High

Figure 3.17 shows an example presenting the answers of a HI professional (in the second group of participants) about the star representation. According to the user answers (cf. Fig. 3.17), the system activates eight rules (R14, R15, R17, R18, R23, R24, R26 and R27). The associated evaluation value obtained is equal to 5.7 (Figure 3.18)). By projecting this value on the curve, we find that evaluation is 16% medium and 60% high (cf. Figure 3.18).

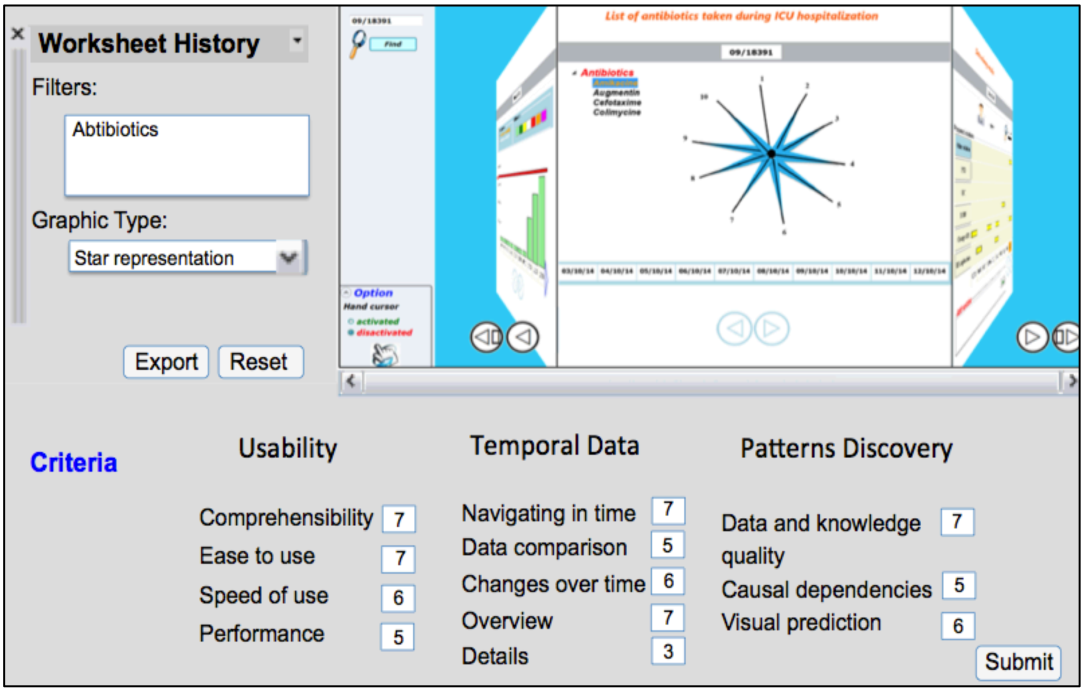

Figure 3.17: Questionnaire user interface of the star representation tool

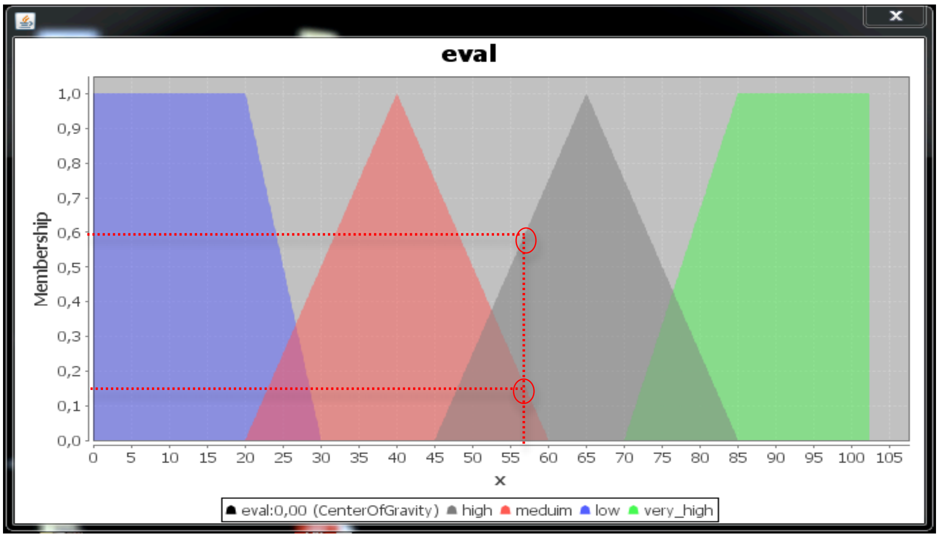

Figure 3.18: Evaluation result of the star representation for the first Health worker

Experiment results discussion: the evaluation results of the visualization tools about the three user profiles are close and the activated rules are sometimes repeated, which allowed to model the vagueness in the initial judgments obtained from users evaluation. These different evaluation values show that users with their different levels of expertise have generally appreciated the use of these visual representations of the intelligent DSS for the fight against nosocomial infections. The use of the fuzzy logic allowed transforming the input evaluation scores into linguistic variables and the linguistic evaluation of overall intelligent DSS visualization tools. The projection of the calculated results proves that the evaluation is probabilistic and cannot be a simple numeric value but that the uncertainty is an inherent part of the evaluation and hence is a crucial component in decision-making.

Evaluation procedure discussion: our method is quite general and could be applied to different kinds of temporal visualization tools of intelligent DSS. We briefly discuss such application in the following points:

- The first set of questions aims at collecting the participants' background information. This step allows judging the entire evaluation results.
- The training session is required for all new visualization tools. It is ended by: (1) asking participants to find answers to temporal data queries and visually analyze hidden relationships in the dataset, and (2) give information about the questions' difficulty and the time of their completion.
- The second set of questions stores overall user opinion about the visualization tool usability, temporal data manipulation and patterns discovery capacity. Such questions are necessary for visual analytics tools evaluation.
- And finally, the second step that consists of applying the fuzzy logic to analyze this overall user opinion and eliminate uncertainty in interpreting input variables and generating final evaluation result.

3.3.3.3 Discussion

The conducted utility and usability evaluation was based on a preliminary study of the system architecture 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 3.9 shows that the overall performance is better than the results obtained in the two previous versions of our system presented in [Ben Ayed et al. 2010] and [Ltifi et al. 2013].

Table 3.9: comparison of the different versions of the iDSS

<table>
<tr><th></th><th>The first version of DSS [Ben Ayed et al. 2010]</th><th>The second version of dynamic DSS [Ltifi et al. 2013]</th><th>Current version of dynamic DSS</th></tr>
<tr><td>Study level</td><td>Master</td><td>Ph.D. thesis</td><td>Post-Doc</td></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
- Multi-agent architecture</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>- 12 participants
- Three user profiles
- 12-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.</td><td>- The system is dynamic.
- The prediction results are measured.
- The usability evaluation is</td><td>- The system is dynamic.
- The prediction results are measured and the efficacy rates were increased.</td></tr>
</table>

	- The usability evaluation is not done in situ.	done in situ.	- The usability evaluation is based on the fuzzy logic technique for intelligent analysis - The usability evaluation is done in situ and presents interesting results.

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 dynamic viDSS, the challenge is to decode the decision-makers behaviors. Many of these behaviors are, in fact, largely modulated and directed by cognitive agents for functional representations [Jang et al. 2012]. Therefore, it seems necessary for the accurate analysis of a dynamic multi-agent based 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.

3.4. Conclusion

This chapter has presented some works that propose cognitive and architectural methods in order to provide better modeling of visual intelligent decision support systems. These methods were applied for the development of a viDSS for the fight against nosocomial infections in the intensive care units. We have evaluated the prototype under the utility and usability dimensions. Concerning the usability evaluation, we have proposed and applied a new evaluation method that consists of two steps: (1) collecting users background information and their overall opinion (in terms of values) about the tool to evaluate, and (2) applying the fuzzy logic to analyze these values.

Chapter 4 : Conclusions and research perspectives

4.1. Introduction

Decision support systems based on visual data mining is currently gaining wide importance in the research community. This report has presented the research that I have conducted in that direction. Since my master degree (2007), I have been working in research of intelligent decision-making. I explored in theory and in practice, design and evaluation methods. In the next section (§ 4.2) I present a synthesis of my contributions. Based on this analysis, I propose some research perspectives that I plan to work on (§ 4.3).

4.2. Synthesis of Contributions

In this document, I articulated my various contributions around the viDSS development problematic. Three main areas were investigated: cognitive modeling, multi-agent systems and usability evaluation.

Through my work I have highlighted three different contributions:

- First, we have defined a cognitive approach to effectively design and implement a complex DSS based on data mining and visualization technologies in a dynamic environment. This approach aims to take into account the decision maker behaviors.
- Secondly, we have proposed a complementary theoretical framework for viDSS based on Multi-agent System. Intelligent agents represented a significant solution to optimize the knowledge management and improve the decision-making quality in the real-time environment. The design of viDSS is realized based on the first and second contributions. The application context was the fight against nosocomial infections in the hospital Intensive Care Unit.
- Then, we have introduced an evaluation method based on the fuzzy logic to study the conceptual and practical implications of the proposed system design. The proposed method is applicable for evaluating any visualization generated by iDSS for visual analysis purposes.

These contributions allowed making the dynamic viDSS more efficient in terms of prediction and usability results (cf. Table 3.6). The characteristic of complementarity that I wanted to make in my research work, between cognitive architectural design and evaluation of viDSS, appear, at present, as increasingly critical.

In the remainder of my research work, I plan to continue to model and assess such kind of dynamic system to be able to offer original and best-adapted solutions to decision-makers needs. Thus, the work presented above naturally opens up a number of perspectives that can be summarized around the following areas of research:

- A cognitive enhancement of existing visual data mining process,
- The proposition of a knowledge visualization framework. The knowledge represents the discovered patterns by dynamic data mining algorithms.

- The application of the Neural Network technique for the visualizations evaluation learning,

We plan to continue to apply our future contributions to the enrichment of the medical viDSS prototype for use in the ICU of the Habib Bourguiba Hospital of Sfax, Tunisia.

4.3. Research perspectives

4.3.1 Cognitive visual data mining process

Different tracks are available to us on the cognitive modeling aspect of our work. In the short term, we plan to study the visual data mining process for dynamic decision-making. Such process allows the decision-makers to interactively search temporal information, detect important relations and identify interesting models to be used for the decision support. The visualization supports this process by involving decision-makers to exploit their human capacity for perceiving, abstracting and understanding available complex data.

Our theoretical proposal aims to adapt the visual analytics process of [Wijk 2005] under the temporal dimension of data, the data mining tasks and the cognitive aspects. Such adapted process suggests three main steps to be followed by the decision-makers for creating cognitive visual data mining representations (cf. Figure 4.1).

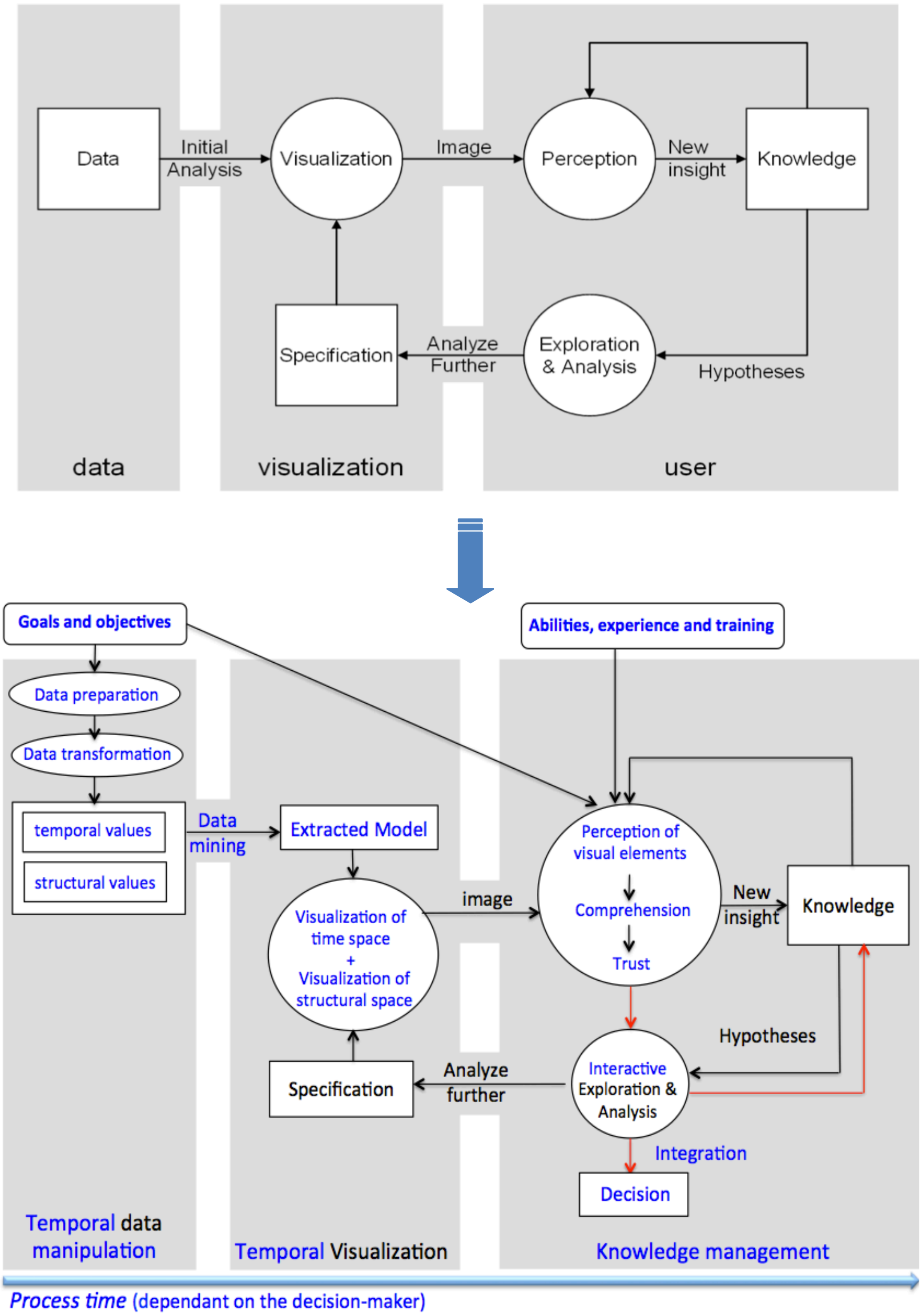

Figure 4.1: From the visual analytics process to the enhanced visual data mining process

Step 1: temporal data manipulation: the proposed process begins with a set of defined goals and objectives of the real-time decision-making problem. Related temporal data sources must be selected. While raw data can contain errors and missing values [Fayyad et al. 1996], it seems critical to prepare them in order to construct the temporal data set to be used for exploration. In fact, applying data mining on data, which has not been carefully assessed for complex dynamic problems, can generate highly misleading patterns. Therefore, prediction results depend on the quality of the prepared temporal data. A temporal data is defined as the combination of temporal and structural dimensions.

Temporal data transformation aims to let the user (i.e. decision-maker) understand what data to manipulate. It is an analytical transformation. It consists of extracting from the temporal values the time representation (granularity, periodicity and dimensionality) and from the structural values the data representation.

Data mining techniques will be applied to the prepared and transformed temporal data to extract models that might help decision-makers to interactively evaluate and make appropriate alternatives. In dynamic DSS, the choice of the data mining technique must consider the dynamic aspect of the decisions [McNaught et al. 2009] [Ltifi et al. 2012a].

Step 2: temporal visualization: the data mining technique(s) involve(s) extracting useful models from the prepared and transformed temporal data, which the user did not already know about. These output models take the form of probabilities, decision trees, rule induction, regression models or neural networks [Han et al. 2006]. They are characterized by their accuracy and understandability [Linoff et al. 2011], especially with their temporal aspect. It is then important to translate them into a visual solution.

As there are several ways to graphically represent a model, the used visualizations must be selected to maximize the value for the user. The design of such visualizations involves the user's needs understanding. Since the viewer (i.e. decision maker) is not an expert in data modeling, it seems crucial to translate the extracted model into a more natural image for him/her. For this purpose, we propose to design the time space and the structural space of the model by: (1) transforming the time values onto displayable time space, and (2) transforming the analytical representation of the structural data onto values to be displayed.

The result of this step is a model visual mapping composed by a perceptible rendering of its temporal dimension combined with a perceptible rendering of its structural dimension. Such combination must fit together and must inspire confidence as the visualization is traversed. It must include the specification that involves the ability to navigate data values over time and to explore in some optimal way the interaction modes such as zooming, filtering, labeling.

Step 3: Knowledge management: once provided the visualization, the decision-maker perceives the image. Such human perception is affected by the initial system objectives but also by the user abilities, domain experience and performed trainings. These are cognitive aspects, which the decision-makers can depend on to perceive the data-mining model.

Behind the model perception, the decision-maker must understand it. A model comprehension consists of utilizing the model to understand what is actually going on. It must involve the context. Visualizing the output model allow each decision-maker discussing and describing the logic behind it with the other decision-makers. The comprehension of the visual model logic is part of building the decision-makers' trust in the results. If the decision-makers can understand what has been discovered in the context of their decision issues, they will trust it and make it into use. Knowledge is the direct result of comprehending and trusting the temporal model, which is with the use of the problem solving.

The knowledge management step depicts the knowledge as feeding interactive exploration. The decision-maker interacts within the temporal visualization using the specification consisting of a set of manipulation techniques. The manipulation of the visualization dynamically allows the decision-maker to get a feel for the test whether something really counter-predictive happens. The *Exploration-visualization-perception* process continues until the decision-maker could see the actual knowledge behind the model. Finally, knowledge will be integrated into the with decision support.

It should be noted that this work is still in its theoretical stage. It remains to validate it by the development of a visual data mining technique and compare its predictive ability relative to others already under use (such as the Dynamic Bayesian Network technique).

4.3.2 Visualization of data mining patterns

We aim in this work to assist decision-makers to analyze and interpret the generated patterns by the data-mining algorithm using an appropriate visualization process (cf. Fig. 4.2). To achieve this goal we plan to propose a knowledge visualization framework based on three perspectives of [Burkhard 2005]:

1. Knowledge type: to identify the type of knowledge that needs to be transferred (declarative, procedural knowledge, experimental, etc.)
2. Recipient (decision-maker) type: to identify the target group and the context of the recipient (individual, team, an organization or a network of persons).
3. Visualization type: While the first two taxonomies are established, the visualization type perspective is new. To this context, we aim to contribute by proposing a cognitive process (cf. Fig. 4.2) to:
   - Select the appropriate visualization technique according to the data type and the possible tasks to be performed by the decision-maker.
   - Transform the textual data of the patterns into interactive graphic elements, and
   - Assess the created visual representation by applying a cognitive model (or propose one) in order to minimize the cognitive load exerted by the decision-maker to make the right decision.

   In fact, the study of the cognitive status of the decision-maker improves the knowledge visual representation. We propose in particular to study the patterns extracted using: (1) the dynamic Bayesian Networks, and (2) the dynamic associations rules.

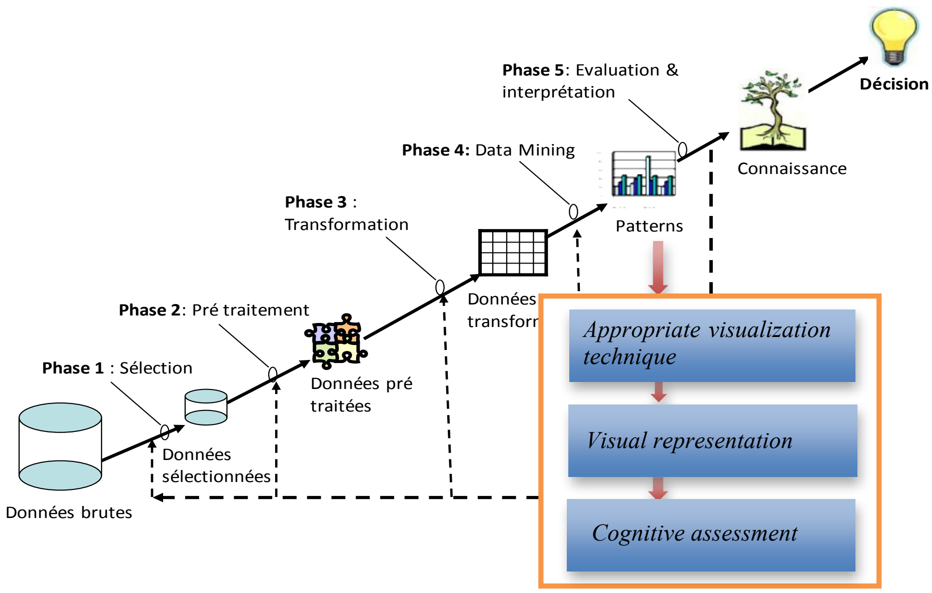

Figure 4.2: the knowledge visualization process

4.3.3 Neural Network for the visualization evaluation learning

The goal of this work is to improve the usability evaluation methodology, based on the fuzzy logic (cf. section 3.2.3), to assess the temporal iDSS visualizations. It is output is a crisp number representing the evaluation score to measure these visualizations usability.

In fact, we propose to use a neural approach to natural language processing in evaluation procedure for learning and adaptation. The method uses natural language expression to interactively communicate with its human environment; it follows the conversation's context and understands the meaning of each sentence of user evaluation, and then executes it. It is capable of learning in real-time, based on user environmental feedback and past experience, and is capable of adjusting its internal perception of the world with every interaction with the environment that holds some change or innovation. For this reason, we plan to implement novel learning algorithm to learn new abstract terms and to adjust existing ones in performing its evaluation task.

Our proposition consists of:

1. The design of a dynamic intelligent methodology capable of interactively communicate with its human environment using natural language. It interacts with the user via text input and combines into a single mechanism: (1) neural network learning and adaptation capabilities with (2) the numeric representation of the imprecise natural real world (outputs of our fuzzy system presented in the section 3.3.3.2). It is capable of processing naturally expressed data having been initialized with a minimal initial knowledge that reflects past experience acquired from examples.
2. The presentation of real world examples to demonstrate the principles of our application. The proposed methodology will be developed for evaluating the existing medical viDSS under use in the Teaching Habib Bourguiba Hospital of Sfax, Tunisia and compare the results relative to those presented in the section 3.3.3.2. Moreover, such methodology must not only be limited to this system's type and the procedure remains functional based on input criteria changes according to the different environment aspects.

4.4. Conclusion

This document has presented the main research I have developed after finishing my doctorate. Working in the REGIM-Lab, I had the opportunity to search for decision support based on visualization and knowledge discovery, a research area that interested me since my Master in computer science.

Decision-making is an area that must respond to the continuous evolution of visual dara mining technology to ensure taking the best decision. Therefore, a lot of work has still to be done. I described in this document some of the research perspectives I plan to work in the next years. However, new challenges will also emerge, and new research will be necessary to address these challenges.

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Contribution to the design and evaluation of visual intelligent Decision Support Systems, application to the healthcare domain

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الخلاصة :
في هذا التقرير التجميعي للتأهيل وصفنا العمل الرئيسي بشأن النمذجة (المعرفي والمعماري) والتقييم الذكي المحرز في مجال أنظمة دعم اتخاذ القرار التي تعتمد على استخراج البيانات المرئية هذا العمل يفتح عددا من الآفاق ذات صلة باستخراج إدراكي وبصري للبيانات وتصور للمعرفة.

Résumé : Dans ce rapport de synthèse d'habilitation universitaire nous avons décrit nos principaux travaux de modélisation (cognitive et architecturel) et d'évaluation intelligente (basée sur la logique floue) réalisés dans le domaine des Systèmes Interactifs d'Aide à la Décision (SIAD) basés sur la fouille visuelle des données. Ce travail ouvre un certain nombre de perspectives en relation avec la fouille cognitive et visuelle de données ainsi que la visualisation de connaissances.

Abstract: In this synthesis report of HDR, we described the main modeling (cognitive and architectural) and intelligent evaluation (based on Fuzzy Logic) made in the field of Interactive Systems Decision Support (DSS) based on visual data mining. This work opens up a number of perspectives in relation with cognitive visual data mining and knowledge visualization.

المفاتيح :
نظام دعم اتخاذ القرار، استخراج البيانات، التصور، النمذجة الإدراكية، المعمار المتعدد الوكيل، التقييم

Mots clés : Système d'Aide à la Décision, fouille de données, Extraction de Connaissances à partir de Données, Visualisation, Modélisation cognitive, Multi-Agent, Evaluation.

Key words: Decision Support System, Data Mining, Visualization, Knowledge Discovery from Data, Cognitive Modeling, Multi-Agent, Evaluation.